Gain controls based on luminance and contrast in the early visual system

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GAIN CONTROLS BASED ON LUMINANCE AND CONTRAST IN THE EARLY VISUAL SYSTEM

A dissertation submitted to the
SWISS FEDERAL INSTITUTE OF TECHNOLOGY ZURICH

for the degree of
Doctor of Natural Sciences

presented by

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Zusammenfassung


proportional zur Helligkeit, und die Verstärkung des zweiten Schaltkreises proportional zur Potenz des Kontrasts.


Summary

The responses of neurons in the early visual system are shaped by two powerful, fast gain control mechanisms, luminance gain control and contrast gain control. These mechanisms rapidly regulate the gain and integration time of neurons depending on the locally prevalent luminance and contrast. For large luminance or contrast, gain and integration time are reduced, thus optimizing the use of the limited dynamic range of the responses.

Current models of gain control are tailored to predict responses to simple, laboratory stimuli and do not generalize to arbitrary, complex stimuli such as those occurring in natural vision. An important limitation of current models is that they lack a definition of luminance and contrast that applies to arbitrary stimuli. Moreover, luminance and contrast gain control have typically been studied separately, using stimuli of fixed contrast or luminance. Thus, little is known about how gain control affects responses during natural vision, where both luminance and contrast vary.

Our goal was to develop a model of luminance and contrast gain control that provides a unified description of the large body of results obtained with simple stimuli and at the same time can make predictions of responses to natural stimuli. To constrain the design of such a model, we characterized gain control in the responses of the lateral geniculate nucleus (LGN) of anesthetized and paralyzed cats.

In a first set of experiments, we asked whether the effects of luminance gain control and contrast gain control are independent of each other. Independence has been assumed most studies of gain control, although it was never directly tested. We characterized the effects of gain control on both gain and integration time by estimating the impulse response of LGN neurons for many combinations of luminance and contrast. We found that over ranges similar to those encountered during natural vision, luminance and contrast have independent effects on the impulse response. This independence is likely to have evolved as an adaptation to the properties of natural images, in which luminance and contrast are statistically independent.

In a second set of experiments, we focused on formulating a general definition of contrast. We estimated the impulse response of LGN neurons from the responses to stimuli of various contrast and spatial extent and found that increasing the extent of a stimulus, similarly to increasing its contrast, reduces gain and integration time. The effects of spatial extent on the impulse response were consistent with a model in which contrast is integrated over a region of visual space roughly coextensive with the receptive field, with locations close to the center being weighted more than far locations.

We incorporated these experimental findings into a model of luminance and contrast gain control. In the first stage of the model the stimulus is convolved with a spatio-temporal receptive field (RF), which has center-surround organization in space and biphasic impulse response in time. The output of the convolution is shaped by luminance and contrast gain control. The gain control mechanisms are modeled with two series of resistor-capacitor circuits, whose conductances depend on luminance and contrast. Luminance is a filtered version of the light
falling on the RF-surround while contrast is the integrated output of a pool of subunits covering the RF. The subunits do not undergo contrast gain control, but are in all other respects identical to the model neuron. The model provides good fits of the responses to simple stimuli, with luminance gain inversely proportional to luminance and contrast gain decreasing as a power of contrast.

We used this model of gain control to predict the responses to natural movies and compared its predictions to those of the receptive field alone. Because we constrained model parameters from responses to simple stimuli we were able to compare the two models on an equal footing, despite their different complexity. Even though the receptive field correctly predicts the timing of the response elicited by natural movies, it over- or underestimates response amplitude when luminance or contrast differ from their average values. Because gain is adjusted dynamically in the full model, it provides better predictions of the responses.

In conclusion, we formulated a model of LGN responses that captures a large number of nonlinear phenomena that have been separately ascribed to gain control. The model effectively summarizes the complex computations performed in the retina, and describes the input to the visual cortex.
Preface

This work has been performed in the laboratory of Matteo Carandini and is the fruit of a close collaboration with Vincent Bonin. It was initiated in 2001 at the Institute of Neuroinformatics in Zurich. It was pursued from December 2002 until September 2005 at the Smith-Kettlewell Eye Research Institute in San Francisco.

Part of this work is in press or has appeared in conference abstracts. Chapter 1 was the subject of a poster presentation at the 2002 meeting of the Society for Neuroscience (Mante et al. 2002). Chapters 2, 3, and 4 are in press (Mante et al. 2005c) and were the subject of a poster presentation at the 2004 Computational and Systems Neuroscience Conference (Mante et al. 2004b) and of an oral presentation at the 2005 meeting of the Vision Sciences Society (Mante et al. 2005b). Chapter 5 was the subject of an oral presentation at the 2003 meeting of the Society for Neuroscience (Mante et al. 2003). Chapter 6 was the subject of a poster presentation at the 2004 meeting of the Society for Neuroscience (Mante et al. 2004a). Chapters 7 and 8 were the subject of a poster presentation at the 2005 Computational and Systems Neuroscience Conference (Mante et al. 2005a).

Relevant to this work are contributions of a closely-related project led by Vincent Bonin (Bonin 2005). This project also was the subject of presentations in international conferences (Bonin et al. 2002, 2004b, 2003a, 2005a, 2003b, 2004a) and part of it is in press (Bonin et al. 2005b).
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General Introduction

A central goal of visual neuroscience is the development of models of neuronal responses to visual stimuli. Such models are aimed at providing the simplest possible mathematical description of the computations underlying the responses of a neuron. These models provide a unified framework that can link apparently unrelated phenomena, they summarize the processing performed by complex neuronal circuits, and they guide the research of the biophysical mechanisms underlying the responses (e.g., Ulinski et al. 1999).

Current models of the computations occurring in the early visual system are limited in their scope. As one ascends the visual hierarchy from the retina to the lateral geniculate nucleus (LGN) and to the primary visual cortex, linear models of visual responses account for a progressively smaller fraction of the computations performed by the neurons (Wandell 1995). Nonlinear systems are notoriously difficult to study as no tractable, standard approach exists to fully characterize their properties (Olshausen and Field 2005). Most physiologists have thus resorted to simple, laboratory stimuli to isolate one particular nonlinear property of the neurons. This choice has led to models of visual responses that, though successful, are tailored to small sets of simple stimuli. Not much is known about how the nonlinear properties described by these models affect the responses to complex stimuli like those encountered during natural vision.

Two nonlinear mechanisms that have been extensively studied with simple stimuli and that have potent effects on the responses of neurons throughout the visual system are luminance gain control and contrast gain control (Shapley and Enroth-Cugell 1984). These gain control mechanisms regulate the gain and integration time of neurons and are thought to match the limited dynamic range of the responses to the distribution of light intensities in the stimulus (Shapley and Enroth-Cugell 1984; Rodieck 1998). At locations in visual space where luminance or contrast are high, gain and integration time are reduced, while at locations where luminance or contrast are low, gain and integration time are increased. Luminance and contrast are easily defined for simple stimuli like gratings, where they correspond, respectively, to the mean of the distribution of light intensities and to the standard deviation over the mean (Shapley and Enroth-Cugell 1984). However, defining luminance and contrast in natural stimuli is less straightforward. In fact, the lack of satisfactory definitions of luminance and contrast substantially limits the applicability of current models of gain control. Moreover, luminance gain control and contrast gain control have typically been studied in isolation, by using stimuli in which either luminance or contrast were fixed. Thus, little is known about how gain control mechanisms shape the responses during natural vision, when both luminance and contrast vary.

Our goal was to develop a model of gain control that provides a unified description of the large body of results obtained with simple stimuli and whose formulation is general enough to allow predictions of responses to natural stimuli. We characterized gain control in the responses of the LGN, which receives and processes a large fraction of the output of the retina and projects its output to primary visual cortex. A model that captured the effects of gain control during natural vision promises to come close to a complete description of how the LGN responds to
visual stimuli. Such a description would implicitly summarize the computations performed by the retinal and thalamic circuitry and amount to a full understanding of the visual inputs received by primary visual cortex, and would thus represent a fundamental step towards a complete understanding of the computation performed by the early visual system.

The receptive field

The fundamental component of any model of LGN responses is the receptive field, which accurately describes the responses to stimuli of fixed luminance and contrast. The receptive field specifies a set of weights that the neuron applies when summing light intensities over space and time. It can be thought of as a linear filter, whose convolution with the stimulus yields the membrane potential of the neuron. The receptive field of LGN neurons consists of a center and a larger, antagonistic surround (Hubel and Wiesel 1961), whose response is subtracted from that of the center. The center and surround each integrate light intensities over a circular region of visual space and weigh contributions from the recent and less recent past with opposite polarity (Reid et al. 1997; Cai et al. 1997). The receptive field accurately predicts how LGN responses depend on attributes of simple stimuli. For instance, the spatial profile of the receptive field underlies the spatial-frequency selectivity of LGN neurons (Kilavik et al. 2003; Einevoll and Plesser 2002; So and Shapley 1981) while its temporal profile underlies the selectivity for temporal frequency (Benardete and Kaplan 1999; Kremers et al. 1997). The receptive field also captures the basic features in the responses to natural stimuli, as long as luminance and contrast do not vary substantially over time (Dan et al. 1996).

Gain control and simple stimuli

Because of the effects of gain control, the receptive field alone does not predict the responses of LGN neurons when the luminance and contrast of simple stimuli are varied. For instance, the receptive field predicts that for a fixed contrast the responses should grow linearly with the luminance of a stimulus while for a fixed luminance they should grow linearly with contrast. The responses of LGN neurons, on the other hand, are often invariant with respect to stimulus luminance (as in retina, Shapley and Enroth-Cugell 1984) and they saturate with contrast (Derrington and Lennie 1984; Sclar et al. 1990). Moreover, the receptive field predicts that the selectivity for temporal frequency is fixed for any given neuron, while in LGN neurons the selectivity for temporal frequency strongly depends on luminance and contrast. At low luminance or low contrast the neurons respond best to low temporal frequencies, while for increasing luminance or contrast the responses to high temporal frequencies are selectively enhanced (Shapley and Enroth-Cugell 1984; Sclar 1987).

The effects of luminance and contrast on the selectivity for temporal frequency imply that the temporal profile of the receptive field is not fixed, but rather is shaped by luminance gain control and contrast gain control. The temporal profile of the receptive field corresponds to the impulse response of the neuron, i.e. its response to a brief pulse of light. The impulse response can be derived from the temporal frequency selectivity of the neuron (Victor 1987; Benardete and Kaplan 1999; Lee et al. 1994). For increasing luminance or contrast, the impulse response becomes progressively smaller (reflecting the smaller gain of the neuron) and progressively faster.
(reflecting the smaller integration time)(Purpura et al. 1990; Victor 1987; Baccus and Meister 2002). The effects of gain control on the size of the impulse response explain why responses are invariant with luminance and saturate with contrast. The effects of gain control on the time course of the impulse response explain why responses at high temporal-frequencies are selectively enhanced at high luminance or high contrast, thus modifying the overall selectivity for temporal frequency of a neuron.

Luminance gain control and contrast gain control are known to be driven by measures of luminance and contrast that are computed very rapidly and very locally. Both the gain and integration of neurons in the early visual system are adjusted within 150 ms of a change in the luminance (Saito and Fukada 1986; Enroth-Cugell and Shapley 1973a; Lankheet et al. 1993b) or contrast (Victor 1987; Albrecht et al. 2002) of a stimulus. Luminance gain control is driven by the average light intensity falling onto a region of the visual field that is not larger than the surround of the receptive field (Enroth-Cugell and Shapley 1973b; Enroth-Cugell et al. 1975; Cleland and Freeman 1988; Lankheet et al. 1993b). Similarly, contrast gain control is driven only by stimuli lying within the receptive field (Solomon et al. 2002; Bonin et al. 2005b).

**Gain control and natural stimuli**

Gain control is likely to play an important role in shaping the responses of LGN neurons during natural vision. The eyes typically fixate a given location for only 200-300 ms, and typical eye movements place the receptive field of neuron in the early visual system over regions of widely different luminance and contrast (Mante et al. 2005c).

However, even though luminance gain control and contrast gain control have been extensively studied with simple stimuli, very little is known about their role during natural vision. The few studies that have addressed this issue have yielded somewhat contradictory results. The most influential study of responses to natural stimuli in the LGN suggests that gain control plays no role in the responses to such stimuli (Dan et al. 1996). Dan and collaborators modeled the responses of LGN neurons with a linear receptive field, whose output is rectified to obtain firing rates. The authors first estimated the receptive field from the responses to noise stimuli (Cai et al. 1997; Reid et al. 1997) and then used the estimated receptive field to predict the responses to natural movies. Dan and collaborators argued that even though the model does not include gain control mechanisms, its predictions account for all the explainable variance in the measured responses. Thus, one could conclude that gain control affects only the responses to simple stimuli, but not the responses to more complex, natural stimuli.

On the other hand, several later studies have concluded that gain control mechanisms do affect the responses to natural stimuli. In particular, Stanley and collaborators demonstrated that during the responses to natural movies the gain and integration time of LGN neurons are not fixed, but rather are adjusted dynamically throughout the movie (Lesica et al. 2003; Stanley 2002). In agreement with the expected effects of gain control, gain and integration time are small when the luminance or contrast in the movie are high. Such adaptive changes are not consistent with the model of Dan et al. (1996), in which the receptive field is fixed over time. Further indirect evidence for a role of gain control in natural vision comes from a very different approach. Rather
than attempting to predict the responses of LGN neurons to natural stimuli, Stanley et al. (1999) tried to reconstruct natural stimuli from the responses they elicited in a large population of LGN neurons. If LGN neurons were essentially linear, then one should be able to reconstruct the stimuli with linear decoding techniques. However, linear decoding allows only an approximate reconstruction of the stimulus and fails to capture its details. Even though this result could be explained by a number of nonlinear mechanisms, it is at least consistent with the effects of gain control.

These later studies are not necessarily inconsistent with the results obtained by Dan and collaborators (1996). In fact, it is possible that the natural movies used by Dan et al. contained only small variations in luminance and contrast, which did not cause noticeable changes in the gain and integration time of the neurons. Under such conditions, LGN responses can indeed be accurately described by a fixed, linear receptive field.

The contributions of gain control to the response to natural stimuli could be easily assessed with a model of gain control that is general enough to predict the responses to arbitrary stimuli. However, presently such a model does not exist. Current models of visual responses in the early visual system provide only partial accounts of the effects of gain control. For instance, by far most models of luminance gain control describe only responses to spatially uniform stimuli (e.g., Fuortes and Hodgkin 1964; Sperling and Sondhi 1968; Baylor et al. 1974; Brodie et al. 1978) while models describing both spatial and temporal aspects of luminance gain control do not account for the effects of contrast gain control (Gaudiano 1994; Sperling 1970; Dahari and Spitzer 1996). Similarly, models of contrast gain control typically describe only its spatial (Sceniak et al. 2001; Cavanaugh et al. 2002a; Bonin et al. 2004b) or temporal (Victor 1987) properties and do not account for the effects of luminance gain control. One model that implemented both luminance gain control and contrast gain control (van Hateren et al. 2002) was designed to predict the responses to spatially uniform stimuli and thus cannot be used to predict responses to natural stimuli.

To overcome these limitations, in this thesis we developed a model of LGN responses that incorporates mechanisms for both luminance gain control and contrast control and that describes both their spatial and temporal aspects. Crucially, the model is general enough to predict responses to natural stimuli. The fundamental element of the model is the receptive field, whose impulse responses is dynamically modified by luminance gain control and contrast gain control based on local measures of luminance and contrast. To constrain the design of the model and to estimate its parameters we characterized the effects of gain control on the responses of LGN neurons to large sets of simple stimuli. Having estimated the parameters of the model with simple stimuli, we then tested the model on responses to natural stimuli.

The model is designed to capture the responses X-cells, one of the two major classes of relay neurons in the LGN (Hochstein and Shapley 1976b). The properties of Y-cells, the other major class of relay neurons, are in many ways similar to those of X-cells. However, responses of Y-cells to simple stimuli have revealed additional nonlinear mechanisms that are absent in X-cells. These additional nonlinearities have been shown to be closely related to the mechanisms underlying contrast gain control in X- and Y-cells (Hochstein and Shapley 1976b; Victor and
Shapley 1979b; Hochstein and Shapley 1976a; Enroth-Cugell and Freeman 1987; Shapley and Victor 1979; Freeman 1991). Thus, the general formulation of contrast gain control developed in this thesis might also represent an important step towards a general model of Y-cell responses to arbitrary stimuli.

**Thesis overview**

In Chapter 1 we illustrate the strengths and the limits of a model of LGN responses that is based exclusively on the receptive field. We show that the receptive field accurately captures the selectivity of LGN neurons to the attributes of moving gratings but that it fails to fully account for the responses to natural stimuli. In part, the shortcomings of the receptive field can be accounted for by the lack of a realistic spike-generation mechanism in the model. However, we show evidence that luminance gain control and contrast gain control shape the responses to our natural stimuli and are likely to contribute to the shortcoming of the receptive field.

In Chapter 2 we then start characterizing the effects of luminance gain control and contrast gain control on LGN neurons. We show that the effects of gain control on the responses to moving gratings can be fully captured by allowing the impulse response of the neurons to vary with the luminance and contrast of the stimuli. Moreover, we demonstrate that gain control operates very rapidly, as both the gain and the integration time of the impulse response are adjusted within 150 ms of a change in luminance or contrast. Unlike previous studies, we estimate how the impulse response varies with both luminance and contrast, which will allow us (in Chapter 4) to test whether the effects of luminance gain control and contrast gain control are independent of each other.

In Chapter 3 we show that slow adaptation mechanisms do not contribute to the estimated impulse responses. Because of slow adaptation, the responsivity of neurons in the retina and LGN is reduced after long presentations of appropriate high-contrast stimuli. However, we find that the estimated impulse responses do not depend on the history of visual stimulation. This result validates our methods and suggests that slow adaptation is engaged only by a limited set of stimuli.

In Chapter 4 we demonstrate that the effects of luminance gain control and contrast gain control are independent of each other. Indeed, over ranges of luminance and contrast similar to those encountered during natural vision the impulse response is well described by a separable model that incorporates the assumption of independence. In the separable model the impulse response is described as the convolution of three filters, one that is fixed for a given neuron and two that are variable. The first variable filter depends only on luminance and describes the effects of luminance gain control, while the second filter depends only on contrast and describes the effects of contrast gain control. The accuracy of the separable model greatly simplifies the design of a unified model of gain control. Moreover, it strengthens and validates a large body of research that implicitly assumed that luminance gain control and contrast gain control are functionally independent.

In Chapter 5 we develop a parametric description of the variable filters of the separable model. We describe the two filters as the impulse responses of two resistor-capacitor (RC)
circuits, each consisting of a resistor and a capacitor. While the capacitance of the capacitors is fixed, the conductance of the first resistor depends on luminance, while the conductance of the second resistor depends on contrast. This simple model captures the steady-state effects of gain control on both the gain and integration time of the impulse response. Moreover, by comparing how the conductances depend on luminance and contrast we quantify the differences between the effects of luminance gain control and contrast gain control.

In Chapter 6 we study how contributions of stimuli at different locations in visual space are combined to yield a measure of local contrast. We demonstrate that increasing the size of gratings has the same effects on the impulse response as increasing its contrast. The effects of size are consistent with a model in which local contrast (i.e. the signal driving contrast gain control) is computed by integrating contrast over the suppressive field, a region of visual space coextensive with the receptive field. This result is the basis for a definition of local contrast that can be applied to natural stimuli. It also provides a unified account of the findings of a number of studies on contrast gain control, which typically quantified only its spatial properties or only its temporal properties.

In Chapter 7 we develop a dynamic model of gain control that can be used to predict responses to arbitrary stimuli. The dynamic model is an extension of the steady-state model of Chapter 5, and includes definitions of local luminance and local contrast that can be applied to arbitrary stimuli. Local luminance is a filtered version of the light falling on the receptive-field surround while local contrast is the integrated output of a pool of subunits covering the receptive field. We validate the dynamic model on the responses to large sets of simple stimuli whose luminance and contrast vary over both space and time.

In Chapter 8 we test the dynamic model on the responses to natural stimuli and compare its predictions to those of a simpler model that is based only on the receptive field. Because we estimated the parameters from responses to simple stimuli we can compare the two models on an equal footing, despite their different complexity. Even though the receptive field correctly predicts the timing of the response elicited by natural stimuli, it over- or underestimates response amplitude when luminance or contrast differ from their average values. Because in the full model response gain is adjusted dynamically, it provides better predictions of the responses. This result provides a stringent validation of the dynamic model and demonstrates that gain control shapes LGN responses during natural vision.
Chapter 1

The receptive field and its limitations

1.1 Introduction

The most fundamental component of any model of LGN responses is the receptive field. The receptive field specifies a set of weights that the neuron applies when summing light intensities over space and time. The receptive field can be thought of as a linear filter, whose convolution with the stimulus yields the membrane potential of the neuron. In most models of LGN responses, the membrane potential is simply rectified to obtain firing rates (e.g., Dan et al. 1996). In more realistic models the rectification stage is preceded by a mechanism generating bursts (Lesica and Stanley 2004) or is entirely replaced with a spike generation mechanism (Smith et al. 2000; Keat et al. 2001).

The receptive field of LGN neurons consists of a center and an antagonistic surround (Hubel and Wiesel 1961). The center and surround each integrate light intensities over a small, circular region of visual space. The surround region is concentric with the center region but larger, and its output has opposite polarity and is delayed with respect to the output of the center (Xu et al. 2002; Kremers et al. 2004; Cai et al. 1997; Reid et al. 1997). This antagonistic arrangement favors responses to light distributions that vary over space and thus result in different responses of the center and surround. Similarly, both the center and the surround favor light distributions that vary over time, since the contributions from the recent and remote past are weighted with opposite polarity (Saul and Humphrey 1990; Cai et al. 1997; Reid et al. 1997).

Models based on the receptive field accurately predict how the responses of LGN neurons depend on many attributes of simple stimuli. In particular, the spatial profile of the receptive field is typically modeled as a difference of Gaussians (Rodieck 1965; Enroth-Cugell and Robson 1966). This model predicts the spatial frequency selectivity of LGN neurons (Kilavik et al. 2003; Einevoll and Plesser 2002; So and Shapley 1981) and can be extended to capture the weak selectivity for orientation (Soodak et al. 1987). Similarly, simple descriptive models of the temporal profile of the receptive field capture the selectivity for temporal frequency (Benardete and Kaplan 1999; Kremers et al. 1997) as well as interactions between spatial and temporal frequency (Enroth-Cugell et al. 1983; Dawis et al. 1984).

However, neurons throughout the early visual system are endowed with gain-control mechanisms that affect the responses to simple stimuli in ways that are not predicted by the receptive field. In particular, luminance gain control and contrast control regulate the gain and integration time of neurons based on the locally prevalent luminance and contrast (Shapley and Enroth-Cugell 1984) and thus responses depend on luminance and contrast in ways that are not predicted by the receptive field. For instance, as a consequence of gain control, the responses of LGN neurons saturate with contrast (Kremers et al. 2001; Sclar et al. 1990) and are suppressed by large stimuli (Solomon et al. 2002; Jones et al. 2000; Ozeki et al. 2004). Moreover, because of
gain control, the temporal-frequency selectivity of neurons in the early visual system depends on luminance and contrast (Sclar 1987; Shapley and Victor 1978; Benardete and Kaplan 1999; Tranchina et al. 1984; Purpura et al. 1990; Shapley and Enroth-Cugell 1984) an effect that is not predicted by the receptive field alone.

Even though luminance gain control and contrast gain control have been extensively studied with simple stimuli, very little is known about their role during natural vision. The few studies that have addressed this issue have yielded somewhat contradictory results. On one hand, Dan and collaborators (1996) have argued that linear predictions based on the receptive field capture all the features in the responses to natural stimuli, suggesting that gain control plays no role in these responses. On the other hand, it has been shown that the gain and integration time of LGN neurons are not fixed during the responses to natural movies (Lesica et al. 2003; Stanley 2002). Rather, gain and integration time are being dynamically adjusted to the prevalent luminance and contrast, in agreement with the expected effects of gain control. It is possible that the differences between the conclusions of these studies simply reflect differences in the respective stimuli. It is possible that the natural movies used by Dan et al. (1996) contained only small variations in luminance and contrast, which did not cause noticeable changes in the gain and integration time of the neurons. Under such conditions, LGN responses can indeed be accurately described by a fixed, linear receptive field.

To address these issues, in this chapter we followed the approach of Dan et al. (1996) and tried to predict the responses of LGN neurons to natural movies solely on the basis of the receptive field. We estimated the receptive field by fitting a model to the response to a small set of simple stimuli. These stimuli differed in their spatial and temporal frequency as well as in their horizontal and vertical position in visual space. Similar methods to estimate the receptive field have been used in a number of studies on retinal ganglion cells and LGN neurons (Rodieck 1965; Enroth-Cugell and Robson 1966; Kilavik et al. 2003; Einevoll and Plesser 2002; So and Shapley 1981; Soodak et al. 1987; Benardete and Kaplan 1999; Kremers et al. 1997; Enroth-Cugell et al. 1983; Dawis et al. 1984). We then used the estimated receptive field to predict the measured responses to natural movies. Unlike Dan et al. (1996), we found that the receptive field captures only the basic features, but not the details of the responses to the movies. We will argue that these shortcomings of the receptive field are consistent with the well known effects gain control.

1.2 Results

1.2.1 The receptive field of LGN neurons

We modeled the receptive field of LGN neurons (Figure 1-1) as the difference of a center and surround filter (Rodieck 1965; Enroth-Cugell and Robson 1966; Cai et al. 1997). Both filters are separable in space-time, meaning that they are described as the product of their spatial (top) and temporal (right) profiles. The spatial profiles of center and surround are described as 2d-Gaussians. The two Gaussians have matching locations in visual space but differ in size. The temporal profiles are described with a simple biphasic function (Cai et al. 1997). In the simplest case, the temporal profiles of center and surround have identical shapes. However, in some neurons the surround filter is delayed with respect to the center filter (as in Figure 1-1, right).
When there is no delay between center and surround the receptive field is separable, since the temporal profiles of center and surround are identical. In this simplest case, the impulse response of the receptive field (i.e. its response to a brief pulse of light) corresponds to the temporal profile of the center (or of the surround, since the two are identical). On the other hand, the receptive field is not separable when the surround is delayed with respect to the center (as in Figure 1-1, center). In this case the impulse response depends not only on the temporal profiles but also on the spatial profiles of center and surround.

However, throughout the thesis we will always refer to the temporal profile of the center as the \textit{impulse response of the receptive field}, even though strictly speaking the two are equivalent only for a vanishing delay between center and surround.

![Figure 1-1. The model receptive field of LGN neurons. The receptive field is obtained by subtracting contributions of the center (thin) and surround (thick). Both center and surround are separable in space-time and have Gaussian profile in space (top) and biphasic impulse response in time (right). In this ON-center cell the response of the surround is delayed with respect to the center (right) and thus the resulting space-time receptive field (center) is inseparable.]

1.2.2 Responses to simple stimuli

Responses based on the receptive field provide excellent fits of the responses to simple stimuli like gratings. Here we use the receptive field to predict the selectivity to 4 basic attributes of gratings: spatial frequency (Figure 1-2A), temporal frequency (Figure 1-2B), horizontal position (Figure 1-3A), and vertical position (Figure 1-3B). From fits of the selectivity to these attributes we constrain all the parameters of the receptive field.

The selectivity for spatial frequency of a typical LGN neuron is bandpass; the response of the neuron peaks at an optimal spatial frequency and falls off for larger or smaller frequencies (Figure 1-2A). Since we measured the selectivity of the neuron with gratings drifting with constant temporal frequency, we consider only the \textit{fundamental} component of the response, i.e. the one at the temporal frequency of the stimulus. Both the amplitude (Figure 1-2A) and phase
(Figure 1-2C) of the fundamental response are needed to constrain the parameters of the receptive field.

As expected, the receptive field predicts how the amplitude and phase of the response depend on the spatial frequency of the grating (Figure 1-2A and C, blue). When the receptive field is separable, the predictions of the spatial frequency selectivity depend only on the spatial profiles of the center and surround, which are fully constrained by the amplitude of the responses (Figure 1-2A). However, with respect to the amplitude of the response, increasing the delay between center and surround has very similar effects than decreasing the strength of the surround. These two contributions can be disentangled by considering also the phase of the responses (Figure 1-2C), which especially at high temporal frequencies depends strongly on the delay between center and surround (Enroth-Cugell et al. 1983).

![Figure 1-2. The selectivity of an LGN neuron to spatial and temporal frequency. Stimuli are drifting gratings varying in spatial (A and C) and temporal (B and D) frequency. We plot the amplitude (A and B) and phase (C and D) of the measured (dots) and predicted (blue) first harmonic of response at the temporal frequency of the stimulus. Error bars are plotted only for amplitude and represent the standard deviation. A: Response amplitude as a function of spatial frequency. B: Response amplitude as a function of temporal frequency. C: Response phase as a function of spatial frequency. D: Response phase as a function of temporal frequency.](image)

The receptive field also predicts how the responses of the neuron depend on the temporal frequency of the stimulus (Figure 1-2B and D). In this case, the predictions of the model (blue)
depend only on the temporal profile of the receptive field. In fact, they depend mostly on the
temporal profile of the center, since we measured the selectivity for temporal frequency with
gratings of optimal spatial frequency, which elicit only weak responses in the surround. This is
only a minor limitation, however, since center and surround have similar temporal profiles (Cai et
al. 1997).

Finally, the receptive field predicts how the responses of the neuron depend on the position of
a small stimulus (Figure 1-3). We measured the selectivity for stimulus position with drifting
gratings that were shown through a circular window covering only a small portion of the
receptive field. By moving the center of the window along the horizontal (A and C) or vertical (B
and D) axis of the screen we then selectively stimulated different portions of the receptive field.

Figure 1-3. The selectivity of an LGN neuron to stimulus position. Stimuli are drifting gratings shown
through a small circular window. We varied the horizontal and vertical spatial position of the stimulus
center. Spatial and temporal frequency are optimal. Same neuron and conventions as in Figure 1-2. A:
Response amplitude as a function of horizontal position. B: Response amplitude as a function of vertical
position. C: Response phase as a function of horizontal position. D: Response phase as a function of
vertical position.

The selectivity for position measured with these stimuli does not directly reflect the spatial
profile of the receptive field. For instance, the responses in Figure 1-3A are not symmetric around
the position eliciting the strongest response, despite the fact that the receptive field itself is
circularly symmetric. This asymmetry in the responses is a consequence of the delay between the
center and the surround. Indeed, when the receptive field is not separable, its space-time
representation locally contains oriented features (Figure 1-1, center). These oriented features imply that the receptive field is selective for the direction of motion of gratings that are appropriately positioned on the receptive field (Adelson and Bergen 1985). The structure of the receptive field is such that the preferred direction of a small grating always points towards the center of the receptive field. Crucially, since the direction of motion is fixed across all positions in Figure 1-3A, the gratings moves either towards or away from the receptive field center depending on its position along the horizontal axis.

The precision with which the receptive field describes the responses to simple stimuli is reflected in the quality of the predictions shown in Figure 1-2 and Figure 1-3. On average over all stimuli, the predictions of the receptive field explain 98% of the stimulus-driven variance in the amplitude of the responses measured in the example cell. Thus, the mean square distance between the predictions and the average responses across trials are barely larger than the variance in the trial-by-trial noise (B.5.3). We obtained similar prediction qualities for the other neurons in the population (Figure 1-5A); over the whole population, the predictions explain 96% (median) of the stimulus-driven variance in the measured responses.

These high values, however, might also reflect our definition of response. In fact, so far we have used the receptive field only to predict the fundamental component of the response, which oscillates at the temporal frequency of the stimulus. Thus, since the convolution between the stimulus and the receptive field contains only the fundamental component, we have evaluated the quality of the predictions only on the fraction of the response that can be predicted by the receptive field. Of course, this choice is no guarantee that the response does not contain additional components that the receptive cannot predict.

In fact, the receptive field often fails to predict the full response of the neurons. This is illustrated in Figure 1-4, where we plot the average firing rates (gray) obtained in response to three gratings, drifting at 3, 8, and 20 Hz. These three stimuli are part of the set that we used to measure the temporal frequency selectivity of the neuron (Figure 1-2B and D). The predictions of the receptive field (blue) are simply obtained by rectifying the predicted membrane potential.

At all three temporal frequencies the measured firing rates (Figure 1-4, gray) are more transient than the predicted ones (blue). However, by far the largest deviations between the measured and predicted responses occur at the lowest frequency, 3 Hz. At this low frequency, each cycle of the measured responses begins with a short, prominent transient. These transients are a well studied feature of LGN responses; they correspond to bursts of actions potentials generated by a specialized, slow calcium channel (see next section. For a review see Sherman 2001). Bursts occur only at low temporal frequencies, since de-inactivation of the responsible channels requires a hyperpolarization lasting about 100 ms. On the other hand, the transient character of the response at high frequencies is likely to be caused by the spike generation mechanism itself, which is known to generate spikes trains whose trial-by-trial variability is smaller then predicted by the rectified membrane potential (Pillow et al. 2004; Keat et al. 2001). Crucially, however, the receptive field correctly predicts the fundamental component in the responses to these stimuli (Figure 1-2B and D), despite the differences between the measured and predicted firing rates.

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Figure 1-4. Fits of the firing rate responses to simple stimuli. Same neuron as Figure 1-2. Stimuli have optimal spatial frequency; temporal frequency is shown on the left. Firing rates (gray) were obtained by filtering the spike trains with a running Gaussian window (std = 5ms) and averaging over 4 repeats. Predictions of the receptive field are shown in blue. The amplitude and phase of the first harmonic in the response are shown in Figure 1-2B and D. Fit quality for the three stimuli is 51, 76 and 82% (top to bottom).

However, the differences between the measured and predicted firing rates are reflected in the quality of the predictions, which are substantially worse than the predictions of the fundamental component. For instance, the receptive field explains 51, 76 and 82% of the stimulus-driven variance in the firing-rates responses shown in Figure 1-4 (top to bottom). Across all the stimuli used in Figure 1-2 and Figure 1-3, the predictions explain 84% of the stimulus-driven variance in the firing-rates (compared to 98% on the fundamental component). Over the entire population (Figure 1-5B), the median quality is 73% (compared to 96%).

Figure 1-5. Quality of the receptive-field predictions of responses to simple stimuli. The quality of predictions is the fraction of stimulus-driven variance in the responses explained by the predictions of the receptive field. A: Quality of predictions measured on the fundamental component of the responses. B: Quality of predictions measured on the firing-rates. Arrows point to medians of the distributions, 96% (A) and 73% (B).
1.2.3 Tonic and burst firing

The spikes generated by LGN neurons can be grouped into two categories: tonic spikes and burst spikes (for a review see Sherman 2001). Both tonic and burst spikes are generated when the membrane potential reaches spiking threshold, thus initiating the sequence of events resulting in an action potential (Hodgkin and Huxley 1952). However, tonic and burst spikes differ in the history of the membrane potential that led to the generation of the action potential.

The cell membrane of relay neurons in the LGN contains a specialized calcium channel that generates characteristic firing patterns in these neurons. These calcium channels open when the membrane potential is depolarized above a given activation threshold. Typically, the activation threshold lies between the resting potential of the neuron and the spiking threshold. The opening of the channels results in a long lasting calcium influx that further depolarizes the membrane potential and eventually inactivates the channels. The resulting depolarization typically causes the membrane potential to cross the spiking threshold, and results in a burst of 2-6 spikes. Burst spikes are defined as the spikes generated by the onset of the calcium current; all the other spikes are called tonic spikes.

Figure 1-6. Tonic and burst spikes in the responses to simple stimuli. The contributions of putative tonic (gray) and burst spikes (black) to the firing rate are shown separately. Same data and predictions as in Figure 1-4.

Burst and tonic spikes can be identified from intracellular recordings of the membrane potential and also, under appropriate circumstances, from extracellular recordings. Intracellularly, the opening of the calcium channels results in a stereotypical, slow depolarization. All spikes “riding” on top of this depolarization are burst spikes (Lu et al. 1992). Extracellularly, burst and tonic spikes can sometimes be distinguished based on their timing relative to preceding and subsequent spikes. In particular, two properties are shared by all burst spikes. First, spikes in a burst are separated by very short inter-spike-intervals (ISIs). These short ISIs are a consequence of the strong depolarization caused by the opening of the calcium channels. Second, the first spike in a burst is always preceded by a relatively long period of silence, corresponding to the hyperpolarization needed to deinactivate the calcium channels. Typically, bursts have been
identified extracellularly as sequences of spikes preceded by at least 100 ms of silence and containing spikes separated by ISIs of 4 ms or less (Lu et al. 1992; Guido et al. 1992).

We used these two criteria to identify tonic and burst spikes in the responses to gratings of various temporal frequencies (Figure 1-6). The contribution of the putative tonic spikes to the firing rate is shown in gray, while the contribution of the putative burst spikes is shown in black. At the lowest temporal frequency (Figure 1-6, top) tonic and burst spikes make very different contributions to the firing rate. Burst spikes occur only at the beginning of each cycle of the response, and result in a very brief and strong increase in firing rate. The burst is followed, over the remaining duration of the cycle, by tonic spikes at a substantially lower firing rate. Similarly, at the intermediate temporal frequency (middle) the first spikes of the cycle are part of a burst and are followed by tonic spikes. However, the contributions of tonic and burst spikes are less distinct than at low temporal frequency. At the highest temporal frequency (bottom) essentially all spikes are tonic spikes, as the interval between successive cycles of the response is shorter than 100 ms. For these three stimuli, bursts contain 43, 48, and 1% of the total number of elicited spikes.

However, it is possible that this categorization of spikes into tonic and burst spikes leads to a substantial overestimation of the number of burst spikes. In fact, there is no reason to assume that stimuli providing a strong enough drive to a neuron could not generate sequences of tonic spikes separated by less than 4 ms from each other (Lu et al. 1992; Guido et al. 1992). If such a stimulus were to occur after a period of silence longer than 100 ms, the resulting spikes would be erroneously characterized as burst spikes. Thus, at least in the response to stimuli that strongly drive a neuron, the two criteria are necessary, but not sufficient, to characterize a spike as belonging to a burst. Only for stimuli that provide little drive the criteria are also sufficient for a correct categorization. In the response to the intermediate temporal frequency (Figure 1-6, middle), which is close to optimal for this neuron (Figure 1-2B), many or all burst spikes might be miscategorized.

The distributions of ISIs in the responses of Figure 1-6 also suggest that a substantial fraction of burst spikes might be miscategorized. All the ISIs obtained from the responses in Figure 1-6 are shown in Figure 1-7. We plotted the ISIs in a format that is particularly useful to identify putative bursts, as a histogram of successive ISIs (McCarley et al. 1983; Weyand et al. 2001). The abscissa of the histogram represents the interval separating a given spike from its preceding spike, while the ordinate represents the interval to the following spike.

The positions of the spike clusters in these histograms are mainly determined by the structure of the stimulus. The cluster on the bottom-right of the histograms corresponds to the first spikes of a cycle: they are preceded by a long silence and are followed by other spikes within a short interval of time. Similarly, the cluster on the top-left corresponds to the last spikes in a cycle: they are preceded by other spikes within a short interval and are followed by a long silence. The duration of the silent periods corresponds roughly to half the duration of a stimulus cycle. Thus, as temporal frequency is increased (from left to right in Figure 1-7) these two clusters move towards smaller ISIs. The remaining spikes, in the bottom-left, are those occurring between the first and the last spike of the cycle.
Figure 1-7. Interspike intervals in the responses to simple stimuli. Each putative burst spike corresponds to a black dot, each putative tonic spike to a gray dot. The abscissa of the histogram represents the interval separating a given spike from its preceding spike, while the ordinate represents the interval to the following spike. Red, dashed lines represent standard criteria for the identification of bursts (see text for details). Same responses as in Figure 1-6.

To a smaller extent, the spike clusters also correspond to the two categories of burst and tonic spikes. Burst spikes are plotted in black, while tonic spikes are plotted in gray. The two dashed, red lines correspond to the two criteria used to identify burst spikes. Spikes lying within the box on the bottom-right are preceded by at least 100 ms of silence, and are followed by another spike within 4 ms. Thus, based on these criteria, these spikes all correspond to the first spike in a burst. The following spikes in the burst lie on the left of the vertical line, as they are preceded by another burst spike by less then 4 ms. Crucially, the putative burst (black) and tonic (gray) spikes fall into separate clusters only at the lowest temporal frequency (Figure 1-7A). At the intermediate frequency (Figure 1-7B) the two criteria seem to result in a rather arbitrary categorization. In fact, had we chosen a slightly higher temporal frequency, essentially all the burst spikes in Figure 1-7B would have been categorized as tonic spikes, as in Figure 1-7C. As we argued above, burst and tonic spikes in Figure 1-7A fall into separate clusters only because the temporal frequency of the stimulus is far from optimal, and thus tonic spikes are separated by long ISIs.

For similar reasons, any other attempt to distinguish tonic and burst spikes exclusively from extracellular measurements is likely to be of limited use for stimuli that elicit strong responses. However, in the remainder of this chapter we will continue to categorize burst and tonic spikes based on the two standard criteria described above. Even though these criteria might overestimate the number of burst spikes, they will allow us to determine an upper limit to the contribution of bursts to the failures of the receptive field model.

1.2.4 Responses to complex stimuli

To evaluate the predictions of the receptive field on stimuli that more closely resemble those encountered during natural vision we also measured the responses of LGN neurons to short movie clips. The movies lasted 12-17 seconds, and were either sequences taken from a cartoon (Tarzan,
Disney) or movies collected with camera that was mounted on the head of a cat roaming through the forest (Catcam, Betsch et al. 2004; Kayser et al. 2003).

The responses of a typical LGN neuron to two example movies are shown in Figure 1-8. We focus on the responses to two short movie sequences; one sequence is taken from a Tarzan movie (left) and the other one from a Catcam movie (right). The responses to the two movies are very similar, in that short events of high firing rate are interleaved with periods during which no spikes are elicited.

To test whether the measured responses to the movies (Figure 1-8C) are explained by the properties of the receptive field, we generated predictions of the receptive field based on the parameters estimated from responses to simple stimuli (like those in Figure 1-2 and Figure 1-3). In fact, the responses to simple stimuli described in the previous section fully constrain all the parameters of the model.

The predictions of the receptive field capture the basic feature of the response, but they fail to predict the details (Figure 1-8C, blue). Indeed, the receptive field correctly predicts the timing of the firing events but fails to predict their amplitudes. In particular, the most apparent failure of the receptive field is that it mostly underestimates the responses to the Tarzan movie (left), while it mostly overestimates the responses to the Catcam movie (right). It seems likely that some difference in the attributes of the two movie sequences might underlie this difference in the errors of the predictions. However, the prediction of the receptive field also fail on a more “local” scale, i.e. within a movie, as it often wrongly estimates the relative amplitudes of closely firing events.

Figure 1-8. Responses to movies and predictions of the receptive field. A: The stimuli are sequences taken from a cartoon (Tarzan, Disney) and from a camera mounted on the head of a cat (Catcam, Betsch et al. 2004). B: The spikes recorded from an LGN neuron on 10 presentations of the movies. C: The measured firing rates and the predictions of the receptive field (blue). The firing rates were obtained by smoothing the spike trains (B) with a Gaussian window (std = 5ms) and averaging over all presentations of the movies. The contributions of tonic (gray) and burst (black) spikes were computed separately and then added. The predictions of the receptive field were obtained with parameters estimated from fits like those in Figure 1-2 and Figure 1-3.
To some extent, the differences between the predicted and measured responses resemble those observed for simple stimuli (Figure 1-4). In particular, the measured responses to the Tarzan movie are much more transient than the predictions of the receptive field (Figure 1-8C, left). To some extent, the transient character of the responses reflects the presents of bursts in the response. The contribution of burst spikes to the firing rates is shown in black, while the contributions of tonic spikes are shown in gray. In the responses to these two sequences not more than 17% (Tarzan) and 11% (Catcam) of the spikes are part of a burst. Most spikes are tonic, as can also be seen from the measured ISIs (Figure 1-9).

Overall, the quality of predictions on the response to movies are considerably lower than those we obtained for the simple stimuli (Figure 1-5B). For example, the predictions explain 58% of the stimulus-driven variance in the responses shown in Figure 1-8. Over the entire population of neurons (Figure 1-10) the predictions explain 46% (median) of the stimulus-driven variance. In comparison, the fits of receptive field on the same population of neurons explain 78% (median) of the stimulus driven variance in the firing rate.

This difference in prediction quality might partly reflect the simplified assumptions underlying our model of the receptive field. For instance, in the model we assume that the spatial profiles of the center and surround are centered on the same location in visual space, and that both are well described by 2d-Gaussian. Both assumptions are known not to hold in many neurons. Indeed, center and surround can be slightly displaced with respect to each other (Soodak et al. 1987), both can have elliptical or asymmetric profiles and can contain hotspots (Soodak et al. 1987; Dawis et al. 1984; Passaglia et al. 2002). These and similar assumptions are likely to have less of an effect on the response to simple stimuli, which span a far less-dimensional stimulus-space than the movies.

However, rather than reflecting shortcomings of our particular implementation of the receptive field, the errors in the predictions might also point to genuine limitations of any model that is based on the receptive field alone. In particular, the different errors across the Tarzan and Catcam movies seem consistent with the effects of luminance gain control. Indeed, the average pixel-luminance is lower during the Tarzan sequence. Arguably, because of luminance gain control, the
lower average luminance would result in a larger luminance gain. This difference in gain could explain why the model predictions mostly underestimate the responses to the Tarzan movie, while they mostly overestimate the response to the Catcam movie. Similarly, the locally prevalent contrast in the movies is also likely to vary over time. Because of contrast gain control, such variations in contrast would cause gain adjustments that could explain the more local errors in the predictions of the receptive field.

![Figure 1-10. Quality of the prediction of the receptive field on the responses to natural movies. Arrow points to the median of the distribution (46%).](image)

**1.2.5 Gain control in complex stimuli**

To demonstrate that the receptive field does not capture all the features in the responses to complex stimuli we also used a more direct approach, which does not involve predicting the responses from the stimulus. In fact, the receptive field makes a simple prediction, namely that scaling the contrast of the stimulus should scale the resulting response by the same amount. Since it is well known that LGN responses to simple stimuli saturate with contrast (Kremers et al. 2001; Sclar et al. 1990) it would be surprising if the responses to complex stimuli were linear in contrast.

We tested the linearity of LGN responses to complex stimuli with an appropriate set of movies, which we obtained by modifying the original Tarzan and Catcam movies. Based on each original movie we constructed two modified movies that were identical other than for their contrasts. If LGN neurons were linear, then the responses to the two movies should simply be scaled versions of each other, where the scaling factor should correspond to the ratio of the contrasts of the two movies.

As expected, we found that LGN responses are not linear in the contrast of the modified movies. This is illustrated for a typical neuron in Figure 1-11, for two contrasts differing by a factor of five. We thus constructed the linear prediction of the responses at low contrast (bottom, blue) by dividing the responses measured at high contrast (top, gray) by a factor of five. Clearly, the predicted responses (bottom, blue) are a poor description of the measured responses (bottom, gray). Indeed, the measured responses are both larger and less transient than the predicted ones.
Figure 1-11 Effect of contrast on the responses to natural movies. The stimuli are two modified versions of a “catcam” movie. The two movies have different contrasts but are otherwise identical. The mean luminance of the frames (32 cd/m²) does not vary over time. The measured responses to the high contrast (top) and low contrast movies (bottom) were computed as in Figure 1-8C. The response measured at low contrast is compared to the predictions of the receptive field (blue). The prediction was obtained by scaling the responses measured at high contrast (top) by the ratio of the contrasts in the two movies.

These effects of contrast are consistent with the well known consequences of contrast gain control (Shapley and Victor 1978; Sclar 1987). Indeed, as contrast is reduced, contrast gain control results in a progressively larger gain and longer integration time, and thus in responses that are larger and slower than predicted by a linear model.

Other mechanisms that could underlie the shortcomings of the linear prediction seem to play less of role in this neuron. For instance, the shortcomings are not explained by bursting, since the responses in Figure 1-11 contain virtually no bursts. As above, the contribution of bursts spikes is shown in black, while the contribution of tonic spikes is shown in gray. The distributions of ISIs for these two movies are shown in Figure 1-12.

Figure 1-12. Effect of contrast on the interspike intervals in the responses to movies. Same responses as in Figure 1-11. Same conventions as in Figure 1-7.

1.3 Discussion

In this chapter we have introduced a model for the receptive field of LGN neurons that will be the basis for all the models of LGN responses that we will discuss throughout this thesis. We have
shown that the parameters of this model can be fully constrained from the fits of the responses to a small set of simple stimuli. These fits will be the first implicit step in every subsequent chapter.

The results of this chapter also allowed us to briefly review the most important strengths and limitations of a model of LGN responses that is based exclusively on the receptive field.

As we have shown, the great strengths of the receptive field are its simplicity and its generality. Because of its simplicity, we were able to constrain all the parameters of our model on the responses to a very small set of simple stimuli. Because of its generality, we were able to directly use the receptive field estimated from the responses to simple stimuli to predict the responses to complex stimuli.

The great limitation of the receptive field is, of course, that it does not predict any of the nonlinear properties of LGN neurons. For instance, the mechanisms generating spikes and bursts can deform the responses of the neurons and make them nonlinear. The effects of these mechanism are clearly visible on the responses to gratings, but are known to affect also the responses to complex stimuli (Lesica and Stanley 2004; Keat et al. 2001; Pillow et al. 2004). Moreover, we have have briefly discussed the effects of luminance gain control and contrast gain control on the responses of LGN neurons. We argued that, at least qualitatively, the effects of gain control are consistent with the observed differences between the measured responses to the movies and the predictions of the receptive field.

However, despite its limitations and its simplicity, the receptive field captures the basic features in the response of LGN neurons to complex stimuli (Dan et al. 1996; Stanley et al. 1999; Keat et al. 2001). Thus, any successful model of LGN responses will likely extend the receptive field model, by adding to it the nonlinear mechanisms needed to predict the nonlinear properties of LGN neurons (e.g., Victor 1987; Lesica et al. 2003; Keat et al. 2001; Lesica and Stanley 2004).

Indeed, recent studies have shown that predictions of the responses to complex stimuli improve when nonlinear mechanisms are added to the receptive field. For instance, the predictions of the receptive field on natural movies improve with the addition of a bursting mechanisms (Lesica et al. 2003). The bursting mechanism operates after the convolution between the receptive field and the stimulus and before the rectification of the membrane potential. Similarly, predictions of the receptive field of neurons in the retina and LGN are improved by the addition of a spike generation mechanism (Keat et al. 2001; Pillow et al. 2004).

However, the implementation of these nonlinear mechanisms is not complicated by the complexity inherent in natural images, since they operate on the output of the receptive field. Gain control mechanisms, on the other hand, affect the receptive itself and, crucially, are thought to be driven by luminance and contrast, two properties of the images (Shapley and Enroth-Cugell 1984). Even though luminance and contrast are easily defined for simple stimuli, so far there is no consensus on how to define luminance and contrast in natural images or natural movies.

Thus, in this thesis we will move towards a general formulation of luminance gain control and contrast gain control that can be used to predict the responses to arbitrary stimuli. The ultimate test for such a model will be that it should improve the predictions of the receptive field presented in this chapter.

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1.4 Methods

1.4.1 Cell population

We recorded from 54 X-cells and 14 Y-cells in 9 adult cats. Of these 68 neurons, 39 were located in layer A, 25 in layer A1, and 4 in layer C. We recorded from both On-center cells (39/68 neurons) and Off-center cells (29/68 neurons). The median eccentricity of the receptive field center over all neurons was 9.3 degrees; 56/68 neurons had receptive fields with eccentricities between 2.2 and 17.9 degrees (10th and 90th percentiles).

In this and in the following chapters, we report only responses of neurons that fulfilled the two following selection criteria. First, the action potential of the neurons had to be very well discriminated from the background noise. In most cases, for any given experiment we analyzed only the action potentials of a single neuron. In rare cases, we analyzed the action potentials of pairs of neurons recorded simultaneously on a single electrode. Second, we report only the responses from recordings that were stable over long periods of time. This selection criterion is a consequence of the large number of experiments needed to characterize each neuron. After having isolated the action potential of a neuron, we characterized its basic visual properties with a series of 8-10 experiments. In this chapter we discuss typical responses obtained from 4 of these basic experiments (with stimuli varying in spatial and temporal frequency and in horizontal and vertical position). This first series of experiments, typically lasting 30-40 minutes, was followed by one or more of the additional experiments discussed throughout this thesis. Each of these additional experiments lasted 20-30 minutes or longer. In this and in the next chapters we report only about neurons for which we completed at least one of the additional experiments. Thus, the recordings from each of these neurons were stable for at least 1 hour, and typically for 2-3 hours.

1.4.2 Stimuli

We employed two types of stimuli, simple and complex ones.

Simple stimuli

The simple stimuli were drifting gratings of fixed luminance (32 cd/m²) and contrast (50%) presented through a circular window. In separate experiments we varied either the spatial frequency, the temporal frequency, or the horizontal or vertical position of the stimulus center.

When varying spatial or temporal frequency, the stimuli were approximately centered on the receptive field and the circular window extended well beyond the borders of the receptive field. On the other hand, when varying position each stimulus covered only a small fraction of the receptive field. Attributes not being varied were chosen to maximize responses.

Complex stimuli

The complex stimuli consisted of movie sequences each lasting 12-17 seconds. The movies were shown through a circular window with a diameter of 13 deg, and thus typically covered the entire receptive field of the neurons (receptive field size for the entire population is shown in Figure 6-10). The original movies were recorded at a frame rate of 30 Hz. Since we displayed them at 125 Hz, each frame was repeated 4 or 5 times.
We used three types of movies:

1. The *Tarzan movies* consist of sequences taken from a Tarzan cartoon (Disney, 1999). We rescaled the luminance of the original sequences to match the range of our monitor.

2. The *Catcam movies* are derived from sequences of longer movies recorded from the head of a cat roaming through the forest (Betsch et al. 2004; Kayser et al. 2003). We normalized the luminance the Catcam movies such that (i) their average luminance over pixels and frames corresponds to the average luminance of the simple stimuli (32 cd/m²) and (ii) their maximum luminance corresponds to the maximum luminance that can displayed on our screen (64 cd/m²).

3. The *modified movies* are constructed by spatial bandpass filtering of the Tarzan and Catcam movies. In the modified movies the local average of pixel-luminance is approximately constant across space and frames, and corresponds to the average luminance of the simple stimuli. Each modified movie comes in two versions, whose contrasts differ by a factor of five. In the high contrast version the luminance of 5% of the pixels is saturated.

### 1.4.3 Receptive-field model

We implemented two equivalent formulations of the receptive-field model, the *space-time* formulation and the *frequency-space* formulation. In both formulations, the output of the model is the time-varying firing rate of the neuron.

Typically, we used the space-time formulation to predict the responses to complex stimuli and the frequency-space formulation to predict the response to simple stimuli.

**Space-time formulation**

In the space-time formulation, the first stage of the model consists of the convolution between the stimulus $s(x,y,t)$ and the linear receptive field $h_{rf}(x,y,t)$:

$$ r_{rf}(t) = \left[ h_{rf} * s \right](x_0, y_0, t). $$

where $x_0$, $y_0$ are coordinates of the receptive field center. The output of the first stage represents the stimulus driven-component in the membrane potential relative to rest.

The receptive field $h_{rf}(x,y,t)$ has center-surround organization:

$$ h_{rf}(x,y,t) = g_c(x,y) f_{rf}(t) - g_s(x,y) f_{rf}(t-\delta). $$

where $g_c$ and $g_s$ are Gaussian spatial profiles for center and surround, $\delta$ is the delay between center and surround, and $f_{rf}(t)$ is the temporal band-pass filter. The latter is identical for center and surround, and is given by a difference of Gamma functions $g(t)$ (Cai et al. 1997):

$$ f_{rf}(t) = p \cdot \left[ g_1(t) - k g_2(t) \right], \quad k \geq 0 $$

where $p$ sets the gain of the receptive field and
\[ g_i(t) = [t - \tau]^n \exp \left( \frac{t - \tau}{\phi_i} \right) \]

with \( \phi_i, \tau > 0 \), \( [ \ ] \) indicating rectification, and \( j = 1, 2 \). We imposed \( \phi_i > \phi_j \), to insure a physiologically plausible shape of \( f_{ij}(t) \).

The output of the convolution, \( r_{ij}(t) \), is added to a constant and rectified to obtain the firing rates \( r(t) \):

\[ r(t) = \left[ r_{ij}(t) + r_0 \right], \tag{3} \]

where \( r_0 \) is the difference between the spiking-threshold and the resting potential.

**Frequency-space formulation**

In frequency-space, the convolution in eq. (1) is equivalent to a product:

\[ R_{ij} = H_{ij} \cdot S, \]

where \( H_{ij}, S \), and \( R_{ij} \) are the frequency representations of the corresponding lower-case functions.

For a drifting gratings of temporal frequency \( f_t \), \( R_{ij} \) is different from zero only at the temporal frequency \( f_t \). Thus, \( r_{ij}(t) \) is sinusoidally modulated in time:

\[ r_{ij}(t) = \text{real} \left[ R_{ij} e^{j\omega t} \right] \text{ with } \omega = 2\pi f_t. \]

As in eq. (3), \( r_{ij}(t) \) is then added to the constant \( r_0 \) and rectified to obtain firing rates \( r(t) \).

For the model receptive field defined in eq. (2) we can separate \( R_{ij} \) into a spatial and a temporal component:

\[ R_{ij} = R_{\text{space}} \cdot R_{\text{time}} \]

The spatial component is:

\[ R_{\text{space}} = \left( R_c - k_s R_s e^{j\phi_s} \right) e^{j\phi_c}, \]

where \( R_c \) and \( R_s \) are the frequency-space representations of the 2d-Gaussians of the center and surround:

\[ R_c = \frac{1}{\sqrt{2\pi}} e^{-\sigma_c^2 (x f_t)^2} \text{ and } R_s = \frac{1}{\sqrt{2\pi}} e^{-\sigma_s^2 (x f_t)^2}, \]

where \( f_t \) is the spatial frequency of the grating.

The phase difference between the responses of the center and the surround depends on the delay \( \delta \):

\[ \phi_s = 2\pi f_t \cdot \delta \]
On the other hand, the overall phase of the response depends on the distance $d$ between the receptive-field center and the stimulus center, measured along the direction of motion of the grating:

$$\varphi_d = 2\pi \cdot f_s \cdot d.$$ 

The temporal component is the frequency-space representation of the temporal band-pass filter $f_T$:

$$R_{time} = p \cdot (G_1 - kG_2)$$

where:

$$G_i = \frac{1}{\sqrt{2\pi}} e^{i\omega t} \left( \frac{1}{1-i\omega t} \right)^{\imath n}$$

1.4.4 Model fits

We fitted the parameters of the receptive field on responses to simple stimuli. We proceeded in three steps. For each step, we estimated the resting potential $r_0$ from the average response $r_b$ to a blank screen, by setting $r_0 = r_b$.

1. **Selectivity for spatial position.** We first fitted all the parameters of the receptive field to responses to gratings presented at various horizontal and vertical positions (Figure 1-3). The estimated horizontal and vertical positions of the receptive field, $x_0$ and $y_0$ were kept fixed in the two subsequent steps.

2. **Selectivity for spatial frequency.** We then fitted the remaining parameters of the receptive field to the responses to gratings of various spatial frequencies (Figure 1-2A). This procedure estimated spatial parameters of the receptive field, as well as the delay between center and surround.

3. **Selectivity for temporal frequency.** In the last step we fitted the temporal parameters of the receptive field to the gratings of various temporal frequency (Figure 1-2B).

1.4.5 Model predictions

We used the parameters of the receptive field estimated from the responses to simple stimuli (1.4.4) to predict the response to complex stimuli (Figure 1-8, blue). As for the simple stimuli, we estimated the resting potential $r_0$ from the response to a blank screen. The only parameter that we fitted directly to the responses to complex stimuli was the overall gain $p$. 

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Chapter 2

The effects of gain control

2.1 Introduction

In the early visual system, two rapid adaptive mechanisms control the gain of neural responses (Shapley and Enroth-Cugell 1984), luminance gain control and contrast gain control. Luminance gain control (also known as light adaptation) occurs largely in retina. It matches the limited dynamic range of neurons to the locally prevalent luminance (light intensity) by reducing gain in those locations of the visual field where mean luminance is high, and increasing gain where mean luminance is low (Shapley and Enroth-Cugell 1984; Rodieck 1998; Sakmann and Creutzfeldt 1969). Contrast gain control begins in retina (Shapley and Victor 1978; Shapley and Enroth-Cugell 1984; Victor 1987; Baccus and Meister 2002), and is strengthened at subsequent stages of the visual system (Sclar et al. 1990). It regulates gain based on the locally prevalent root-mean-square (RMS) contrast, the standard deviation of the stimulus luminance divided by the mean luminance. Rather than depending linearly on contrast, responses are reduced in locations where average contrast is high, and increased where average contrast is low. Both gain control mechanisms must operate rapidly, because the eyes typically fixate a given location for only 200-300 ms, and eye movements bring the receptive fields of neurons in the early visual system over image patches that can have different luminance and contrast.

The effects of luminance gain control and contrast gain control are strongly dependent on the temporal frequency content of the stimulus. At low temporal frequencies, luminance gain control operates perfectly (i.e., it follows Weber’s law) in that the amplitude of the response to a stimulus of fixed contrast does not depend on mean luminance. On the other hand, at high temporal frequencies luminance gain control has barely any effect and, for a fixed contrast, the amplitude of the response grows approximately linearly with mean luminance (Tranchina et al. 1984; Purpura et al. 1990; Shapley and Enroth-Cugell 1984). Similarly, contrast gain control is strong at high but not at low temporal frequencies. Thus, response amplitude saturates with contrast at low frequencies and is approximately linear in contrast at high frequencies (Shapley and Victor 1978; Benardete et al. 1992; Sclar 1987). As a consequence, the temporal frequency selectivity of neurons in the early visual system strongly depends on luminance and contrast. At low luminance or contrast the neurons respond mostly to low frequencies, while for increasing luminance or contrast the responses to high temporal frequencies are selectively enhanced. These effects are thought to optimize signal transmission in the neurons, since the noise is most prevalent at low luminance or contrast and occurs mostly at high frequencies (Van Hateren 1993).

The effects of gain control depend on temporal frequency because for increasing luminance or contrast not only the gain but also the integration time of the neurons is reduced (Yoon 1972; Enroth-Cugell and Shapley 1973a; Victor 1987; Enroth-Cugell and Jakiela 1980). While the reduction in gain suppresses responses at all frequencies, the reduction in integration time
selectively enhances the responses at high frequencies and, at these frequencies, compensates for 
the reduction in gain. Both the effects on gain and integration time can be captured by 
considering how gain control affects the impulse response (i.e. the temporal profile of the 
receptive field) of the neurons (Purpura et al. 1990; Victor 1987; Baccus and Meister 2002). As 
luminance or contrast are increased, the impulse response becomes smaller (corresponding to the 
reduction in gain) and faster (corresponding to the reduction in integration time). This description 
of the effects of gain control is largely equivalent to one based on the temporal frequency 
selectivity, since the impulse response can be derived from the temporal frequency selectivity 
(Saul and Humphrey 1990; Victor 1987; Benardete and Kaplan 1999; Lee et al. 1994).

In this chapter we illustrate these well known effects of gain control on the responses of LGN 
neurons. To characterize the effects of luminance gain control and contrast gain control we 
estimate the impulse response of the neurons for many combinations of luminance and contrast, 
covering values similar to those encountered during natural vision.

2.2 Results

2.2.1 Effect and time course of gain control

To illustrate the effects and the time course of gain control, we recorded the responses of LGN 
neurons to sudden steps in luminance and contrast. The rapid changes of luminance and contrast 
caused by these steps are similar to those resulting from eye movements during natural vision 
(Frazor and Geisler 2004) and thus are likely to engage the same mechanisms operating in natural 
vision.

In a first experiment, we measured the responses of LGN neurons to a step in luminance, 
while keeping contrast fixed. We stimulated the neurons with a drifting grating of optimal spatial 
and temporal frequency, which elicits a periodic response at its temporal frequency (Figure 2-1, 
gray histograms). In the example of Figure 2-1, the mean luminance of the grating first steps 
from 32 to 56 cd/m² and then back to 32 cd/m². The resulting luminance profile for one pixel of 
the stimulus in shown in the bottom of Figure 2-1. As the mean luminance of the grating is 
increased, the amplitude of the luminance modulation is also increased by the same factor. As a 
result, the contrast of the grating, namely the ratio of the modulation amplitude over the mean, 
remains constant.

As can be seen in Figure 2-1, LGN responses are barely affected by the sudden step in 
luminance. In particular, the amplitude of the response is much smaller then predicted by a linear 
model based on the receptive field alone (blue curve). We computed the predictions of a linear 
model by scaling the average response to a cycle of the stimulus before the step (dashed curve) 
by the ratio of the mean luminance after and before the step. This linear prediction is based on the 
assumption that, because of the bandpass properties of the receptive field, the neuron does not 
respond to the mean luminance of the stimulus.

In addition to being smaller then predicted by the linear model, the responses also occur faster. 
This is illustrated in Figure 2-1B, where we compare the average response to a cycle before the 
step (dashed) to the average response after the step (black). The black curve is slightly advanced
with respect to the dashed curve, indicating that the integration time of the neuron is shorter when luminance is high.

The reduction in gain and integration time that underlie the differences between the measured and the predicted responses are well known effects of luminance gain control. Luminance gain control is thought to operate very quickly, in less than 100 ms (Lankheet et al. 1993b; Saito and Fukada 1986; Enroth-Cugell and Shapley 1973a). Indeed, in our example both the reduction in gain and the change of dynamics occur well within a cycle of the drifting grating (80 ms in Figure 2-1).

Figure 2-1. Effect and time course of luminance gain control in LGN. A: Response of an LGN neuron to a drifting grating of constant contrast (14%), whose luminance steps from 32 to 56 cd/m² (left) and back to 32 cd/m² (right). Spatial frequency and temporal frequency (12.5 Hz) are optimal for this neuron. The temporal profile of the stimulus is shown below the responses. Histograms (gray) where obtained by convolving the spike trains with a Gaussian window (σ = 5 ms), and averaging over 3 stimulus presentations. From the histograms we computed the average response to a cycle of the stimulus before (dashed) and after (black) the step in luminance. The linear prediction (blue) was obtained by scaling the response before the step (dashed) by the ratio of the two luminances. B: Comparison of average responses to low luminance (dashed) and high luminance (black), and of the response expected in the absence of gain control (blue).

In a second experiment, we measured the responses of LGN neurons to a step in contrast, while keeping luminance fixed (Figure 2-2). The stimulus was again a drifting grating of optimal spatial and temporal frequency. In the example of Figure 2-2, the contrast of the grating first steps from 31 to 100% and then back to 31%. The resulting luminance profile for one pixel of the stimulus is shown in the bottom of Figure 2-2.

The effects of the contrast step on the response are similar to the effects of the step in luminance. In particular, the step in contrast affects both the gain and the dynamics of the response. First, the amplitude of the response at high contrast (Figure 2-2, black) is smaller than predicted by the linear model (blue), indicating a reduction in the gain of the neuron. Second, the response at high contrast (black) occurs faster than the response at low contrast (dashed), indicating a reduction in time constant.
The effects of contrast on the gain and integration time of the response are the well known effects of contrast gain control. Contrast gain control operated as fast or faster then luminance gain control (Victor 1987; Baccus and Meister 2002). Indeed, both the reduction in gain and in integration time occur well within a cycle of the drifting grating (128 ms in Figure 2-2).

![Figure 2-2](image)

Figure 2-2. Effect and time course of contrast gain control in LGN. A: Response of an LGN neuron to a drifting grating of constant luminance (32 cd/m²) whose contrast steps from 31 to 100 % (left) and back to 31 % (right). Spatial frequency and temporal frequency (7.8 Hz) are optimal for this neuron. Histograms (gray) are the average over 5 stimulus presentations. Same conventions as in Figure 2-1. The linear prediction (blue) was obtained by scaling the response before the step (dashed) by the ratio of the two contrasts. B: Comparison of average responses to low contrast (dashed) and high contrast (black), and of the response expected in the absence of gain control (blue).

### 2.2.2 Estimating the impulse response

To characterize the effects of luminance and contrast gain control on gain and integration time of LGN neurons, we measured their temporal frequency selectivity over a large range of luminances and contrasts (Shapley and Enroth-Cugell 1984). We measured the temporal frequency selectivity by stimulating the neurons with drifting gratings of optimal spatial frequency and size. The temporal frequency of the gratings was increased exponentially with time from 0.5 to 40 Hz over 5 s (Figure 2-4), and returned to 0.5 Hz in the subsequent 5 s (not shown). The responses of an example cell to three stimuli differing in luminance or contrast are shown in Figure 2-4 (gray histograms). The response at a given instant during the stimulus can be interpreted as the selectivity of the neuron for the temporal frequency present in the stimulus at that time.

The selectivity for temporal frequency is strongly dependent on luminance and contrast. At low luminance and contrast (Figure 2-4, top), only low temporal frequencies elicit large response. On the other hand, at high contrast (middle) or luminance (bottom) high frequencies elicit robust responses, and the optimal temporal frequency of the neuron occurs at higher frequencies.
Figure 2-3. The descriptive model. Stimulus luminance is integrated by the spatial receptive field (not shown), filtered by the impulse response (red), added to Gaussian noise and rectified. The impulse response depends on the locally prevalent luminance and contrast.

Figure 2-4. Estimating the impulse response of LGN neurons. The first stimulus (top row) has low mean luminance ($L = 6 \, \text{cd/m}^2$) and low contrast ($c = 10\%$, Michelson contrast). The second stimulus (middle row) has the same mean luminance as the first, but full contrast ($c = 100\%$). The third stimulus (bottom row) has the same contrast as the first, but with high mean luminance ($L = 54 \, \text{cd/m}^2$). A: Responses of an X-type, On-center cell. Histograms (gray) were obtained by averaging over 10 stimulus presentations. Red curves are predictions of the descriptive model (Fig. 4a). Stimuli were sinusoidal gratings at optimal spatial frequency (icons). The temporal profile of the stimuli is shown under the responses; drift rate
increased exponentially with time, from 0.5 to 40 Hz in 5 s, and back (not shown). B: Impulse responses used for the predictions in A. An increase in contrast (middle row) or mean luminance (bottom row) results in a smaller and faster impulse response.

The amplitude of the responses to the three stimuli is remarkably similar, considering their very different contrast and luminance. For instance, the contrast of the middle stimulus, and thus the amplitude of the luminance modulation, is 10 times as large as in the top stimulus. The response to the high contrast stimulus, on the other hand, is only two or three times larger as the response to the low contrast stimulus. As discussed in the previous section, this implies that gain is reduced at high contrast. At high temporal frequencies, this reduction in gain is compensated by the reduction in integration time. Indeed, the responses at the high temporal frequencies grow approximately linearly with contrast, and thus the selectivity of the neuron shifts to higher temporal frequencies as contrast is increased. Luminance gain control has similar effects, as can be seen by comparing the response to the top stimulus and the response to the bottom stimulus, whose luminance differs by a factor of 9.

To obtain a compact description of the effect of luminance and contrast on the temporal frequency selectivity, we estimate the impulse response of the neuron for the different levels of luminance and contrast. We estimate the impulse response by fitting a descriptive model (Figure 2-3) to the responses. In this model the stimulus is filtered by a linear receptive field, whose output is added to Gaussian noise and rectified. The impulse response is estimated independently for each stimulus Figure 2-4; the remaining model parameters are kept constant across stimuli.

Figure 2-5. Model fits, plotted on a logarithmic time scale. Same responses and fits as in Figure 2-4. By plotting time on a logarithmic axis the responses are expressed as linear in temporal frequency. This allows a better assessment of the quality of the fits at high temporal frequencies.
The descriptive model captures the amplitude and phase of the responses over the entire range of tested temporal frequencies (red curves in Figure 2-4 and Figure 2-5). For over half of the cells in our population (N=40) it accounts for more than 85% of the stimulus-driven variance in the responses (Figure 2-6). On the responses of the example cell in Figure 2-4, the descriptive model also explains 85% of the variance. Differences between predicted and measured responses are due largely to short transients occurring at the onset of the rising phase of a cycle. These transients correspond to bursts of action potentials (Sherman 2001), which the model is not designed to produce.

![Figure 2-6](image)

Figure 2-6. Quality of fits with the separable model. Quality of fits is the percentage of stimulus driven variance in the firing rates explained by the model. Arrow points to the median (85%).

### 2.2.3 Effects of gain control on the impulse response

We estimate the impulse response over a wide range of mean luminance (6-56 cd/m²) and contrast (10-100% Michelson contrast; 0.07 – 0.7 RMS contrast). Mean luminance and contrast thus cover a range extending over a factor of 10, similar to the excursion seen within any given natural scene (Frazor and Geisler 2004, 2005). The impulse responses estimated for all possible combinations of luminance and contrast are shown in Figure 2-7A. The upper right corner of the matrix is empty, as it corresponds to combinations of luminance and contrast that are not physically realizable on a screen with limited dynamic range.

Increasing the luminance of the stimulus (i.e. moving to the right along a row of the matrix) or increasing contrast (i.e. moving up a column) both result in a smaller and faster impulse response (Figure 2-7A, see also Figure 2-4). The height of the impulse response is proportional to the gain of the neuron, and thus a smaller impulse response implies smaller gain. The duration of the impulse response sets the integration time of the neuron; as luminance or contrast are increased, the neuron integrates luminance over a shorter window of time in the past.

These effects of luminance and contrast gain control on the impulse response explain the influence of luminance and contrast on the temporal frequency selectivity of the neuron. The Fourier transformation of the impulse response yields the corresponding transfer function of the neuron. The amplitude of the transfer function (Figure 2-7B) then describes how gain depends on temporal frequency. As shown in Figure 2-7B, gain is reduced as luminance or contrast are increased. However, this reduction in gain occurs only at low temporal frequencies, while at high frequencies is approximately constant. These different effects at low and high temporal frequencies are explained by the effects on the impulse response. The reduction in the size of the
impulse response corresponds to an equal reduction of gain at all temporal frequencies. At high temporal frequencies the reduction in gain is compensated by the shorter integration time of the neuron, which selectively enhances responses to high temporal frequencies.

Figure 2-7. Effect of luminance and contrast on the impulse response and transfer function. A: The impulse response of the neuron, estimated at many combinations of luminance and contrast. B: The amplitude of the transfer functions (i.e. the Fourier transform of the impulse responses in A). The amplitude of the transfer function describes gain as a function of temporal frequency. Temporal frequency is plotted on a logarithmic axis, and ranges from 0.5 to 40Hz.

2.3 Discussion

In this chapter we have illustrated some well known effects of luminance gain control and contrast gain control. We have shown that the effects of gain control on the responses to moving gratings can be captured by allowing the gain and integration time of the impulse response to vary with luminance and contrast. Luminance gain control and contrast gain control operate very fast, since the effects on gain and integration time are completed within 100 ms of a change in luminance or contrast. Unlike previous studies, we estimate how the impulse response varies with both luminance and contrast, which will allow us (in Chapter 4) to test whether the effects of luminance gain control and contrast gain control are independent of each other.

One limitation of our methods is that we attributed all the effects of contrast gain control to changes in the impulse response of the neurons. In principle, contrast gain control might also affect the spatial receptive field (Nolt et al. 2004) or the resting potential (Baccus and Meister 2002; Solomon et al. 2004a). In practice, however, a model where contrast gain control leaves constant both the spatial receptive field and the resting potential provides an excellent fit to the responses of LGN neurons to stimuli of different contrasts, sizes, and spatial frequencies (Bonin 2005). In ganglion cells, moreover, resting potential seems to be affected only very slightly by changes in contrast (Zaghloul et al. 2005).
Similarly, we have not quantified the effects of luminance gain control on the spatial receptive field and on the resting potential. The surround of retinal ganglion cells becomes relatively weaker at lower luminances (Derrington and Lennie 1982; Troy et al. 1999), but this weakening takes place only at the lowest levels of luminance, and is barely noticeable when one compares responses within a limited range of luminances, as we do here. Mean luminance might affect the resting potential, but this effect is small and variable, at least as gauged from the resting firing rate (Derrington and Lennie 1982). Indeed, in our models we have left the resting potential free to vary with mean luminance, but the resulting estimates did not vary by much and did not depend on luminance in an orderly fashion.

Finally, in both X-cell and Y-cells (Hochstein and Shapley 1976b) we have characterized gain control through its effects on the impulse response, even though the impulse response fully captures the responses to our stimuli only in X-cells. Indeed, the response of Y-cells consists of two components: the first, linear component is analogous to the response of an X-cell and is captured by the impulse response of the receptive field; the second, nonlinear component can be modeled as the output of a large pool of subunits covering the receptive field (Victor and Shapley 1979a, b; Enroth-Cugell and Freeman 1987; Hochstein and Shapley 1976a). Both components of Y-cell responses are shaped by contrast gain control (Shapley and Victor 1980; Enroth-Cugell and Freeman 1987; Hochstein and Shapley 1976a). With our analysis, on the other hand, we have established independence in the effects of luminance gain control and contrast gain control only for the linear component. However, it is plausible that independence also holds for the nonlinear component of the responses, since in retinal ganglion cells the effects of contrast gain control on the gain and integration time of the putative subunits are very similar to the effects on the gain and integration time of the receptive field (Shapley and Victor 1980; Freeman 1991).

2.4 Methods

2.4.1 Cell population

We recorded from 32 X-cells and 8 Y-cells in 6 adult cats. Of these 40 neurons, 28 were located in layer A, 11 in layer A1, and 1 in layer C. We recorded from both On-center cells (26/40 neurons) and Off-center cells (14/40 neurons). The median eccentricity of the receptive field center was 12.3 degrees; 34/40 neurons had receptive fields with eccentricities between 2.2 and 21.4 degrees (10th and 90th percentiles).

2.4.2 Stimuli

We estimated the impulse response of the neurons from the responses to gratings whose temporal frequency varied over time (Figure 2-4). Temporal frequency was increased exponentially with time from 0.5 to 40 Hz over 5 s (Figure 2-4), and returned to 0.5 Hz in the subsequent 5 s (not shown). Spatial frequency and position were optimal. For neurons that were strongly suppressed by large gratings, stimulus size was set to the optimal value, as measured with gratings at 50% contrast and 32 cd/m²; for the other neurons the stimuli covered the entire receptive field. Combinations of mean luminance (4-6 values between 6 and 56 cd/m²) and contrast (3-5 values between 10 and 100%) were presented in a randomized order (12-25 stimuli)
repeated 6-12 times). The appearance of a grating was preceded by 2-2.5 s of uniform screen at the mean luminance of the stimulus.

2.4.3 Definition of luminance

Rather than reflecting the perception of lightness in cats, the definition of stimulus luminance is based on human psychophysics. The luminance of a stimulus is computed by integrating the energy of the light emitted by the screen over the wavelength $\lambda$. Crucially, contributions from different wavelengths contribute to the integral with different weights (Wiszecki and Stiles 1982). The weights $V(\lambda)$ describe how the sensitivity of the visual system depends on the wavelength of the incoming light. The main determinants of the shape of $V(\lambda)$ are the absorption spectra of the three human cone types. In particular, this measure of luminance is not affected by light at wavelengths that do not elicit responses in any of the three cone types.

Strictly speaking, a meaningful definition of luminance for cats would incorporate their wavelength sensitivity through a different weighting function $V^*(\lambda)$. However, for the purpose of this thesis a definition of luminance based on $V^*(\lambda)$ is not necessary. All the stimuli described in this thesis have a fixed spectral content, i.e. only the absolute, but not the relative, contributions of different wavelength vary across stimuli. For such stimuli, the two definitions of luminance based on $V(\lambda)$ and $V^*(\lambda)$ would yield luminance values that differ only by a fixed scalar factor. Thus, even though the two definitions would yield different absolute luminance levels, they would result in the same luminance ratio for any pair of stimuli. Only the effects of such relative luminance differences are discussed in this thesis.

2.4.4 Model

As in Chapter 1, the first stage of the descriptive model is the convolution between the linear receptive field $h_{rf}(x,y,t)$ and the stimulus $s(x,y,t)$

$$r_{rf}(t) = [h_{rf} * s](x_0, y_0, t)$$

where $r_{rf}(t)$ is the stimulus-driven membrane potential relative to rest, and $x_0, y_0$ are coordinates of the receptive field center. The stimulus $s(x,y,t)$ is the luminance distribution obtained by subtracting the mean from the luminance shown on the screen. The receptive field $h_{rf}(x,y,t)$ has center-surround organization:

$$h_{rf}(x, y, t) = G_c(x, y) f_{L,C}(t) - G_s(x, y) f_{L,C}(t - \delta)$$

where $G_c$ and $G_s$ are Gaussian spatial profiles for center and surround, $\delta$ is the delay between center and surround, and $f_{L,C}$ is the temporal impulse response at mean luminance $L$ and contrast $C$. The latter is identical for center and surround. The parameters of $G_c$ and $G_s$ and the delay $\delta$ were fixed for a given neuron.

The impulse response $f_{L,C}$ (Figure 2-7A) is a difference of Gamma functions $g_i(t)$ (Cai et al. 1997):

$$r_{L,C}(t) = \frac{p}{g_i(t) - kg_2(t)}, \ k \geq 0$$
where $p$ determines the gain of the neuron and

$$g_j(t) = (t - \tau)^n e^{-\beta t}$$

with $j = 1, 2$, and $\square$ indicating rectification.

The second and third stages of the model add Gaussian noise $n(t)$ with fixed variance $\sigma^2$ to the visual response $r_{2f}(t)$, and rectify the result to yield the firing rate (Passaglia and Troy 2004; Carandini 2004)

$$r(t) = \left[ r_0(L) + r_{2f}(t) + n(t) \right]$$

where $\square$ indicates rectification and $r_0$ is the difference between the spiking-threshold and the resting potential. The variance of the Gaussian noise was fixed for a given cell, whereas the resting potential was allowed to vary with mean luminance $L$ to account for changes in spontaneous firing rate seen at different mean luminances.

2.4.5 Parameter estimation

We first estimated the size, position and relative strength of center and surround, as well as the delay between them, by fitting the responses to gratings of varying position and spatial frequency (1.4.4). These stimuli had preferred temporal frequency and were shown at 50% contrast with mean luminance 32 cd/m2.

Second, we estimated $r_0(L)$ from the responses to a uniform screen of luminance $L$. For a uniform screen, $r_{2f}(t) = 0$ by definition, and therefore the probability $p(f)$ of observing a firing rate $f$ is:

$$p(f) = \begin{cases} 0 & f < 0 \\ \int_{-\infty}^{0} \left[ r_0(L) + G(r) \right] dr & f = 0, \\ \left[ r_0(L) + G(r) \right] & f > 0 \end{cases}$$

where $G$ is a Gaussian with variance $\sigma^2$ (the variance in the membrane potential noise). We estimated $r_0(L)$ and $\sigma$ by maximizing their likelihood given the observed firing rates (Carandini 2004).

Finally, we estimated the parameters of the impulse response $f_{l,C}$ by least squares fitting of the full descriptive model (Figure 2-3) to the responses of a temporal frequency sweep of luminance $L$ and contrast $C$ (Figure 2-4).
Chapter 3
Slow adaptation

3.1 Introduction

The responsivity of neurons in the visual system is affected by a number of mechanisms operating over a variety of time scales. In addition to the fast gain control mechanisms described in the previous chapter, slow adaptation mechanisms also modify the responsivity of neurons. Although slow adaptation has been originally described in cortex (Maffei et al. 1973; Movshon and Lennie 1979; Ohzawa et al. 1982; Vautin and Berkley 1977) more recently similar mechanisms have been found operate also in the retina and the LGN of a number of species. For instance, slow adaptation mechanisms have been demonstrated in vitro in the retina of salamander (Kim and Rieke 2001), rabbit (Brown and Masland 2001; Smirnakis et al. 1997) and monkey (Chander and Chichilnisky 2001) as well as in vivo in the LGN of cat (Sanchez-Vives et al. 2000) and monkey (Solomon et al. 2004a).

The effects of slow adaptation are evident both during and after long presentations of a high contrast stimulus. In a subset of LGN neurons the amplitude of the responses to a high contrast stimulus decays over time. Over the course of tens of seconds after the onset of the stimulus, response amplitude typically decays to about 80-90% of its initial value (Sanchez-Vives et al. 2000). The strongest effects of adaptation, however, are evident after the presentation of the high contrast stimulus, even in neurons that show no response reduction during the high contrast stimulation. Immediately after stimulation with a high contrast stimulus, the response to a low contrast stimulus is strongly suppressed and then slowly recovers over the course of 10-20 seconds (Sanchez-Vives et al. 2000; Solomon et al. 2004a). Responses are suppressed even in the absence of a stimulus (Solomon et al. 2004a) suggesting that the effects of slow adaptation are mediated by a tonic hyperpolarization of the membrane potential (Baccus and Meister 2002). We replicated these effects of slow adaptation on a small sample of LGN neurons using the paradigm of Solomon et al. (2004a). Gain was reduced strongly after long presentations of a high contrast grating in Y-cells and to a lesser degree also in X-cells.

Potentially, the mechanisms underlying slow adaptation could be engaged also by the stimuli that we used in Chapter 2 to estimate the impulse response of the neurons. Indeed, the stimuli we used are relatively long, they contain many high temporal frequencies, which have been shown to result in the strongest adaptation (Solomon et al. 2004a), and at least some of the stimuli have very high contrast. Slow adaptation during the presentation of the stimuli would affect our estimate of the impulse response. In particular, we would expect slow adaptation to result in a reduction of the estimated gain of the impulse response (Baccus and Meister 2002) that could be confounded with the effects of luminance gain control and contrast gain control.
3.2 Results

To assess whether our estimate of the impulse response depends on the previous history of visual stimulation we reanalyze the responses presented in Chapter 2. If slow adaptation, or other mechanisms with a slow dynamics, did affect our estimate of the impulse response, we would expect the gain or shape of the impulse response to change over the duration of the stimulus.

To test whether the impulse response changes over time we estimated two separate impulse responses from the two halves of the stimulus and compared them to each other. The stimuli in the two halves are essentially mirror symmetric versions of each other along the time axis: during the first half the temporal frequency increases over time, while during the second half it decreases over time (Figure 3-1). Effects of slow adaptation, or the effects of any other mechanism that depends on the particular time course of the stimulus would cause the impulse responses estimated from the two halves to differ from each other.

The impulse response estimated from the first half of the stimulus (Figure 3-1 inset, red) is very similar to the impulse response estimated from the second half (Figure 3-1 inset, orange). The responses predicted from the two impulse responses (Figure 3-1, red and orange curves) are equally good: the red prediction (based on the red impulse response) explains 90% of stimulus driven variance in the responses during the first half and the orange prediction (based on the orange impulse response) explains 91% of the stimulus driven variance in the response during the second half.

![Figure 3-1](image)

Figure 3-1. Assessing the effects of slow adaptation on the impulse response. The impulse response estimated from the first half of the stimulus and the corresponding fit of the responses are shown in red. The impulse response estimated from the second half of the stimulus and the corresponding fit of the responses are shown in orange. Luminance is 6 cd/m², contrast is 100 %. Same cell and stimulus as in Figure 2-4, middle row.

The impulse responses estimated from the two halves of the stimulus are essentially undistinguishable from each other for all combinations of luminance and contrast in the stimulus set (Figure 3-2). In particular, any differences between the impulse responses estimated from two halves of the same stimulus are much smaller then the differences between impulse responses estimated from different stimuli, i.e. different luminances and contrast.
To quantify the similarity between the impulse responses estimated from the two halves we computed overall measures of gain and integration time. As a measure of overall gain (Figure 3-3A) we took the average of the transfer function between 0.5 and 15 Hz (at higher frequencies gain is barely affected by changes in luminance and contrast). The gain of the impulse response varies by more than an order of magnitude over the entire range of luminance and contrast. Gain is large (i.e. the impulse response is large) when luminance or contrast are low and is small when luminance or contrast are high. Crucially, differences in the gain of the impulse response across the two halves of a stimulus are negligible compared to the differences due to differences in luminance or contrast. As an overall measure of integration time we took the slope of the best-fitting line relating the phase of the transfer function to frequency, weighted by the amplitude at each frequency (Reid et al. 1992). Like gain, integration time also varies substantially across luminance and contrast (Figure 3-3B). Integration time is large (i.e. the impulse response is slow) when luminance or contrast are low and is small when luminance or contrast are high. For most stimuli, the differences in integration times across the two halves are again small compared to the differences due to changes in luminance or contrast.

Figure 3-2. The impulse response estimated from the two halves of the stimulus, for all combinations of luminance and contrast. As in Figure 3-1, the impulse response estimated from the first half is shown in red while the impulse response estimated from the second half is shown in orange. For many combinations of luminance and contrast the orange and the red impulse responses lie on top of each other, indicating that they are very similar.

However, the estimated integration time varies more across the two halves than the estimated gain. The largest differences occur when integration time is large, i.e. when contrast or luminance are small. Therefore, these differences are not likely to be a consequence of slow adaptation, which is thought to have the largest effects for high contrast stimuli, and thus at small integration times. This suggests that other factors underlie the observed differences. In particular, for low luminance or contrast the responses are large only at low temporal frequencies. At these low
frequencies small differences in integration time have little effect on the phase of the response and thus on the quality of the predictions. The estimate of integration time is thus inherently more affected by noise for low luminance and contrast, a problem that further increased by the low signal noise ratio in the responses to these stimuli.

Figure 3-3. Gain and integration time in the first vs. second half. Each point corresponds to a stimulus. A: Overall gain. B: Overall integration time. Same neuron as in Figure 3-2.

On average over the entire population of neurons (N = 45) the differences in the gain across the two halves are negligible (Figure 3-4A). On the other hand, the average integration time is systematically different across the two halves (Figure 3-4A). On average, integration time is larger during the second half of the stimulus. However, as for the example cell in Figure 3-3, the differences across the two halves are substantially smaller than the differences across stimuli. Nonetheless, our estimate of integration time seems to be by far less accurate than the estimate of integration time, as indicated by the size of the error bars in Figure 3-4.

Figure 3-4. Gain and integration time in the first vs. second half, population averages. A: Overall gain. For each neuron, the largest estimated gain was normalized to 100%. B: Overall integration time. For each neuron, the smallest and largest integration times were set to 0 and 100%. We binned the normalized gain and integration time during the first half and then averaged the corresponding gain and integration time during the second half. Error bars represent standard deviation.
To estimate to what extent these small differences in gain and integration time affect the predictive power of the impulse response, we used the impulse response estimated from one half of the stimulus to predict the responses measured in the other half. We compared the quality of this prediction to the quality of the actual fit used to estimate the impulse response (the fits are shown in Figure 3-1). For the example cell of Figure 3-3, the fits explain 85% of the stimulus driven variance in the responses over in the entire set of stimuli. In comparison, the predictions with the “wrong” impulse response explain 81% of the variance. We obtained similar results over the rest of the neurons (Figure 3-5, N = 45): the median values over the population are 85% and 81%.

![Figure 3-5. Quality of fits and predictions. A: Stimulus driven variance in the responses explained by the fits used to estimate the impulse responses. B: Variance explained by the prediction of the responses in the first half using the impulse response estimated from the second half and vice versa. The quality of both fits and predictions are computed over all stimuli and averaged across the two halves. Arrows point to the medians of the distributions, 85% (A) and 81% (B).](image)

### 3.3 Discussion

Slow adaptation mechanisms make only very small (if any) contributions to the estimates of the impulse response obtained with the methods discussed in Chapter 2. On average, the impulse responses estimated from the first and the second half of the stimuli have essentially identical gain, irrespective of stimulus contrast. (Figure 3-4A). On the other hand, we found the integration time of the impulse to be, on average, somewhat longer during the second half of the stimulus (Figure 3-4B). However, over the ranges of luminance and contrast covered by our stimuli, the effects of gain control on the integration time are at least an order of magnitude larger than the effects of stimulus history.

The lack of an effect of stimulus history on the gain of the impulse response, combined with the small effect on the integration time, seems inconsistent with the reported consequences of slow adaptation. In fact, slow adaptation is thought to affect mostly the resting potential of the neuron (Baccus and Meister 2002; Solomon et al. 2004a). Since in our model the resting potential is fixed across the two halves of the stimulus, slow adaptation would result in a reduction of gain, which we do not observe. Therefore, other mechanisms that are somehow related to the stimulus history are likely to underlie the observed effects on integration time.

One possible candidate are bursts of action potentials (Jahnsen and Llinas 1984a, b; McCormick and Feeser 1990; Sherman 2001), which occur only after hyporpolatizations lasting
more than 100 ms, and thus are more likely to occur at the beginning of the stimulus (Guido et al. 1992; Lu et al. 1992). Bursts effectively advance the phase of the response to drifting gratings, since they occur only at the beginning of the rising cycle of the response (Smith et al. 2000; Mukherjee and Kaplan 1995). If this phase advance were to occur mostly during the first half of the stimulus it could contribute to difference in integration time across the two halves.

Our analysis also implies that the parameters of the estimated impulse responses are robust with respect to overfitting to the noise. In fact, when predicting the responses to one half of the stimulus with the impulse response estimated from the other half we are effectively testing the impulse response on a set of responses that has not been used for the fits. The difference between the quality of the predictions and the quality of the fits is small (Figure 3-5). This difference in quality represents an upper bound to the contribution of overfitting to the quality of the fits. Indeed, not only overfitting, but also the difference in the integration time across the two halves of the stimuli contributes to the difference in quality.

The total lack of an effect of slow adaptation on the responses to our stimuli is somehow puzzling. Not even for stimuli of 100% contrast did we observe a reduction in gain across the two halves of the stimulus. This is surprising, given that the stimuli contain many high temporal frequencies, which have been shown to elicit the strongest adaptation (Solomon et al. 2004a).

The lack of effects of slow adaptation is likely to be due to differences between our stimuli and those typically used to elicit adaptation (Baccus and Meister 2002; Smirnakis et al. 1997; Sanchez-Vives et al. 2000; Solomon et al. 2004a) rather then to differences in the preparation or in the population of neurons. In additional experiments on a small sample of neurons, we reproduced the typical effects of slow adaptation using the paradigm of Solomon et al. (2004a). Gain was reduced strongly after long presentations of a high contrast grating in Y-cells and to a lesser degree in X-cells. It is possible that the section of our stimuli (Figure 3-1) containing high temporal frequencies is too short to cause adaptation or, alternatively, that slow adaptation occurs only when the temporal frequency content of the stimulus does not vary over time.

3.4 Methods

The methods used in this chapter are by and large the same as those described in Chapter 2. We again estimate the impulse response of a neuron by fitting a descriptive model to its responses. Both the descriptive model (Figure 2-3), the stimuli, and the cell population are the same as in Chapter Chapter 2.

The only difference here is that we separately estimate two impulse responses from the two halves of the temporal frequency sweeps. We estimate the first impulse response from the first 5 seconds of the stimulus, when temporal frequency is increased from 0.5 to 40 Hz (Figure 3-1, red). We estimate the second impulse response from the subsequent 5 seconds, when temporal frequency is reduced from 40 Hz back to 0.5 Hz (Figure 3-1, orange). The impulse responses shown in the previous as well as in the following chapters were estimated from the entire 10 seconds of stimulation, even though for simplicity we always show only responses obtained from the first half of the stimulus.
To average overall gain and integration time over the population of neurons we first normalized both measures and then binned the gain and integration time estimated from the first half of the stimuli and averaged the gain and integration time obtained from the second half (Figure 3-4). We normalized gain such that the largest gain estimated from the first half of the stimulus was 100% for every neuron. Similarly, we normalized integration time such that the longest and the shortest integration times estimated from the first half of the stimulus were 100% and 0%.
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Chapter 4

Independence of gain control mechanisms

4.1 Introduction

When we explore a natural environment with our eyes, the luminance and the contrast that fall within the receptive field of a given visual neuron change from one fixation to the next. These changes in luminance and contrast occur at a rapid pace, since the eyes typically fixate a given location for only 200-300 ms. Presumably the statistical properties of these variations in luminance and contrast have had a substantial influence, through natural selection, on the design of the mechanisms of luminance gain control and contrast gain control operating in the visual system. In fact, there is much circumstantial evidence for a close relation between the statistics images encounter in natural vision and the design of the visual system (for reviews see Simoncelli and Olshausen 2001; Geisler and Diehl 2002).

A recent study by Frazor and Geisler (2005; Frazor and Geisler 2004) demonstrated that luminance and contrast vary independently of each other during vision. These authors first measured the joint distribution of luminance and contrast in small, non-overlapping patches selected from natural images and found that luminance and contrast are statistical independent of each other. They then showed that gaze shifts are mostly large enough that from one fixation to the next there is little correlation in the luminance and contrast within the receptive field of a typical neuron in the early visual system.

Given that luminance and contrast are independent dimensions during natural vision, it would seem advantageous to regulate the gain of responses independently along these two dimensions. Indeed, any dependency in the effect of luminance gain control and contrast gain control would have seemingly undesired consequences. To pick an extreme example, if the visual system adjusted gain only on the basis of luminance, and assumed that contrast depends on luminance, it would be making the wrong adjustment because contrast is independent of luminance.

Even though luminance gain control and contrast gain control have been extensively studied in isolation, little is known about whether and how they interact. The prevailing, though mostly implicit assumption is that the effects of luminance gain control and contrast gain control are independent of each other (Shapley and Enroth-Cugell 1984; Shapley 1986; Troy and Enroth-Cugell 1993; Shapley and Man-Kit Lam 1993). However, independence has never been tested, since typically the effects of luminance gain control have been studied with stimuli of fixed contrast, while the effects of contrast gain control have been studied with stimuli of fixed luminance. Any exceptions to this design were of limited scope and in particular did not address the effects of gain control on the integration time of the neurons (Troy and Enroth-Cugell 1993).

To overcome these limitations, in Chapter 2 we estimated the impulse response of LGN neurons for many combinations of luminance and contrast, covering ranges similar to those
encountered in natural vision. Based on these measurements we can now directly test if the effects of luminance gain control and contrast gain control are independent of each other.

4.2 Results

In Chapter 2 we estimated the impulse response of LGN neurons at many combinations of luminance and contrast (Figure 2-7, replotted in Figure 4-2, red). As discussed Chapter 2, we estimated the impulse response by fitting a descriptive model (Figure 2-3) to the responses. In the descriptive model the stimulus is filtered by a linear receptive field, whose output is added to Gaussian noise and rectified. The impulse response is estimated independently for each stimulus, while the remaining model parameters are kept constant across stimuli.

To test whether luminance gain control and contrast gain control operate independently of each other, we asked whether their effects can be explained by a separable model (Figure 4-1), which has far fewer parameters than the descriptive model (Figure 2-3), and embodies the assumption of independence. In this model the impulse response is described by a fixed filter (pink) followed by two variable filters; a filter for luminance gain-control (blue), which depends only on mean luminance, and a filter for contrast gain-control (green), which depends only on contrast. The impulse response at a given luminance and contrast is the convolution of the three appropriate filters.

Because in frequency space a convolution corresponds to a product, the separable model has a very simple formulation in terms of the transfer function of the neuron. For a given combination of luminance and contrast, the transfer function of the neuron is given by the product of the transfer functions of the appropriate filters in Figure 4-1 (see Methods). The separable model thus makes a very strong prediction: the effects on the transfer function of going down one column in Figure 2-7B (or in Figure 4-2B, red) should be the same for all columns, and the effects of going along one row should be the same for all rows.

![Figure 4-1](image)

Figure 4-1. The separable model. The impulse response is the convolution of three filters: a fixed filter (pink), a luminance gain filter (blue) and a contrast gain filter (green).

To find the set of filters of the separable model that best describe the estimated transfer functions we used singular value decomposition on the estimated matrix (Figure 2-7B). We compute the singular value decomposition separately at each temporal frequencies, and used a smoothness constraint on the model transfer functions to combine the decomposition of different temporal frequencies.
This calculation yielded the fixed filter (Figure 4-2, pink), six snapshots of the filter for luminance gain-control, one for each luminance tested (Figure 4-2, blue), and five snapshots of the filter for contrast gain-control, one for each contrast tested (Figure 4-2, green). The convolution of the impulse response of the three appropriate filters yields the fit of the impulse response of the neuron (yellow), and the product of the corresponding transfer functions yields the fit of the transfer function of the neuron. As expected, the impulse response of the variable filters in the model becomes smaller and faster as luminance or contrast are increased (Figure 4-2A). Thus, the amplitude of the corresponding transfer functions is reduced at low temporal frequencies, and is approximately constant at high frequencies.

Figure 4-2. Fits of the separable model. Same cell as in Figure 2-7. A: impulse responses predicted by the separable model (yellow), compared to those predicted by the descriptive model (red, replotted from Figure 2-7A for comparison). The latter are barely visible in the superposition, indicating that the predicted impulse responses are extremely similar. Each impulse response (yellow) is the convolution of the fixed filter (pink) with the luminance gain filter in the appropriate column (blue) and a contrast gain filter in the appropriate row (green). B: the amplitude of the transfer functions predicted by the separable model (yellow), compared to those predicted by the descriptive model (red, replotted from Figure 2-7B for comparison). Each transfer function (yellow) is the product of the fixed filter (pink) with the luminance gain filter in the appropriate column (blue) and a contrast gain filter in the appropriate row (green). The descriptive and separable models explain 85% and 81% of the stimulus driven variance in the firing rate.

The separable model provides excellent fits to the data. Indeed, it predicts impulse responses that are barely distinguishable from those estimated by the descriptive model (Figure 4-2, compare yellow and red curves). This is the case not only for the On-center, X-type cell in Figure 4-2, but also for Off-center cells and Y-type cells (Figure 4-4).

To gauge the performance of the separable model, we also considered how it predicts the effects of a luminance and contrast on the overall gain and integration time of the impulse response (Figure 4-3). As in Chapter 3 (Figure 3-3), we computed overall gain by averaging the transfer function (Figure 4-2B) between 0.5 and 15 Hz (at higher frequencies gain is barely
affected by changes in luminance and contrast). Changing the contrast (Figure 4-3A) or luminance (Figure 4-3B) has the effect of shifting the estimated gain (dots) along the vertical axis. The separable model (lines) predicts these effects. Indeed, in the separable model luminance gain control and contrast gain control have the effect of multiplying the gain of the fixed filter. Because gain is plotted on a logarithmic axis in Figure 4-3A and B, the multiplication corresponds to a vertical shift. As an overall measure of integration time we took the slope of the best-fitting line relating the phase of the transfer function to frequency, weighted by the amplitude at each frequency (Reid et al. 1992). The effects of gain control on the estimated integration time (Figure 4-3C and D, dots) are also captured by the predictions of the separable model (lines). The effects are less intuitive than those on gain, as integration time is affected both by the amplitude and phase of the transfer function.

Figure 4-3. Estimated and predicted gain and integration time. Dots correspond to the estimated gain and integration time (computed from the estimated impulse responses, Figure 4-2A, red). Lines correspond to the predicted gain and integration time (computed from the predicted impulse responses, Figure 4-2A, yellow). A: Gain as a function of luminance for different contrasts. B: Gain as a function of contrast for different luminances. Because gain in A and B is plotted on a logarithmic axis, the multiplicative effect of gain control in the separable model corresponds to a vertical shift of the predicted gain. C: Integration time as a function of luminance for different contrasts. D: Integration time as a function of contrast for different luminances. In A and C the brightness of the dots and lines is proportional to contrast. In B and D the brightness of the dots and lines is proportional to luminance.

The separable model predicts the firing rate responses almost as well as the descriptive model (compare Figure 4-5A and B). The percentage of stimulus driven variance explained by the two
models is comparable, with a median across cells of 81% for the separable model (Figure 4-5B) vs. 85% for the descriptive model (Figure 4-5A). For example cell in this chapter (and in Chapter 2) fit quality happens to be the same as the median values, 81% and 85%.

This performance is remarkable, given that the separable model has many fewer degrees of freedom than the descriptive model. To predict the responses, the descriptive model requires 25 filters (i.e. one impulse response for each combination of mean luminance and contrast) while the separable model requires only 10 filters: the fixed filter plus the snapshots of the variable filters for 5 luminances and 4 contrasts (the snapshots for the highest luminance and contrast are fully constrained, see Methods).

Figure 4-4. Separability holds in On- and Off-center cells, as well as in X- and Y-type cells. The plotting conventions are the same as in Figure 4-2A. A: an Off-center, X-type cell. The descriptive model explains 85% of the variance in the responses of this cell, compared to 84% for the separable model. B: an On-center, Y-type cell. The descriptive model explains 57% of the variance in the responses of this cell, compared to 56% for the separable model.

To gauge the quality of the separable model we also tried to predict the full set of responses with a one-dimensional subset of impulse responses. Such a subset could account for the responses if the effects of luminance and contrast were due to the effects of only one gain control mechanism, which could operate based on luminance alone, contrast alone, or any combination of the two. We predicted the responses with the impulse responses estimated at combinations of luminance and contrast lying close to the diagonal running from top-left to bottom-right in Figure 4-2 (red curves). For each luminance, the impulse response nearest to the line was used to predict the responses obtained at all contrasts. This method yielded poor fits, explaining only 35% (median) of the stimulus-driven variance of the responses. Even though our method is not guaranteed to find the one-dimensional set that best explains the full matrix, it is unlikely that other methods would yield much larger values. By reducing the number of filters from 25 (in the descriptive model) to 10 (in the separable model) the quality of predictions is reduced by only 4%.
(from 85% to 81%, Figure 4-5). When discarding 4 more filters (in the one-dimensional subset) quality of predictions plummets by 46% (from 81% to 35%, median values). This demonstrates that the separable model captures the most informative dimensions in the matrix of impulse responses.

Figure 4-5. Quality of fits. A: Percentage of stimulus driven variance in the firing rate response explained by the descriptive model. Replotted from Figure 2-6 for comparison. B: Percentage of stimulus driven variance in the firing rare responses explained by the separable model. Arrows point to the medians of the distribution, 85% (A) and 81% (B).

4.3 Discussion

The independence of gain controls for luminance and contrast may not seem very surprising at first, given the common assumptions that the output of luminance gain control (1) removes all effects of mean luminance, and (2) depends linearly on contrast. If these assumptions were correct, then contrast could be simply computed by taking the standard deviation of the output of luminance gain control. However, both assumptions are not accurate.

First, the output of the mechanisms performing luminance gain control does depend on mean luminance: It emphasizes the low temporal frequencies at low mean luminance, and the high temporal frequencies at high mean luminance (Figure 2-4). Thus, at high temporal frequencies a stimulus of low contrast and high luminance can elicit the same response as a stimulus of high contrast and low luminance. To interpret these responses and estimate stimulus contrast, a subsequent contrast gain control stage would have to know the mean luminance.

Second, the output of the mechanism performing luminance gain control does not grow linearly with contrast (Lankheet et al. 1991b; Lee et al. 2003). For a high-contrast stimulus, the gain and integration time of the receptive field can vary over time, since local luminance is computed very locally and very rapidly (Shapley and Enroth-Cugell 1984). This is illustrated in the response of a horizontal cell in (Figure 4-6). Because luminance gain control operates very rapidly, gain and integration time are reduced when the luminance over the receptive field is larger than average, and increased when luminance is smaller than average. Thus, the responses to luminance increments during a high contrast stimulus (black, lower trace) are smaller and occur earlier then predicted by a linear model (blue), while the responses to luminance decrements are larger and occur later. These effects can not be attributed to contrast gain control,
which affects responses only at later stages of visual processing (Baccus and Meister 2002) and does not depend on the polarity of the stimulus (Bonin 2005; Bonin et al. 2005a; Victor 1987).

Figure 4-6. Effects of contrast on the responses of an horizontal cell in the monkey retina. We compare the membrane potential of the cell in response to a stimulus of low (top) and high (bottom, black) contrast. The response to the high contrast stimulus is compared to prediction of a linear model (blue), which was obtained by scaling the response to the low contrast stimulus by the ratio of the two contrasts. Positive deflections of luminance cause negative deflection of the membrane potential. Modified from Lee et al. (2003).

Since luminance gain control occurs at the very first stages of retinal processing, the signal driving contrast gain control (i.e. contrast) must be computed from the output of luminance gain control (Figure 4-7). Thus, to compute contrast and to achieve independence in the effects of luminance gain control and contrast gain control the visual system might need to compensate for the effects of mean luminance and contrast on the output of luminance gain control. For instance, if local contrast were computed by taking the standard deviation of the output of luminance gain control (Shapley and Enroth-Cugell 1984) the effects of luminance gain control and contrast gain control would be strongly dependent.

Figure 4-7. The computation of local luminance and local contrast in the early visual system. Local luminance can be computed directly from the image. On the other hand, local contrast has to be computed from the output of luminance gain control, as the latter occurs before contrast gain control, at the very first stages of retinal processing.

The independence in the effects of luminance gain control and contrast gain control is likely to reflect the independence of luminance and contrast in natural images (Frazor and Geisler 2004, 2005). Indeed, as we argued in the introduction, any dependency in the effects of the two gain control mechanisms would have seemingly undesired consequences. The simplicity of this design, in which two gain control mechanisms operate independently along two independent
dimensions, is further emphasized by closely related results from our lab. Given that gain control operates along the mean (i.e. luminance) and the variance (i.e. contrast) of the luminance distribution falling on the receptive field, it not unthinkable that gain control would operate also along different, higher-order moments of the distribution. To assess if higher order moments affect the gain or integration time of LGN neurons we thus estimated the impulse response from the responses to stimuli that varied either in the second moment (i.e. skewness) or in the third moment (i.e. kurtosis) of their luminance distributions. Since we found that only very small effects of these higher-order moments on the impulse response (Bonin 2005; Bonin et al. 2005a), we conclude that gain control operates not only independently but also exclusively along the two dimensions of luminance and contrast.

Our results add to the growing body of evidence for a close match between the statistical properties of natural scenes and the processing of contrast in visual systems. For example, there appears to be a close correspondence between the range of local contrasts in natural images and the dynamic range of single neuron responses in the eye (Laughlin 1981; Ruderman 1994) and in the LGN (Tadmor and Tolhurst 2000). Similarly, the statistics of natural images, together with the observation that signal strength, compared to noise strength, is smaller at low contrasts, can predict how the shape of the impulse response changes across contrasts (Van Hateren 1993). There is also computational evidence that for natural images rapid local contrast adaptation enhances faint contours (Ruderman 1994) and increases statistical independence (reduces the redundancy) in the responses of orientation and spatial frequency selective neural populations in visual cortex (Schwartz and Simoncelli 2001). Ultimately, however, a naturalistic explanation of the computational advantages of contrast gain control will have to account for the large differences seen across species across the different retinogeniculate streams such as the M and P pathways in primates (Lennie 1980).

Our results also provide direct support for the hypothesis (Shapley and Enroth-Cugell 1984; Shapley 1986; Troy and Enroth-Cugell 1993; Shapley and Man-Kit Lam 1993) that contrast is a fundamental independent variable encoded by the early visual system. Thus, they strengthen and validate a large body of neurophysiological, psychophysical, and theoretical research that implicitly assumed that luminance and contrast gain control are functionally independent.

4.4 Methods

4.4.1 Model

The separable model (Figure 4-1) differs from the descriptive model described in Chapter 2 (Figure 2-3) only in the definition of the impulse response \( f_{LC} \).

In the separable model the impulse response \( f_{LC} \) is approximated by the convolution of three filters:

\[
f_{LC}(t) \approx [f_0 * f_L * f_C](t),
\]

where \( f_0 \) is fixed, \( f_L \) depends only of mean luminance (it describes the effects of luminance gain control) and \( f_C \) depends only of contrast (it describes the effects of contrast gain control).
4.4.2 Estimation of separable filters

To find the filters $f_0, f_L,$ and $f_C$ we take the Fourier transform of both sides of eq (4):

$$F_{L,C}(\omega) \approx F_0(\omega) \cdot F_L(\omega) \cdot F_C(\omega),$$

where $\omega$ is frequency and capital letters are transforms of the corresponding lower case variables. If $L$ assumes $m$ values and $C$ assumes $n$ values, then, for each frequency $\omega$, $F_{L,C}(\omega)$ is an $m$ by $n$ rectangular matrix. If all values in the matrix are defined, then Singular Value Decomposition (SVD) yields two vectors $F_L(\omega)$ and $F_C(\omega)$ whose product, up to the constant $F_0(\omega)$, is the best separable approximation of the measured $F_{L,C}(\omega)$ (Golub and van Loan 1989). The constant filter $F_0(\omega)$ was chosen such that $F_{L_{\text{max}}}(\omega) = 1$ and $F_{C_{\text{max}}}(\omega) = 1$, where $L_{\text{MAX}}$ and $C_{\text{MAX}}$ are the largest tested values for $L$ and $C$ (Figure 4-2B, yellow). The inverse Fourier transform of $F_0(\omega) \cdot F_L(\omega) \cdot F_C(\omega)$ yielded the impulse responses used to predict the responses to sweeps (Figure 4-2A, yellow).

This procedure worked well for all frequencies $\omega$ below about 50 Hz. Above this value, there is little power in the response, and the problem becomes ill constrained. We therefore imposed $F_L(\omega) = 0$ and $F_C(\omega) = 0$ for $\omega > 50$ Hz.

A technical difficulty with the application of the SVD method to our data is that it requires that a matrix have no empty entries. Our matrices, instead, contained empty values in the top right corner (e.g. Figure 4-2A), corresponding to those few combinations of $L$ and $C$ that were not physically realizable. To estimate these entries we performed a simple extrapolation based again on the principle of separability.
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Chapter 5

A steady-state model of gain control

5.1 Introduction

The independence of the effects of luminance gain control and contrast gain control (Chapter 4) considerably simplifies the design of a general model of gain control. Because the effects are independent, we can capture them with a simple separable model (Figure 5-1A). In the model, the impulse response is described as the convolution of three filters: a fixed filter; a filter that depends only on luminance (performing luminance gain control); and a filter that depends only on contrast (performing contrast gain control). Because the model is separable, the filter of luminance gain control can be fully characterized from impulse responses estimated at a single contrast, and likewise the filter of contrast gain control can be fully characterized from impulse responses estimated at a single luminance. Based on this limited set of measurements, the separable model predicts the impulse at all combinations of luminance and contrast used to characterize its filters.

However, the separable model also has an important limitation, namely that it can predict the impulse response only at luminance or contrast values at which its filters have been estimated. For instance, if the filter of contrast gain control has been estimated at 10 and 30% contrast, the separable model makes no prediction on how the impulse response would look like at 20% contrast.

To overcome this limitation, in this chapter we will develop a parametric model of the effects of luminance and contrast on the filters of the separable model. We will show that the effects of gain control on the impulse response can be captured with only two parameters, one that depends only on luminance and the other that depends only on contrast. By interpolating the values of these two parameters we will then be able to predict the impulse response at any new combination of luminance and contrast.

The model presented here is in many ways similar to the models of luminance gain control (e.g., Fuortes and Hodgkin 1964; Sperling and Sondhi 1968; Baylor et al. 1974; Shapley and Enroth-Cugell 1984; Purpura et al. 1990; Brodie et al. 1978) and contrast gain control (e.g., Shapley and Victor 1981; Victor 1987; Carandini et al. 1997; Benardete and Kaplan 1999) that have been proposed in the past. Typically, the design of these models is analogous to the design of the separable model, as the impulse response is described as the convolution of a fixed filter and a variable low- or highpass filter. However, even small differences between the models complicate a comparison of the properties of luminance gain control and contrast gain control. Here we overcome this limitation by using the same model to describe both the effects of luminance gain control and contrast gain control.
5.2 Results

5.2.1 Model description

To capture the effects of gain control on the impulse response, we use a model whose structure is based on the separable model introduced in Chapter 4. In the separable model (replotted in Figure 5-1A) the impulse response is described as the convolution of three filters. The first filter (red) is fixed for a given neuron. The second filter (blue) depends only on the luminance of the stimulus, and captures the effects of luminance gain control. The third filter (green) depends only on contrast, and captures the effects of contrast gain control. This arrangement results in independent effects of luminance and contrast on the impulse response.

While in Chapter 4 we did not impose any particular shape for the filters, here we introduce a parametric description of the filters. We implement the filters performing luminance gain control and contrast gain control as series of resistor-capacitor (RC) circuits (Figure 5-1B). The first series of \( n_L \) RC-circuits performs luminance gain control, while a second series of \( n_C \) RC-circuits performs contrast gain control.

![Figure 5-1. The steady state model of luminance and contrast gain control. A: The separable model, replotted from Figure 4-1 for comparison. B: The steady-state model. The model consists of three stages: (1) a fixed bandpass filter; (2) a series of \( n_L \) resistor-capacitor (RC) circuits, which models the effects of luminance gain control; (3) a series of \( n_C \) RC-circuits, which models the effects of contrast gain control. The conductance \( g_L \) of the first series of RC-circuits depends only on luminance. The conductance \( g_C \) of the second series of RC-circuits depends only on contrast. All other model parameters are fixed across luminance and contrast. For simplicity, we illustrate the case where \( n_L = 1 \) and \( n_C = 1 \). Each RC-circuit is characterized by the capacitance \( C \) of its capacitor and by the conductance \( g \) of its resistor. When the value of \( C \) and \( g \) are fixed, each RC-circuit acts as a linear filter, which is completely characterized by its impulse response or, alternatively, by its transfer function.](image-url)
Adding the RC-circuits in series then corresponds to convolving the impulse response of each circuit and thus again results in a linear filter.

In the simplest case, illustrated in Figure 5-1, \( n_L = 1 \) and \( n_C = 1 \) and thus the model consists of the fixed impulse response and two RC-circuits. The effects of luminance and contrast are implemented by changing the conductance of the RC-circuits while keeping their capacitance fixed. The conductance \( g_L \) of the first RC-circuit depends only on luminance while the conductance \( g_C \) of the second RC-circuit depends only on contrast.

The conductances of the RC-circuits control the overall gain and integration time of the impulse response. When the conductance of one of the RC-circuits is increased, its impulse becomes faster, i.e. integration time is reduced (Figure 5-2, blue background; conductance increases from left to right). Because the height of the impulse responses is not affected by the change in conductance, the reduction in integration time results in a smaller area under the impulse response and, thus, in a smaller overall gain. Both the reduction in gain and the reduction in integration time are reflected in the impulse response of the model, i.e. the convolution of the three filters in Figure 5-1B. Thus, the effects of the conductance on the impulse response of the model are at least qualitatively similar to the effects of luminance and contrast on the impulse response of LGN neurons.

The relation between the effects of conductance on overall gain and on integration time depends on \( n_L \) and \( n_C \), i.e. on the number of RC-circuits in the two gain control stages. In the model only the first RC-circuit of a series affects the overall gain of the impulse response, while all subsequent RC-circuits affect only its integration time (see Methods for details). Thus, changing \( n_L \) or \( n_C \) has no effects on the relation between conductance and overall gain. On the other hand, a given change in conductance results in a small change in integration time when \( n_L \) or \( n_C \) are small and in a large change in integration time when \( n_L \) or \( n_C \) are large.

### 5.2.2 Fitting the effects of luminance

To constrain the parameters of RC-circuit performing luminance gain control we estimated the impulse response at various luminances while keeping contrast fixed (Figure 5-2, red curves). As shown in the previous chapters, increasing luminance results in a smaller and shorter impulse response.

The model provides a very good description of the effects of luminance on both the size and shape of the impulse response (Figure 5-2, top row). The fitted impulse responses (black) lie on top of the estimated impulse responses (red) for all stimuli. The only model parameter that is allowed to vary across the different stimuli is the conductance of luminance gain control, \( g_L \). All other model parameters, specifying the shape of the initial bandpass filter and the RC-circuits of contrast gain control, are fixed.
Figure 5-2. Effect of luminance on the estimated and fitted impulse response. The estimated impulse responses for an example LGN neuron are plotted in red, the fitted impulse responses are plotted in black (top row). In this example the estimated and fitted lie essentially on top of each other. The fixed filter (red background) and the impulse response of the RC-circuit performing luminance gain control (blue background) are plotted in the bottom row. The impulse responses where estimated at luminances logarithmically spaced between 13 and 51 cd/m². Contrast was fixed at 25%.

As luminance is increased, the conductance of luminance gain control increases as well (Figure 5-3). In good approximation, when luminance is doubled, the conductance is doubled as well. Indeed, the points in Figure 5-3 lie on a line with a slope of 1, implying that conductance is proportional to luminance.

Figure 5-3. Conductance of luminance gain control. The red line is obtained from linear regression on the plotted points. The slope of the line (0.94) corresponds to the exponent of the power law relating luminance to conductance.

The effects of the RC-circuit on the amplitude of the responses depend on the temporal frequency of the stimulus. This can be illustrated by computing the Fourier transform of the impulse responses in Figure 5-2, yielding the transfer function of the various filters. In Figure 5-4 we plot only the amplitude of the transfer function, which describes how gain depends on temporal frequency.
When conductance is increased, the gain of the RC-circuit is strongly reduced at low temporal frequencies, while at high temporal frequencies it is approximately constant (Figure 5-4, blue background). The transfer function of the model is the product of the fixed transfer function (red background) with the transfer function of the RC-circuit at the appropriate luminance (blue). Thus, as luminance is increased, the gain of the neuron is reduced at low temporal frequencies but not at high temporal frequencies. As a consequence, the optimal temporal frequency of the neuron (i.e. the one with the largest gain) moves to higher values for increasing luminance.

As discussed in Chapter 2, the effects of gain control on the transfer function are a direct reflection of the effects of gain control on the impulse response. As luminance is increased, the impulse response becomes smaller and faster (Figure 5-2). The reduction in size corresponds to an equal reduction in gain at all temporal frequencies. The reduction in integration time, on the other hand, selectively enhances gain at high temporal frequencies and, at these frequencies, compensates for the effects of the reduction in size.

As we show in the discussion, there is a simple relation between the gain of the model at low temporal frequency and the conductance of the RC-circuit. Namely, gain at low temporal frequency is inversely proportional to conductance. Because conductance is proportional to luminance, this implies that gain at low temporal frequency is inversely proportional to luminance. Thus, over the ranges of luminance that we tested, luminance gain control is perfect: the amplitude of the response to a low temporal frequency stimulus is independent of its luminance. Luminance gain control thus follows Weber's law (Lee et al. 1994; Yeh et al. 1996; Purpura et al. 1990; Enroth-Cugell et al. 1977; Daw and Pearlman 1969).
Like in the previous chapters, we assess the quality of the fits by using the fitted impulse responses to predict the underlying responses. For the example cell, the model explains 91% of the stimulus driven variance in the response. In comparison, the estimated impulse responses explain 92% of the stimulus driven variance. The difference in quality between the two predictions is similar over the entire population of neurons (Figure 5-5). The median values over the population are 81% and 83%.

5.2.3 Fitting the effects of contrast

As we have seen in the previous chapters, the effects of contrast on the impulse response are very similar to those of luminance. When contrast is increased, the estimated impulse response becomes smaller and faster (Figure 5-6). In the model these effects are captured by the second series of RC-circuits, whose conductance $g_C$ depends on contrast. The capacitance of the RC-circuits is fixed across all stimuli, as was the case when fitting the effects of luminance.

![Figure 5-6. Effect of contrast on the estimated and fitted impulse response, same cell as in Figure 5-2. The estimated impulse responses are plotted in red, the fitted impulse responses are plotted in black (top row). The fixed filter (red background) and the impulse response of the RC-circuit performing contrast gain control (green background) are plotted in the bottom row. The impulse responses where estimated at contrasts logarithmically spaced between 3 and 100 %. Luminance was fixed at 32 cd/m$^2$. The model accurately captures the effects of contrast on both the size and shape of the estimated impulse response (Figure 5-6). The largest deviations between the estimated and fitted responses is 8% for both prediction schemes.](image)
impulse responses occur at low contrast, where both response amplitude as well as the signal-to-noise ratio are small. Our estimates of the impulse responses are likely to be less accurate at these low contrasts, which might at least in part account for the differences between the estimated and fitted impulse responses.

Figure 5-7. Conductance of contrast gain control. The red line is obtained from linear regression on the plotted points. The slope of the line (0.68) corresponds to the exponent of the power law relating contrast to conductance.

Similarly to the effects of luminance on the conductance of luminance gain control (Figure 5-3), we find that the conductance of contrast gain control grows with contrast (Figure 5-6). Unlike what we found for luminance, however, the conductance is not proportional to contrast. Indeed, the points in Figure 5-6 lie on a line with slope smaller than 1, indicating a power law relation between contrast and conductance. The slope of the line (0.68 for this neuron) corresponds to the exponent of the power law.

Figure 5-8. Effect of contrast on the estimated and fitted transfer function. Same data as in Figure 5-6. The amplitude of the transfer function is plotted as a function of temporal frequency on a logarithmic scale, between 0.5 and 40 Hz.

As conductance increases, the impulse response of the RC-circuit becomes progressively shorter (Figure 5-6). In terms of the transfer function, the shorter impulse response results in a
smaller gain at low temporal frequencies (Figure 5-8). Because gain and conductance are inversely proportional, contrast and gain at low temporal frequencies are related by a power law.

Unlike luminance gain control, therefore, contrast gain control is not perfect. The reduction in gain causes response amplitude to saturate with contrast, but is not strong enough to make response amplitude independent of contrast. Even though contrast gain control has less effects on gain as does luminance gain control, the reduction in gain over the entire range of contrast (Figure 5-8) is larger than the reduction over the entire range of luminance (Figure 5-4). This, however, is simply a consequence of large range of contrasts (3-100%) compared to the much smaller range of luminance (13-51 cd/m²) used for this neurons.

The fitted impulse responses explain 92% of the stimulus driven variance in the responses of this neuron. In comparison, the estimated impulse responses explain 95% of the stimulus driven variance. We obtained similar results on the entire population of neurons (Figure 5-9). Over the population the values are 81% and 78% (median).

5.2.4 Conductances

Over the entire population of neurons (N = 39) the effect of luminance and contrast on the conductances \( g_L \) and \( g_C \) of the RC-circuits (Figure 5-10) was similar to the effects found for the example cell (Figure 5-3 and Figure 5-7). We normalized the conductances such that \( g_L = 1 \) at the maximum tested luminance and \( g_C = 1 \) at the maximum tested contrast. To estimate the exponents \( p_L \) and \( p_C \) of the power laws relating luminance to \( g_L \) and contrast to \( g_C \) we computed linear regression on \( g_L \) and \( g_C \) in log-log coordinates, after pooling the fitted values over all neurons. Over the entire population, we found \( p_L = 0.90 \pm 0.05 \) and \( p_C = 0.63 \pm 0.04 \) (95% confidence intervals).
5.3 Discussion

5.3.1 Luminance- and contrast-responses

The contrast-response function of neurons throughout the early visual system has often been described with a function of the form (e.g., Albrecht and Hamilton 1982; Derrington and Lennie 1984; Sclar et al. 1990):

$$R = k_c \frac{C^{p_c}}{C_{50}^{p_c} + C^{p_c}}.$$  \hspace{1cm} (5)

This function describes how response amplitude $R$ depends on the contrast $C$ of a grating of fixed mean luminance. The semisaturation contrast $C_{50}$ and the exponent $p_c$ determine the shape of the contrast-response function, while the scaling factor $k_c$ determines the overall amplitude of the responses.

Over the ranges of stimulus contrast typically used in LGN experiments, the predictions of Eq. (5) are largely equivalent with the prediction of the RC-model discussed in this chapter. This is illustrated in Figure 5-11B, where we show prediction of the RC-model (circles) together with fits of Eq. (5) (lines) at three different temporal frequencies. We obtained the predictions of the RC-model using the model parameters of the example cell discussed in this chapter. At each temporal frequency, we then fitted the three parameters of Eq. (5) directly to the predictions of the RC-model. With different sets of parameters, Eq. (5) describes both the strongly saturating contrast-response function observed at low temporal frequencies, as well as the almost linear contrast-response function observed at high temporal frequencies.

Not surprisingly, a similar descriptive function captures how response amplitude depends on the mean luminance $L$ of a grating of fixed contrast:
\[ R = k_L \frac{I_{PL}}{I_{PS0} + I_{PL}}. \]  

(6)

We again fitted the three parameters of Eq. (6) directly to the prediction of the RC-circuit at a given temporal frequency (Figure 5-11A).

Figure 5-11. Effects of gain control at different temporal frequencies. Dots are predictions of the RC-model for luminance gain control (A) and contrast gain control (B). The predictions were computed with the model parameters of the example cell in Figure 5-2 and Figure 5-4. Lines are fits with a descriptive function [Eq. (5) and (6)].

To some extent, \( L_{SO} \) and \( p_L \) in Eq. (6) and \( C_{SO} \) and \( p_C \) in Eq. (5) have similar effects on the shape of the luminance-response and contrast-response functions. In fact, at intermediate and high temporal frequencies Eq. (5) and (6) provide good fits of the luminace- and contrast-response functions even when \( p_L \) and \( p_C \) are fixed to 1 (as in Bonin 2005; Bonin et al. 2005b). However, as discussed in the next section, at low temporal frequencies good fits often require values \( p_L \) and \( p_C \) differing from 1.

5.3.2 Strength of gain control

Having characterized luminance gain control and contrast gain control with the same model (Figure 5-1), we can easily compare their strengths. Intuitively, the stronger gain control, the more invariant are the responses with respect to luminance or contrast. Since invariance in the response amplitude is achieved by reducing the gain of the neuron as luminance or contrast are increased, we can infer the strength of gain control by estimating how gain in the model depends on luminance and contrast. We have shown that an increase in luminance or contrast causes the strongest reduction in gain at low temporal frequencies, while gain at high frequencies is either constant or increases with luminance and contrast. Thus, to characterize the strength of gain control we focus on how it affects gain at the lowest temporal frequencies.

At low temporal frequencies the gain of the RC-circuits is inversely proportional to conductance (see Methods, 5.4.3). We found that the functions relating luminance and contrast to \( g_L \) and \( g_C \) are well approximated power laws:

\[ g_L \propto I_{PL} \text{ and } g_C \propto C_{PC}, \]
where $p_L$ is the exponent of luminance gain control and $p_C$ is the exponent of contrast gain control. On average we found $p_L = 0.9$ and $p_C = 0.6$ (Figure 5-10).

Thus, gain depends on luminance $L$ and contrast $C$ as:

$$
\text{gain} \propto \frac{1}{g_L} \propto \frac{1}{L^{p_L}} \quad \text{and}
$$

$$
\text{gain} \propto \frac{1}{g_C} \propto \frac{1}{C^{p_C}} .
$$

Crucially, these equations describe the gain of the model only in the limit of low temporal frequency or of high luminance and high contrast. Nevertheless, we can use them to quantify the differences between the effects of luminance gain control and contrast gain control.

Consider first how response depends on luminance. If gain were independent of luminance, then the response to a grating of fixed contrast would be proportional to the luminance of the grating. Thus, by taking into account how gain depends on luminance we find:

$$
\text{response} \propto \text{gain} \cdot L \propto \frac{L}{L^{p_L}} \propto L^{1-p_L} \approx L^{0.1} \approx \text{const}
$$

showing that the response grows only very weakly with luminance. In fact, in many neurons $p_L$ is close to 1 and thus response amplitude does not depend on luminance. Thus, at low temporal frequencies luminance gain control in LGN neurons follows Weber's law (Shapley and Enroth-Cugell 1984). This finding is consistent with previous studies of luminance gain control in retinal ganglion cells, whose responses follow Weber's law at luminance levels similar to those of our stimuli (Lee et al. 1994; Yeh et al. 1996; Purpura et al. 1990; Enroth-Cugell et al. 1977; Daw and Pearlman 1969).

Similarly, we can look at how response depends on contrast. If gain were independent of contrast, then the response to a grating of fixed luminance would be proportional to the contrast of the grating. Thus, when taking into account how gain depends on contrast we obtain:

$$
\text{response} \propto \text{gain} \cdot C \propto \frac{C}{C^{p_C}} \propto C^{1-p_C} \approx C^{0.4},
$$

showing that, on average, contrast gain control falls short of Weber's law even at low temporal frequencies (Shapley and Victor 1978; Sclar 1987). On individual neurons the exponent of contrast gain control was as large as $p_C = 0.9$, and thus responses at high contrast and low temporal frequency were almost invariant with contrast (Benardete and Kaplan 1999). However, for the majority of neurons response amplitude at low temporal frequency did saturate with contrast, but saturation was not strong enough to achieve invariance.

Luminance gain control is stronger than contrast gain also at intermediate and high temporal frequencies, even if the above argument holds only for low temporal frequencies. For instance, in the example of Figure 5-11, at 20 Hz response amplitude saturates with luminance, while it grows essentially linearly with contrast.
Equation (8) is closely related to the results of a classic paper about contrast gain control (Victor 1987). With methods that are somewhat different from ours, Victor found that in retinal ganglion cells gain depends on contrast as:

\[
gain \propto \frac{1}{C_{50}^{Pc} + C^{Pc}}.
\]  

Equation (9) is equivalent to Eq. (8) for large contrasts or small values of \( C_{50} \). Our data thus suggests that in LGN \( C_{50} \) is small compared to the smallest contrast used in this chapter. However, the results of the next chapter (Chapter 6) suggest that for even lower contrasts Eq. (9) may indeed describe the gain of LGN neurons better than Eq. (8) (Figure 6-9).

5.3.3 Biophysical correlates

The model of gain control presented in this chapter has a straightforward biophysical implementation, in which the conductance of a neuron is regulated by the luminance and contrast in the image (e.g., Carandini et al. 1997). However, this implementation is unlikely to describe biophysical mechanisms occurring in LGN neurons, which inherit most of the effects of luminance gain control and contrast gain control from the retina (as discussed in 6.3.1). But even with respect to retinal neurons our model is more likely to describe the effects of gain control rather than the underlying mechanisms.

The mechanisms underlying luminance gain control are complex and only partially understood. Luminance gain control is known to begin in the photoreceptors, where it affects the phototransduction cascade at many different stages (for reviews see Pugh et al. 1999; Fain et al. 2001; Korenbrot and Rebrik 2002; Burns and Baylor 2001). However, at luminance levels matching the ranges used in this thesis, luminance gain control is not completed in the photoreceptors. Indeed, Weber's law does not hold in cat horizontal cells, whose responses are thought to reflect the effects of luminance gain control in the photoreceptors (Lankheet et al. 1991b, a; Lankheet et al. 1993b). Thus, since the responses of ganglion cells follow Weber's law (Enroth-Cugell et al. 1977; Daw and Pearlman 1969), luminance gain control in the cat retina has to be refined at later stages of retinal processing. This distributed implementation of luminance gain control is not uncommon in other vertebrate species. For instance, in the retina of catfish the effects of luminance gain control become progressively stronger as one ascends the retinal hierarchy from horizontal cells to bipolar cells, amacrine cells and ganglion cells (Naka et al. 1979; Shapley and Enroth-Cugell 1984).

Little is known about the mechanisms underlying contrast gain control in cat. In salamander retina, the effects of fast contrast gain control appear first in bipolar cells and are refined in amacrine cells and ganglion cells (Baccus and Meister 2002). Similarly, studies of slow contrast adaptation have found contributions across a variety of cells types and mechanisms (e.g., Kim and Rieke 2001; Brown and Masland 2001; Chander and Chichilnisky 2001; Zaghloul et al. 2003; Demb 2002; Baccus and Meister 2002). Such a distributed implementation seems inconsistent with the original proposal that contrast gain control in retinal ganglion cells results from inhibition by amacrine cells (Werblin 1972; Thibos and Werblin 1978; Werblin and Copenhagen
1974) based on a measure of contrast computed by integrating the responses of a pool of bipolar cells (Victor and Shapley 1979a; Enroth-Cugell and Jakiela 1980). Inhibition from amacrine cells underlies effects similar to contrast gain control is some types of ganglion cells (Roska and Werblin 2003; Olveczky et al. 2003) but given the large number of cell types in the retina (Masland 2001; Werblin et al. 2001) so far it is unclear whether similar mechanisms operate in LGN projecting ganglion cells. In fact, to some extent contrast gain control might even arise naturally from the pooling of non-linear inputs at successive stages of retinal processing, without the need of a specific pathway computing an explicit measure of contrast (Borst et al. 2005).

5.3.4 Limits of the model

The model presented in this chapter effectively allows us to predict the impulse response at any combination of luminance and contrast, not only at combinations used to fit the parameters of the model. Indeed, we can use the inferred function (i.e. a power law) relating \( g_L \) and \( g_C \) to luminance and contrast to predict the parameters of the model at any value of luminance and contrast.

However, the model is far from being general enough to predict the response to an arbitrary stimulus. The great limitation of the model is that it does not specify how to compute the luminance and contrast of a stimulus. Indeed, luminance and contrast, together with the stimulus itself, are inputs of the model. This greatly limits its scope, as for most stimuli luminance and contrast are not easily defined. For instance, as we will show in the next chapter, the contrast of a stimulus depends on its spatial extent, and thus the model does not even generalize to stimuli that differ from the fitted ones only in their size.

In order to use the model to predict the responses to arbitrary stimuli, we will first need to define luminance and contrast for such stimuli. This involves finding the answers to a number of questions. For instance, what locations in visual space contribute to the computation of luminance? And how long into the past does the computation of luminance extend? Similarly, what locations in visual space contribute to the computation of contrast? How are the contributions from different locations combined? What spatial and temporal frequencies contribute? What temporal window?

In the next chapter (Chapter 6) we will focus on understanding how contrast is integrated over space. Other aspects of the computation of contrast have been addressed by related work in the our lab (Bonin 2005). For all the remaining questions, we will have to rely on answers provided in the literature on gain control (Chapter 7).

5.4 Methods

5.4.1 Cell population

To model the effects of luminance gain control and contrast gain control, we recorded from 31 X-cells and 11 Y-cells in 6 adult cats. Of these 42 neurons, 28 were located in layer A, 13 in layer A1, and 1 in layer C. We recorded from both On-center cells (26/42 neurons) and Off-center cells (16/42 neurons). The median eccentricity of the receptive field center was 9.5 degrees; 35/42
neurons had receptive fields with eccentricities between 1.6 and 17.6 degrees (10th and 90th percentiles). For 3/42 neurons we characterized only the effects of luminance gain control and for 4/42 neurons only the effects of contrast gain control.

5.4.2 Stimuli

To estimate the impulse response of the neurons we use the same stimuli and methods as in Chapter 2. However, rather than estimating the impulse response for a full matrix of luminance and contrast (Figure 2-7A) we estimate the impulse response for a fixed contrast and variable luminance, or for a fixed luminance and variable contrast (corresponding to a row and a column of the full matrix in Figure 2-7A). To characterize the effects of luminance we used 4 or 5 stimuli whose contrast was fixed typically to 25 or 33%. The luminance of the stimuli was logarithmically spaced between 6 and 58 cd/m². To characterize the effects of contrast we used 4-6 stimuli whose contrast was typically fixed to 32 cd/m². The contrast of the stimuli was logarithmically spaced between 3 and 100%. For most cells discussed in this chapter we characterized the effects of luminance and contrast in two separate experiments. For the rest of the cells we separately analyzed a row and a column of a full matrix of impulse response (Figure 2-7A), which was collected in a single experiment.

5.4.3 Model implementation

The steady-state model is a particular implementation of the separable model (Figure 5-1A). As in the separable model the impulse response $f_{L,C}(t)$ at luminance $L$ and contrast $C$ is described as the convolution of three filters:

$$f_{L,C}(t) = [f_0 * f_L * f_C](t),$$

where $f_0$ is a fixed, $f_L$ depends only on luminance and $f_C$ depends only on contrast. The transfer function $F_{L,C}(\omega)$ at luminance $L$ and contrast $C$ is thus given by the product of the transfer functions of the three filters:

$$F_{L,C}(\omega) = F_0(\omega) \cdot F_L(\omega) \cdot F_C(\omega).$$

Both $F_L$ and $F_C$ are based on the transfer function $H(\omega)$ of a resistor-capacitor (RC) circuit:

$$H(\omega) = \frac{1}{g} \cdot \frac{1}{1 - i\omega\tau}, \quad \tau = \frac{C}{g},$$

where $g$ is the conductance of the RC-circuit, $C$ is its conductance, and $\tau$ is the resulting time constant.

We obtain $F_L$ by adding $n_L$ RC-circuits in series. The $n_L$ RC-circuits all have the same time constant $\tau_L$, but differ in their conductances: for the first RC-circuit conductance is $g_L$, while for all other RC-circuits $g = 1$. The resulting transfer function is:

$$F_L(\omega) = \frac{1}{g_L} \left( \frac{1}{1 - i\omega\tau_L} \right)^{n_L}, \quad \tau_L = \frac{C_L}{g_L}.$$
We model the effects of contrast in the same way:

\[ F_c(\omega) = \frac{1}{g_c} \left( \frac{1}{1-i\omega\tau_c} \right)^{n_c}, \tau_c = \frac{C_c}{g_c} \]

Even though \( F_c \) and \( F_L \) have direct implementations as a series of RC-circuits only for integer values of \( n_L \) and \( n_c \), for simplicity we allowed also non-integer values in the fits.

For \( \omega \ll 1 \) the above equations become:

\[ F_L(\omega) \approx \frac{1}{g_L} \quad \text{and} \quad F_c(\omega) \approx \frac{1}{g_c}, \]

and thus the gain of the model at temporal frequencies is inversely proportional to the conductances of the RC-circuits.

5.4.4 Model fits

We can rewrite the transfer function of all stimuli of common contrast as:

\[ F_{L,c}(t) = K_c(\omega) \cdot F_L(\omega) \]

where \( K_c \) is independent of luminance:

\[ K_c(t) = F_0(\omega) \cdot F_c(\omega). \]

Similarly, we can rewrite the transfer function of stimuli of common luminance as:

\[ F_{L,c}(t) = K_L(\omega) \cdot F_c(\omega) \]

where \( K_L \) is independent of contrast:

\[ K_L(t) = F_0(\omega) \cdot F_L(\omega). \]

To simplify the fitting procedure, in this chapter we do not estimate \( F_0 \) explicitly. Rather, when fitting the effects of luminance at a fixed contrast we estimate only \( K_c \) and \( F_L \), while when fitting the effects of contrast at a fixed luminance we estimate only \( K_L \) and \( F_c \). This simplification is justified by the independence between the effects of luminance and contrast demonstrated in Chapter 4.

For simplicity, in Figure 5-2 and Figure 5-6 we plot \( K_L \) and \( K_c \) as if they corresponded to the fixed filter in the model (Figure 5-1, red background). Strictly speaking this is not correct, as \( K_L \) and \( K_c \) are obtained by multiplying the fixed filter \( K_0 \) with a constant contribution from one of the two RC-circuits.

We describe the impulse responses \( k_L \) and \( k_c \) corresponding to \( K_L \) and \( K_c \) as differences of Gamma functions:

\[ k_q(t) = p \left[ g_q^1(t) - q_p g_q^2(t) \right], q \geq 0 \]

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where $Q = C$ or $L$, and:

$$g'_q(t) = [t - \tau]^\nu \exp\left(\frac{\tau_q - t}{\phi'_q}\right)$$

with $j = 1, 2$, and $\lfloor \rfloor$ indicating rectification.

We fitted the parameters of the model by minimizing the squared distance between the real and imaginary parts of the estimated transfer function and the real and imaginary parts of the model prediction.
Chapter 6

The spatial footprint of contrast gain control

6.1 Introduction

In the past chapters we have focused exclusively on the temporal aspects of contrast gain control. We have characterized contrast gain control by measuring the transfer function of LGN neurons with stimuli of various contrasts and have shown that it operates mostly at low temporal frequencies. Thus, as contrast is increased, the responses at low temporal frequencies saturate while the responses at high frequencies grow approximately linearly with contrast. We captured these effects by allowing contrast gain control to modify the impulse response of the neurons. The effects of contrast on the temporal frequency selectivity can be explained if, as contrast is increased, the gain and integration time of the impulse response is reduced. While the reduction in gain suppresses responses at all frequencies, the reduction in integration time selectively enhances the responses at high frequencies and, at these frequencies, compensates for the reduction in gain.

This description, however, does not address a fundamental aspect of contrast gain control, namely how neurons compute contrast. Shapley and Victor (1979) and others (Jakiela 1978) proposed that a measure of local contrast could be computed by integrating the rectified responses of a pool of small subunits covering the receptive field. The spatial and temporal properties of these putative subunits are consistent with those of bipolar cells (Shapley and Victor 1979; Shapley and Victor 1980; Victor 1988; Jakiela 1978), whose pooled response could regulate the suppression that amacrine cells exert on ganglion cells (Werblin 1972; Thibos and Werblin 1978; Werblin and Copenhagen 1974). This model makes the strong prediction that increasing the size of a stimulus should have the same effects on the impulse response as increasing its contrast. The two manipulations would result in very different distributions of responses across the putative subunits, but in both cases the total response of the pool, and thus local contrast, would increase. Even though this prediction has not been rigorously tested, it is consistent with a number of observations in the retina and the LGN.

Indeed, a number of studies have shown that the gain of neurons is affected by the spatial properties of the stimuli. For instance, the response to a stimulus placed over the center of the receptive field is reduced by the simultaneous presentation of a surrounding stimulus (Levick et al. 1972; Enroth-Cugell and Jakiela 1980; Gulyas et al. 1987; Girardin et al. 2002). These effects are consistent with the effects of contrast gain control, since the surrounding stimulus would recruit more subunits than the center stimulus alone and would thus reduce the gain of the center. Similarly, LGN neurons are “size-tuned”, meaning that responses are maximal for stimuli of intermediate sizes and are suppressed by larger stimuli (Jones et al. 2000; Solomon et al. 2002; Ozeki et al. 2004). Size-tuning is also consistent with the effects of contrast gain control and occurs because for large stimuli an increase in size adds only little excitatory drive to the
responses while it strongly reduces gain (Solomon et al. 2002; Bonin et al. 2004b). Crucially, since contrast gain control affects mostly responses at low temporal frequencies, this explanation predicts that responses to high temporal frequencies should not be size-tuned.

There is also evidence that the spatial properties of the stimuli affect the integration time of the neurons. For instance, the responses of the center become more transient when a stimulus is placed in the surround (Enroth-Cugell and Jakiela 1980; Girardin et al. 2002), an effect that is consistent with a reduction in integration time. Similarly, increasing the size of a drifting grating advances the phase of the response (Solomon et al. 2004b). Finally, placing a stimulus in the periphery of the receptive field has similar effects on the temporal frequency selectivity as does increasing the contrast of a central stimulus (Shapley and Victor 1979).

In this chapter we will develop a unified description that quantitatively links all these phenomena. We will estimate the impulse response of LGN neurons over a wide range of contrasts and sizes and show that increasing the size of a stimulus has the same effects on the impulse response as increasing its contrast. We will also show that size-tuning indeed occurs only at low temporal frequencies, as does the saturation of responses at high contrasts. Finally, we will use a simplified version of the subunit model of Shapley and Victor (1979) to quantitatively account for the effects of both contrast and size.

6.2 Results

6.2.1 Effects of contrast and size

As in previous chapters, we estimated the temporal frequency selectivity of a neuron from the responses to drifting gratings of optimal spatial frequency that were centered on the receptive field. The temporal frequency of the gratings increased exponentially in time from 0.5 to 40 Hz in 5 s (Figure 6-1A) and returned to 0.5 in the subsequent 5 s (not shown). The response of a neuron at a given instant in time then corresponds to the selectivity of the neuron to the temporal frequency present in the stimulus at that time. Thus, the envelope of the response roughly corresponds to the tuning of the neuron for temporal frequency.

Consider first the response of a representative LGN neuron to a small, low contrast grating (Figure 6-1B, gray. Michelson contrast $c = 11\%$, diameter $d = 4$ deg). As is typical for LGN neurons, the response peak at an intermediate, optimal temporal frequency and rapidly falls off as temporal frequency is increased above this optimal value. We will use this response as a reference and compare it to the response obtained when increasing stimulus contrast while keeping size constant (Figure 6-1C) or increasing stimulus size while keeping contrast constant (Figure 6-1D).

As we have shown in previous chapters, increasing the contrast of the stimulus (to 33\%) dramatically modifies the selectivity for temporal frequency (Figure 6-1C). Indeed, the amplitude of the response saturates with contrast only at low temporal frequencies. Thus, at low temporal frequencies the responses at high contrast (Figure 6-1C, gray) are barely distinguishable from those at low contrast (Figure 6-1C, black) while at high temporal frequencies the responses at high contrast are much larger than those at low contrast.
Increasing the size of the low contrast stimulus (to 11 deg) has similar effects as increasing its contrast (Figure 6-1D). Although overall the amplitude of the responses is smaller than for the high contrast stimulus (Figure 6-1C), the shape of the temporal-frequency tuning is similar. Increasing size results in smaller responses at low frequencies and larger responses at high frequencies. Overall, increasing stimulus size causes the neuron to respond preferentially to high temporal frequencies, the same effect caused by an increase in contrast (Figure 6-1C).

Figure 6-1, Effect of stimulus contrast and size on LGN responses. Stimuli are drifting gratings of optimal spatial frequency. A: Temporal profile of the stimuli. Temporal frequency increases exponentially over time from 0.5 to 40 Hz in 5 s and back (not shown). B: Response of X-type, On-center cell to a small (d = 4 deg), low contrast (c = 11%) grating. We computed response histograms (gray) by convolving spike trains with a Gaussian running window (std = 5 ms) and averaging over 9 stimulus presentation. The outline of the histogram (black) is replotted in C and D for comparison. C: Response a grating of the same size as in B, but larger contrast (c = 33%). The effect of increasing contrast depends strongly on temporal frequency: responses are essentially unchanged at low temporal frequencies ("contrast saturation"), while they are greatly increased at high temporal frequencies. D: Response to a grating of the same contrast as in B, but larger diameter (d = 11 deg). The effect of increasing size also depends strongly on temporal frequency: responses are reduced at low temporal frequency ("size-tuning"), while they are enhanced at high temporal frequencies.

Therefore, the effects of contrast and size on the amplitude of the responses have a similar dependency on temporal frequency. Contrast saturation, i.e. the saturation of response amplitude
as contrast is increased (Sclar et al. 1990), is strong at low frequencies and absent at high frequencies (compare (Figure 6-1B and C). Similarly, size-tuning, i.e. the reduction in responses amplitude as size is increased (Jones et al. 2000), is strong at low frequencies and absent at high frequencies (compare (Figure 6-1B and D). This similarity by itself is a strong argument in support of the hypothesis, articulated in the introduction, that size-tuning is a manifestation of contrast gain control. In the next sections, we will try to make this argument in a more quantitative fashion. As a first step, as in previous chapters, we will use the measured responses to estimate the impulse response of the neuron.

6.2.2 Estimating the impulse response

We estimate the impulse response of a neuron by fitting the responses with the descriptive model introduced in Chapter 2 (Figure 6-2A and Figure 2-3). The implementation of the model as well as the procedure to estimate its parameters are the same as in Chapter 2. Briefly, the model consists of three stages. The first stage is the convolution of the stimulus with the receptive field, which has center-surround organization in space (not shown) and biphasic impulse response in time. This convolution yields a noiseless membrane potential that has zero mean. The second stage is Gaussian noise of fixed mean and variance, which is added to the output of the convolution. The final stage is rectification, which transforms membrane potential into firing rates. In the model only the impulse response is allowed to change across stimulus conditions, while all other parameters are fixed for a given neuron.

This model provides a good description of the responses obtained at various combinations of size and contrast (Figure 6-2B). The model adequately predicts both the amplitude and phase of the responses over the entire range of tested temporal frequencies. Over the entire set of tested stimuli (Figure 6-3A), the model explains 80% of the stimulus driven variance in the responses of the example cell. Over the entire population of 34 neurons it explains 81% of the variance (median, Figure 6-5A). The deviations between the measured and predicted responses are similar to those encountered in previous chapters, and have been discussed there.

Increasing either the contrast or size of a stimulus causes strikingly similar changes in the impulse response of the neuron (Figure 6-2D). One effect is on the impulse response's amplitude, which decreases markedly as contrast or size increase. The other effect is on the impulse response's time course, which becomes more transient as contrast or size increase.

These changes in the impulse response occur very rapidly after contrast or size of a stimulus are modified. Indeed, similarly to what we found for stimuli varying in contrast and luminance (Chapter 3), the responses in Figure 6-2B are very similar to those obtained in the successive 5 seconds, when temporal frequency is reduced back to 0.5 Hz (not shown). Impulse responses estimated from the second half of the stimulus are very similar to those shown in Figure 6-2D, indicating that slow adaptation mechanisms play little role in these responses.

The effects of contrast and size on the impulse responses explain why the selectivity for temporal frequency varies with stimulus parameters. Response gain at a given temporal frequency is given by the amplitude of the Fourier transform of the impulse response (Figure 6-2C). Increasing either contrast or size results in very similar changes in response gain. These changes
are consequence of both the reduction in amplitude and duration of the impulse response (Figure 6-3D). The reduction in amplitude, by itself, would reduce gain at all frequencies by a constant factor. The reduction in duration, on the other hand, would cause an increase in gain only at high frequencies, while leaving gain at low frequencies unchanged. The combination of these two effects results in a smaller gain at low frequencies and a larger gain at high frequencies.

Figure 6-2, Estimating the impulse response. A: To estimate the impulse of the neuron for a given combination of contrast and size, we fit a descriptive model to the measured firing rates $R$. The descriptive model consists of three stages: (1) the convolution between the stimulus and the linear receptive field, (2) additive Gaussian noise of fixed mean and standard deviation and (3) rectification of the membrane potential $V_m$. The receptive field has center-surround organization in space and a biphasic impulse response in time. Only the impulse response varies across stimulus conditions. B: Example fits. Same responses and stimuli as in Figure 6-1B-D. C: Estimated response gain as a function of temporal frequency for the three stimuli in B. The gain estimated with the small, low contrast stimulus (top) is replotted in the middle and bottom panels (dashed). D: Estimated impulse response for the three stimuli in B. Same conventions as in C. The gain in C is the amplitude of the Fourier transform of the corresponding impulse response.

The difference in the responses to the large stimulus (Figure 6-2B, bottom) and the high contrast stimulus (Figure 6-2B, middle) are thus due only to the difference in the stimuli, not to differences in the gain of the neuron. In particular, if gain were constant (i.e., if the neuron were linear) then increasing contrast would just scale the responses accordingly. However, responses are scaled only at high frequencies, while at low frequencies the observed decrease in gain
compensates for the expected enhancement of the responses (Figure 6-2B, middle). The same reasoning, with a crucial difference, explains also the effects of size on the response. If gain were constant, increasing stimulus size would leave responses essentially unchanged, because the added portion of the stimulus falls mostly outside the boundaries of the receptive field. Therefore, the reduction in gain at low frequencies and the enhancement at high frequencies are directly reflected in the responses (Figure 6-2B, bottom).

6.2.3 Interactions of contrast and size

To test whether the observed effects of contrast (Figure 6-2D, middle row) occur at any size and whether the effects of size (Figure 6-2D, bottom row) occur at any contrast we estimated the impulse response for many combinations of contrast and size (Figure 6-3A). We typically tested three values of contrast, namely 11, 33 and 100%. The size of the stimuli was adjusted for each neuron. The smallest stimulus was chosen such that at the lowest contrast it still elicited reliable responses. The largest stimulus was chosen to maximize the strength of surround suppression, as measured in separate experiments.

The effects of contrast and size are qualitatively the same across the entire set of stimuli (Figure 6-3B). Independently of size, increasing contrast (i.e. moving up a column in Figure 6-3B) results in a smaller and faster impulse response. Increasing size (i.e. moving along a row) has the same effects, independently of contrast. As a consequence, the largest changes in the impulse response are obtained when contrast and size are increased together, i.e. when moving from the bottom-left corner to the upper-right corner in Figure 6-3B.

![Figure 6-3, Effects of contrast and size on the impulse response. A: The stimulus set. Stimulus contrast is 10, 33 or 100%. Stimulus size was adjusted to the size of the receptive field. For this neuron the diameter was 2.5, 4.1, 6.7 and 11.0 deg. B: The impulse responses estimated from the responses to the stimuli in A. For increasing contrast or size the impulse response becomes progressively smaller (i.e. gain is reduced) and faster (i.e. integration time is reduced). The three impulse responses shown in Figure 6-2D are plotted in gray.](image)
6.2.4 Modeling the effects of contrast and size

We obtain a quantitative description of the effects of contrast and size by fitting a model to the estimated impulse responses in Figure 6-3B. The formulation of the model is based on the results of the previous chapter (Chapter 5). Briefly, the model consists of a series of resistor-capacitor (RC) circuits that modifies the output of a fixed, biphasic impulse response (Figure 6-4A). The conductance of RC-circuits is the only parameter that is allowed to vary across stimuli. Thus, while in the previous chapter the conductance of the RC-circuit performing contrast gain control was allowed to vary only with contrast, here it is allowed to vary with contrast and size. Unlike in the previous chapters, here we do not model the effects of luminance gain control, since all the stimuli share the same mean luminance.

A

\[ g(c,d) \]

100 ms

B

\begin{tikzpicture}
\begin{axis}[
width=\textwidth,
height=\textwidth,
axis lines=middle,
xlabel=Contrast (%),
ylabel=\text{g(c,d) (%)},
]
\addplot[black,mark=*] table [x=Contrast, y=g,collisions=disallow] {data1.csv};
\addplot[red,mark=x] table [x=Contrast, y=g,collisions=disallow] {data2.csv};
\end{axis}
\end{tikzpicture}

C

D

Figure 6-4, Modeling the effects of size and contrast. A: The model. The effects of contrast and size are modeled as the action of a resistor-capacitor (RC) circuit on a fixed impulse response. Only the conductance of the RC-circuit varies with stimulus parameters. B: The conductance of the RC-circuit obtained by fitting the model to the estimated impulse responses in Figure 6-3B. Conductance grows with contrast and size. C: The estimated (black) and fitted (red) impulse responses. D: The fitted impulse response of the RC-circuit. Add scale bars (duration of impulse response).

For a given combination of contrast and size the RC-circuit performs linear filtering on the input and is thus completely described by its impulse response (Figure 6-4D). The net impulse
The model provides very good fits of the estimated impulse responses (Figure 6-4C). Predictions of the responses obtained with the fitted impulse responses explain 78% of the stimulus driven variance in this cell, compared to 80% for the estimated impulse responses. We found the same result over the entire population of 34 neurons (Figure 6-5B). The median values for the percentage of variance are 78% for the fitted impulse responses and 81% for the estimated impulse response.

The model also allows us to describe the effects of contrast and size in a much more compact way. Because the conductance of the RC-circuit is the only model parameter that is varying across the set of fitted impulse responses (Figure 6-4C, red curves) we can capture the difference between the response to different stimuli with only one number. This considerably simplifies the interpretation of the effects of contrast and size compared to the description in Figure 6-3B, where each response is characterized by an entire impulse response.

We find that the conductance of the RC-circuit increases both with the contrast and size of the stimulus (Figure 6-4B). The conductance is smallest for a small, low contrast stimulus and is largest for a large, high contrast stimulus. Over the entire range of contrasts and sizes the value of the conductance covers more than an order of magnitude. In agreement with the results of the previous chapter (Figure 5-7) we find that the function relating contrast to conductance is well approximated by a power law (i.e. a line in a log-log plot).

As conductance increases, the impulse response of the RC-circuit changes (Figure 6-4D). Increasing the conductance has two effects on the impulse response. First, the impulse response becomes smaller, meaning that gain is reduced. Second, the impulse response becomes faster, meaning that integration time is reduced. These are the same two effects of contrast and size as on the estimated impulse responses in Figure 6-3B.

Convolving the impulse response of the RC-circuit with the input corresponds to performing a weighted average over the inputs of the recent past. This averaging extends over a progressively
shorter time as the integration time is reduced. As a result, high temporal frequencies in the input are filtered out by the RC-circuit when conductance is small and instead contribute to the output when conductance in large, which causes the temporal frequency selectivity to depend on contrast and size (Figure 6-2C).

6.2.5 Local contrast is what matters

The compact description of the effects of contrast and size in terms of conductance changes (Figure 6-4B) now allows us to test the hypothesis that contrast gain control is responsible for the effects of both contrast and size. We will first formulate the hypothesis more precisely in terms of a model (Figure 6-6), which is a simplified version of the subunit model of Shapley and Victor (1979). The model extends the description in Figure 6-4A and makes a precise prediction about how conductance should depend on contrast and size. We will then show that the estimated conductances (Figure 6-4B) are consistent with the predictions of the model.

In the model (Figure 6-6) contrast gain control is driven by a measure of local contrast. The effects of gain control are again implemented with a series of RC-circuits. However, the conductance of the RC-circuit depends only on one parameter, i.e. local contrast, rather than depending separately on the contrast and the size of the stimulus as in Figure 6-4A.

Figure 6-6, The suppressive field and the computation of local contrast. In the model, the output of the receptive field is modified by an RC-circuit with variable conductance (as in Figure 6-4A). The conductance of the RC-circuit depends on local contrast. Local contrast is computed by the suppressive field, which integrates contrast over visual space. The profile of the suppressive field determines the weights with which a location in space contributes to the integral. The model does not include luminance gain control, since all the stimuli in this chapter share the same mean luminance.

In the model local contrast is computed by the "suppressive field" of the neuron (Hubel and Wiesel 1961; Levick et al. 1972). The suppressive field obtains an estimate of local contrast by computing a weighted sum of the stimulus contrast present in a small region of visual space. The spatial weighting function corresponds to the profile of the suppressive field. The computation performed by the suppressive field is thus very similar to that performed by the receptive field; in the same way as the receptive field integrates luminance over a small region of space, the
suppressive field integrates contrast. However, unlike the receptive field, the suppressive field
does not directly elicit responses in the neuron, but only indirectly affects the responses by
modulating the gain and integration time of the impulse response.

The suppressive field model can qualitatively account for the observed effects of contrast and
size. Because the suppressive field computes local contrast by integrating contrast over space,
both increasing the contrast of the stimulus as well as increasing its size result in a larger local
contrast (Figure 6-7). If conductance is a monotonically increasing function of local contrast, then
one would expect conductance to increase both with contrast and size, in agreement with our
findings (Figure 6-4B).

Figure 6-7. Effects of contrast and size on local contrast. Local contrast increases with both contrast and
size. A: A small, low contrast grating. Because the grating is small, it elicits responses only in a small
portion of the suppressive field, indicated by the gray shading. Because its contrast is small, the grating
elicits only weak responses, as indicated by the light gray shading. The integral under the suppressive field,
and thus local contrast, are small. B: A small, high contrast grating. Because contrast is higher as in A, the
responses elicited in the suppressive field are stronger, as indicated by the darker shading. Although the
grating covers the same portion of suppressive field, local contrast is thus larger. C: A large, high contrast
grating. The grating elicits responses over the entire extent of the suppressive field. Although locally the
strength of responses is the same as in B, local contrast is thus larger.

The model also makes a strong prediction about how the function relating conductance to
contrast (Figure 6-4B) should depend on stimulus size. It is easy to show (see Methods) that in
terms of the conductance in the model (Figure 6-6) changing the size of the stimulus is equivalent
to scaling its contrast. The scaling factor is larger than 1 if size is increased and smaller than 1 if
size if decreased. Crucially, if conductance is plotted as a function of the logarithm of contrast (as
in Figure 6-4B) then scaling contrast corresponds to shifting the curve relating contrast to
conductance along the contrast axis. Thus, if the model in Figure 6-6 is correct, then the
conductances in Figure 6-4B, which were estimated at 4 different sizes, should lie on 4 curves
that are shifted versions of each other.
Figure 6-8, Conductance is a function of local contrast only. A: Conductance expressed as a function of local contrast. The 4 black curves correspond to conductances estimated at 4 different sizes (Figure 6-4B). We shifted the lower 3 curves along the horizontal axis to align them with the uppermost curve. The local contrast of the grating with largest size and contrast is set to 100%. The red line is obtained by linear regression of the aligned conductances (slope = 0.79). B: The portion of suppressive field covered by the stimuli used to estimate the conductances in A. The larger the shift needed to align the corresponding curve in A, the smaller is the portion of suppressive field covered by the stimulus. We assume that the largest stimulus covers the entire receptive field (i.e., Suppressive field integral = 100%). The black line is a fit of the 4 points with a descriptive function. For this cell the size of the receptive field center is 2.6 deg.

In agreement with the prediction of the model, the 4 curves can indeed all be aligned with the curve measured at the largest size (Figure 6-8A). The magnitude of the shift needed to align a given curve is small for conductances estimated with large stimuli, and becomes progressively larger as stimulus size is increased.

The curve obtained by aligning all the conductances (Figure 6-8A) corresponds to the function relating local contrast to conductance (see Methods). This function describes how the conductance, and thus the impulse response, depends on the “real” signal driving contrast gain control. The impulse response then depends on the contrast and the size of the stimulus only indirectly, through their effects on local contrast.

As expected, conductance is a monotonically increasing function of local contrast. More precisely, the function relating the logarithm of local contrast to the logarithm of the conductance is very well described by a line (as in Figure 5-7). Thus, on linear axes the two are related by a power law. The exponent of the power law corresponds to the slope of the line in Figure 6-8A. For this cell, the exponent is 0.79.

Over the entire population of neurons (Figure 6-9A), the relation between local contrast and conductance is similar to what we found for the cell in Figure 6-8A. For all but the smallest values of local contrast the function relating local contrast to conductance is well described by power law. The exponent of the power law for the population average is 0.66. (compared to 0.63 in Figure 5-10B).
For very small local contrasts, however, the conductance is larger than predicted by a power law (Figure 6-9A). Because the gain of the RC-circuit (at low temporal frequencies) is inversely proportional to conductance (5.3.2), this deviation from a power implies that contrast gain control becomes weaker at very low contrasts. These deviations occur only for local contrasts that are smaller than those used in the previous chapter.

![Figure 6-9](image)

Figure 6-9, Strength of gain control and suppressive field profile, population averages. A: Conductance as a function of local contrast. Points are averages over the entire population of cells (N = 34). Error bars represent standard error. The red line was obtained by linear regression on the conductances at the 5 highest values of local contrast (slope = 0.66). B: The portion of suppressive field covered by stimuli of different sizes. For each neuron, stimulus size was normalized by the size of the receptive field center. Error bars represent standard error.

From the magnitude of the shifts needed to align the 4 curves in Figure 6-4B we can estimate the spatial extent of the suppressive field (Figure 6-8B). In the framework of the model of Figure 6-6 the magnitude of the shift corresponds to the volume of the portion of suppressive field that is not covered by the stimulus (see Methods). This portion of the suppressive field is colored in white in Figure 6-7A and B. For the smallest stimulus (corresponding to the rightmost black curve in Figure 6-8A and the leftmost point in Figure 6-8B) the magnitude of the shift is large because the stimulus covers only a small portion of the suppressive field. As size is increased the stimulus covers a progressively larger portion (Figure 6-8B) and thus the magnitude of the shift becomes smaller. Here we assume that the largest stimulus covers the entire suppressive field (i.e. the ‘suppressive field integral’ is 100% in Figure 6-8B), as its size was chosen to maximize the strength of surround suppression.

The suppressive field of the example cell is strongest in the center of the receptive field (corresponding to the center of the stimulus) and becomes progressively weaker with increasing distance from the center. Indeed, independently of size of the stimulus, a constant increment in diameter results in a constant increment in the integral under the suppressive field (Figure 6-8B). This implies that the suppressive field becomes weaker at larger distances from the center, since a
constant increase in diameter corresponds to a small increase in stimulus area for small stimuli, and to a large increase in stimulus area for large stimuli.

We averaged curves like the one in Figure 6-8B by normalizing stimulus size by the size of the receptive field center (Figure 6-9B). As for the example cell (Figure 6-8B), the suppressive field becomes progressively weaker for increasing distance from the center.

To estimate the size of the suppressive field we fitted a descriptive function to the points in Figure 6-8B and extracted from it the stimulus size that corresponds to 50% of the total integral under the suppressive field. For this neuron, the size of the suppressive field is 5.2 deg, which is as large as the surround of the receptive field and twice the size of the center of the receptive field. We obtained similar results for the other neurons in the population (Figure 6-10): on average, the size of the suppressive field is $3.2 \pm 1.4$ (std) times that of the center and $1.0 \pm 0.6$ that of the surround.

The computation of local contrast is thus spatially very localized: only contrast that falls within the borders of the receptive field affects the gain of an LGN neuron. This finding does not contradict our explanation of the reduction in response amplitude caused by very large stimuli (compare Figure 6-1B and D). We argued that this suppression occurs because for large stimuli an increase in size adds only little excitatory drive to the responses while it strongly reduces gain. This explanation seems to be at odds with the finding that the suppressive field is as large as the receptive field and thus any increase in the output of the suppressive field should be paralleled by an increase in output of the receptive field. It is crucial, however, that we used gratings of optimal spatial frequency, which for large sizes elicit strong responses only in the receptive field center, which is considerably smaller than the receptive field surround.

Figure 6-10, The size of the suppressive field. A: The size of the receptive field center compared to the size of the suppressive field. B: The size of the receptive field surround compared to the size of the suppressive field. See text for details.
6.3 Discussion

The model of Figure 6-6, in which contrast gain control is driven by a measure of local contrast computed by the suppressive field, provides a unified account of two fundamental suppressive influences on LGN neurons. The first is contrast gain control, which has been extensively studied in the retina and is well known to affect both the gain and integration time of retinal ganglion cells and LGN neurons (Shapley and Victor 1978; Sclar 1987). The second is surround suppression, which is evoked by large stimuli and reduces the responsivity to stimuli presented in the center of the receptive field (Enroth-Cugell and Jakiela 1980; Shapley and Victor 1979; Levick et al. 1972; Jones et al. 2000). We have shown that surround suppression does not reduce the gain of LGN neurons but also reduces their integration time. Most importantly, we have established that contrast gain control and surround suppression are two manifestations of the same mechanism, which is driven by the measure of local contrast computed by the suppressive field. Even though a number of authors have argued for a close relation between contrast gain control and surround suppression (e.g., Shapley and Victor 1979; Enroth-Cugell and Jakiela 1980; Girardin et al. 2002) past studies have fallen short of the quantitative link provided by our model.

The model also represents an important step towards a more general model of contrast gain control that could be applied to arbitrary stimuli. In fact, the model discussed in this chapter could potentially predict the response of a neuron to any arbitrary spatial arrangement of gratings. However, the model still has important limitations. For instance, we assumed that the suppressive field, like the receptive field, is circularly symmetric. At least in marmosets, however, this assumption is wrong (Webb et al. 2005). Even though deviations from circular symmetry would not affect the response to the stimuli used in this chapter, they might have important effects in the responses to our natural movies, in which the prevalent orientation varies over time (Betsch et al. 2004). Moreover, even a model based on the suppressive field does not specify how to compute the contrast of an arbitrary stimulus. However, it does provide some important insights. Most importantly, the model points to one fundamental element in the computation of local contrast, namely an integral over visual space. This spatial integral could be trivially computed for a natural image if one could define what has to be integrated.

The likely candidate for the integrand is the temporal contrast (i.e. the root-mean-square contrast) at each location in space. As we have discussed earlier, several studies have suggested that local contrast is computed by integrating the responses of a pool of small subunits covering the receptive field (Enroth-Cugell and Jakiela 1980; Shapley and Victor 1979). If the responses of these subunits were not shaped by contrast gain control, then their responses would indeed grow linearly with temporal contrast. This design will be the basis for the dynamic model of gain control discussed in the next chapter.

6.3.1 Origins of the suppressive field

Potentially, three very different mechanism could contribute to the effects that we have ascribed to the suppressive field: (1) contrast gain control or other suppressive mechanisms
operating in the retina; (2) inhibitory circuits within the thalamus; (3) feedback projections from
cortex.

Several studies that have compared the strength of suppressive effects in LGN neurons to
those found in their retinal afferents support the hypothesis that the suppressive field is entirely of
retinal origin. These studies have compared the strength of suppressive effects in LGN neurons
and in simultaneously recorded S-potentials (McIlwain and Creutzfeldt 1967; Cleland et al. 1971;
Bishop et al. 1958), which reflect the action potentials of the retinal afferents. For instance, Nolt
et al. (2004) found that in LGN neurons the suppression elicited by large stimuli depends on
stimulus contrast. Crucially, they found quantitatively similar effects of size and contrast on the
S-potentials. Similarly, Cheng et al. (1995) found that, on average, the strength of contrast
saturation in LGN and in the retinal afferents is comparable. As we have shown in this chapter,
these measurements of the effects of contrast (Cheng et al. 1995) and size (Nolt et al. 2004) fully
characterize the suppressive field, which thus seems to be entirely of retinal origin.

However, other studies have suggested that suppression in LGN responses is stronger than in
the S-potentials. Kaplan et al. (1987), unlike Cheng and collaborators (1995), found that the
responses of most LGN neurons saturate more than the corresponding retinal afferents. However,
these two studies could be easily reconciled if, as a result of different levels of anesthesia, Cheng
et al. (1995) were recording mostly from neurons in “tonic” mode, while Kaplan et al. (1987)
were recording mostly from neurons in “burst” mode (Sherman 2001). Indeed, in LGN neurons
the transformation of membrane potential into firing rates is approximately linear only in tonic
mode, while it saturates in burst mode (Sherman 2001). Nonetheless, other studies have found
that the suppression elicited by a large disk (Levick et al. 1972; Hubel and Wiesel 1961) or a long
bar (Cleland et al. 1983) is stronger in LGN than in the retinal afferents. These studies, however,
are hard to interpret, since the responses to disks and bars confound contributions by the
suppressive field and by the linear, antagonistic surround. The antagonistic surround is stronger in
LGN than in retinal ganglion cells (Dubin and Cleland 1977), possibly because of intrageniculate
inhibition (Singer and Creutzfeldt 1970), and might underlie the stronger “suppression” to large
stimuli observed in LGN.

However, several other suppressive phenomena that have been studied in LGN are unlikely to
be of retinal origin. For instance, in the “shift effect” sudden displacements of peripheral stimuli
suppress the responsivity of LGN neurons (Felisberti and Derrington 1999; Derrington and
Felisberti 1998), while similar stimuli evoke strong excitatory responses in ganglion cells
(Barlow et al. 1977; Kruger and Fischer 1973; Noda and Adey 1974; Felisberti and Derrington
1999). There is evidence linking the shift effect to intrageniculate inhibitory mechanisms (Eysel
et al. 1986; Eysel and Ringeler 1985). Moreover, suppression in LGN can be driven binocularly
(Pape and Eysel 1986; Sanderson et al. 1971; Wang et al. 1994; Funke and Eysel 1998) and might
thus partly be driven by binocular neuron in the perigeniculate nucleus (Xue et al. 1988;
Sanderson 1971; Uhlrich et al. 1991; Funke and Eysel 1998; Ahlsén et al. 1983). Finally, cortical
feedback has been shown to affect LGN responses. Cortical ablation or inactivation modifies the
gain of the neurons (Przybyszewski et al. 2000; Webb et al. 2002) and reduces size tuning
(Murphy and Sillito 1987; Alitto et al. 2002). Rather than providing direct suppression, the
feedback from cortex might thus regulate the suppressive signals affecting LGN responses (for a complete articulation of this hypothesis see Alitto and Usrey 2003).

6.3.2 Effects of remote stimulation

The very limited extent of the suppressive field seems to be at odds with a number of reports that have demonstrated suppressive influences originating from well beyond the receptive field. In retinal ganglion cells the continuous movement of steady pattern placed outside the receptive field modifies the spontaneous firing rate of the neurons. Stimuli of low spatial frequency and high temporal frequency typically increase the spontaneous firing rate (Passaglia et al. 2001; Ikeda and Wright 1972; McIlwain 1964) while stimuli of high spatial frequency and low temporal frequency decrease it (Passaglia et al. 2001). Both effects are most pronounced in Y-cells and are thought to be mediated by two separate population of rectified retinal subunits (Passaglia et al. 2001). In LGN neurons the rapid shift of a peripheral pattern of low spatial frequency transiently reduces the responsivity to a stimulus presented in the receptive field (Derrington and Felisberti 1998; Felisberti and Derrington 1999). As in retinal ganglion cells, these effects are strongest in Y-cells. In the absence of a central stimulus, the shift in the peripheral stimulus typically suppresses the spontaneous firing rate of LGN neurons, while it increases the responses of retinal ganglion cells (Felisberti and Derrington 1999). This difference supports the hypothesis that the suppressive effects of peripheral stimuli observed in the LGN are not of retinal origin, but rather are mediated by intrageniculate inhibitory circuitry (Eysel and Ringeler 1985; Eysel et al. 1987).

These effects of remote stimulation could potentially affect our estimate of the impulse response. In fact, both the effect on the responsivity of the receptive field as well as the effects on the overall firing rate could contribute to the gain of the estimated impulse responses. However, there are reasons to believe that peripheral effects play a role in the response to our stimuli. First, the suppressive peripheral effects observed in LGN (Derrington and Felisberti 1998; Felisberti and Derrington 1999) are typically elicited with gratings of low spatial frequency, while the stimuli used in this chapter have optimal spatial frequency. Second, the suppressive effects are thought to be elicited by rapid global shifts of the peripheral stimulus, rather than steady motion as in our stimuli. Steady peripheral stimulation is known to modify the spontaneous firing rate of retinal ganglion cells (Passaglia et al. 2001) but these effects are not necessarily reflected in the responses of LGN neurons (Felisberti and Derrington 1999). Third, both in retina and LGN the effects of peripheral stimulation are by far stronger in Y-cells than X-cells (Passaglia et al. 2001; Felisberti and Derrington 1999). Thus, we expect them to have little effect on most cells in our population, which contains only few Y-cells (6/34). Finally, peripheral effects in LGN have been studied with very larger stimuli, extending well beyond the limits of the receptive field surround. In comparison, even the largest stimuli used in this chapter are small and might not be large enough to elicit strong peripheral effects.

6.3.3 Effects of contrast and size in LGN and V1

The responses of neurons in primary visual cortex (V1) depend on the contrast and size of a grating in similar ways as the responses of LGN neurons. When the contrast of a grating is increased, the response of V1 saturate (Maffei and Fiorentini 1973; Dean 1981; Albrecht and
Hamilton 1982) and occur progressively faster (Dean and Tolhurst 1986; Albrecht 1995; Carandini et al. 1997). Moreover, increasing the size of a grating beyond an optimal value causes a reduction in response amplitude (Cavanaugh et al. 2002a; Sceniak et al. 1999; Jones et al. 2001). The effects of size have been attributed to surround suppression originating from a region of visual space extending the borders of the receptive field (Blakemore and Tobin 1972; Hubel and Wiesel 1968; Levitt and Lund 1997; DeAngelis et al. 1994; Vinje and Gallant 2000). The prevailing opinion is that surround suppression is mediated by intracortical inhibition (for a review see, Fitzpatrick 2000).

To some extent the effect of contrast and size observed in V1 might simply reflect the same consequences of contrast gain control seen in the LGN. However, such an explanation could probably not account for all the properties of surround effects in V1. Most importantly, surround suppression is selective for orientation: the strongest suppression is obtained with stimuli whose orientation matches the orientation of the receptive field (Blakemore and Tobin 1972; Li and Li 1994; Cavanaugh et al. 2002b). Moreover, the responses of V1 responses typically saturate more for increasing contrast than the responses of LGN neurons (Sclar et al. 1990), suggesting that additional gain control mechanisms operate within V1 or between LGN and V1.

However, a quantitative comparison between the responses of LGN and V1 neurons would only be possible if the effects of contrast and size were characterized at the same temporal frequency. In fact, we have shown that the responses of LGN neurons saturate with contrast and are suppressed by large stimuli mostly at low temporal frequencies (Figure 6-1). Typically, however, the effects of contrast and size in LGN have been studied with stimuli of optimal temporal frequency (Solomon et al. 2002; Bonin et al. 2004b) which is larger in LGN than in V1 (Cai et al. 1997; DeAngelis et al. 1993). Thus, these studies of LGN responses are likely to have estimated effects of contrast and size that are weaker than those occurring in a typical V1 experiment.

6.4 Methods

6.4.1 Cell population

We recorded from 29 X-cells and 5 Y-cells in 6 adult cats. Of these 34 neurons, 18 were located in layer A, 14 in layer A1, and 2 in layer C. We recorded from both On-center cells (20/34 neurons) and Off-center cells (14/34 neurons). The median eccentricity of the receptive field center was 8.6 degrees; 30/34 neurons had receptive fields with eccentricities between 2.2 and 17.9 degrees (10th and 90th percentiles).

6.4.2 Stimuli

As in Chapter 2, we estimated the impulse response of the neurons from the responses to gratings whose temporal frequency varied over time (Figure 2-4). Temporal frequency was increased exponentially with time from 0.5 to 40 Hz over 5 s (Figure 2-4), and returned to 0.5 Hz in the subsequent 5 s (not shown). Spatial frequency and position were optimal, mean luminance was 32 cd/m². Grating contrast was 10, 33, or 100%. Grating diameter was chosen from one of four logarithmically space values. The largest diameter was chosen to maximize the strength of
surround suppression, based on a separate experiment with gratings of optimal spatial and

temporal frequency at 50 or 100% contrast. The smallest diameter was chosen to elicit reliable
response at the lowest contrast (i.e. 10%). Combinations of contrast and diameter were presented
in a randomized order (12 repeated 6-12 times).

6.4.3 Models

We first estimated the impulse response at each contrasts and size by fitting the separable
model to the response. The implementation of the model and the procedure for the estimation of
its parameters are the same as in Chapter 2.

We then fitted the steady-state model of contrast gain control to the estimated impulse
responses (Chapter 5). In the steady-state model the effects of contrast gain control are modeled
with a series of RC-circuits of variable conductance. We used the same procedure for the
estimation of the model parameters as in Chapter 5, with the only difference that in this chapter
the conductance $g(c,d)$ of the RC-circuits does not depend only on the contrast $c$ but also on the
diameter $d$ of the stimulus.

Finally, we tested the hypothesis that the effects of contrast and diameter on the fitted
conductances are mediated by a single mechanism. In particular, we assume that conductance
depends on a measure of local contrast $c_{local}$ which in depends on contrast and diameter:

$$g = f(c_{local}) = f(c_{local}(c,d)),$$

where $f$ is an arbitrary function. Therefore, in this model contrast and diameter affect the
conductance indirectly, through their effect on $c_{local}$.

6.4.4 Estimating the suppressive field

We assume that local contrast is computed by the suppressive field, which integrates stimulus
contrast over a small region of visual space. More precisely, we define local contrast $c_{local}$ of a
circular grating with contrast $c$ and diameter $d$ as:

$$c_{local} \propto c \cdot I(d),$$

where $I(d)$ is the integral under the suppressive field up to the diameter $d$. In all the plots we
have set the proportionality factor to 1.

The integral under the suppressive field is:

$$I(d) = \int_{x^2+y^2 \leq (d/2)^2} h_{sf}(x,y) dxdy,$$

where $h_{sf}(x,y)$ corresponds to the spatial profile of the suppressive field and the point with
coordinates $(0,0)$ is the center of the stimulus.

The conductance of the RC-circuit then becomes:

$$g = f(c_{local}) = f(c \cdot I(d)).$$
Thus, the conductances $g_1$ and $g_2$ for two stimuli with contrast $c_0$ and diameters $d_1$ and $d_2$ are:

$$g_1 = g(c_0, d_1) = f(c_0 \cdot I(d_1)) \quad \text{and} \quad g_2 = g(c_0, d_2) = f(c_0 \cdot I(d_2))$$

They are related to each other by:

$$g(c_0, d_2) = f(c_0 \cdot I(d_2)) = f\left(\frac{I(d_2)}{I(d_1)} \cdot I(d_1)\right) = f\left(c_0^* \cdot I(d_1)\right) = g(c_0^*, d_1)$$

with $c_0^* = c_0 \cdot \frac{I(d_2)}{I(d_1)}$.

Thus changing the size of the stimulus from $d_1$ to $d_2$ has the same effect on the conductance as scaling the contrast from $c_0$ to $c_0^*$.

When contrast is plotted on a logarithmic axis this scaling corresponds to shifting the curve relating conductance to contrast along the abscissa:

$$\log(c_0^*) = \log\left(\frac{I(d_2)}{I(d_1)} \cdot I(d_1)\right) = \log(c_0) + \log\left(\frac{I(d_2)}{I(d_1)}\right),$$

where:

$$\log\left(\frac{I(d_2)}{I(d_1)}\right) = \log(k)$$

is the magnitude of the shift. By estimating the magnitude of the shifts needed to align conductances obtained with different diameters we can thus infer $I(d)$.

To align the curves relating contrast and conductance obtained at different sizes (Figure 6-4B) we first fitted each curve with a power law (i.e. a line in plots relating the logarithms of contrast and conductance). We then aligned the curve obtained at a given diameter $d_1$ to the curve obtained at the next largest diameter, $d_2$. We found the magnitude $k$ of the shift that resulted in the best alignment by minimizing the vertical distance $\delta(k)$ between $g(c, d_2)$ and $g(c \cdot k, d_1)$:

$$\delta(k) = \int_{c \in O(k)} \left| g(c, d_1) - g(c \cdot k, d_1) \right|.$$

The distance between the two curves is estimated only over the range of tested contrasts:

$$O(k) = [c_{\min}, c_{\max}] \cap [k c_{\min}, k c_{\max}],$$

where $c_{\min}$ and $c_{\max}$ are the minimum and maximum tested contrasts.

From the magnitude of the shift $k$ we estimated $I(d_2)/I(d_1)$. From these ratios we estimated $I(d)$, after setting $I(d_{\max}) = 100\%$, where $d_{\max}$ is the maximum diameter in the stimulus set.
6.4.5 Size of the suppressive field

We defined the size $d_{50}$ of the suppressive field from $I(d_{50}) = 50\%$. We estimated $d_{50}$ by interpolating $I(d)$ with a smooth function $Y(d)$ (Figure 6-8B):

$$Y(d) = y_0 \left( 1 - e^{-\frac{d^2}{2\sigma^2}} \right)^n$$ with $n \in [0.5, 3]$, which corresponds to the integral under a two-dimensional Gaussian for $n = 0.5$.

In analogy to this definition of size for the suppressive field, we defined the size of the receptive center as the size that contains 50\% of the volume under the center, and the size of the surround as the size that contains 50\% of the volume under the surround.

6.4.6 Population averages

To average the curve relating local contrast to conductance (Figure 6-9A) we binned local contrast in 8 bins. The bins covered the entire range of measured local contrasts. The centers of the bins were logarithmically spaced. We then obtained population estimates of conductance for a given local contrast by averaging all points in a bin.

In the same way, we obtained the curve relating stimulus size to the integral under the suppressive field (Figure 6-9B). For each neuron we normalized stimulus size by the size of the receptive field center. We then binned the normalized sizes in 6 bins whose centers were logarithmically spaced and averaged the estimated values of $I(d)$ in each bin.
Chapter 7
A dynamic model of gain control

7.1 Introduction

Even though the model of gain control that we have developed in the previous chapters predicts the responses of LGN neurons to a very large set of stimuli, it is still not general enough to make predictions of the responses to arbitrary stimuli. The model is limited in its scope because it lacks mechanisms that can estimate the luminance and contrast of an arbitrary stimulus. In this chapter we will overcome this limitation by extending the model with explicit computations of luminance and contrast that are based on well established properties of luminance gain control and contrast gain control.

Luminance gain control is known to be driven by an estimate of luminance that is very local in space and in time. This insight comes from experiments in two retinal cell types, horizontal cells and retinal ganglion cells, which in cat retina are the only two cell types that can be easily isolated in the intact eye (Shapley and Enroth-Cugell 1984). In both cell types local luminance is computed very fast, in that only light intensities within a time window of about 150ms contribute to the gain of the neurons (Saito and Fukada 1986; Enroth-Cugell and Shapley 1973a; Lankheet et al. 1993b). These results are consistent with our own experiments (Figure 2-1), which demonstrate that luminance gain control operates very rapidly. Spatially, the computation of local luminance is somewhat different in the two cell types, as it seems to be more localized in retinal ganglion cells. In retinal ganglion cells the gain of the receptive-field center is adjusted based on the average light intensity falling onto a region of visual space that is roughly coextensive with (in X-cells) or smaller than (in Y-cells) the center itself (Enroth-Cugell and Shapley 1973b; Harding 1977; Cleland and Enroth-cugell 1968; Enroth-Cugell et al. 1975; Cleland and Freeman 1988; Lankheet et al. 1993b). In horizontal cells, on the other hand, gain depends on the average light intensity over the entire receptive field (Lankheet et al. 1993a). However, these two findings might not contradict each other, as it is not known how the receptive field of horizontal cells contributes to the center and the surround of retinal ganglion cells.

Similarly, contrast gain control is also driven by a measure of contrast that is very local in space and time. Indeed, in Chapter 6 we have shown that local contrast is computed by integrating contrast over the suppressive field, which is roughly coextensive with the receptive field surround (Solomon et al. 2002). Moreover, Victor (1987) has demonstrated that contrast gain control operates essentially instantaneously, in that gain adjustments in retinal ganglion cells are completed as soon as the receptive field responds to a stimulus. These observations are consistent with a model in which local contrast is computed by integrating the responses of a pool of subunits covering the receptive field (Shapley and Victor 1979; Enroth-Cugell and Jakiela 1980). The selectivity of the subunits to spatial frequency and temporal frequency underlies the selectivity of the suppressive field, which responds mostly to low spatial frequencies and high
temporal frequencies (Shapley and Victor 1979; Enroth-Cugell and Jakiela 1980; Girardin et al. 2002).

However, as we discussed in Chapter 3, the responsivity of neurons in the retina and the LGN is also regulated by slower adaptation mechanisms. For instance, immediately after stimulation with a appropriate high-contrast stimulus, the spontaneous firing rate of LGN neurons is strongly reduced and recovers only over the time course of several seconds (Sanchez-Vives et al. 2000; Solomon et al. 2004a). These effects have been typically interpreted as a slow form of contrast gain control (Smirnakis et al. 1997; Demb 2002). However, similar slow adaptation effects have been observed both in horizontal cells (Lankheet et al. 1993b) and retinal ganglion cells (e.g., Saito and Fukada 1986) when the luminance over the center of the receptive field is suddenly decreased. These effects of luminance are ubiquitous throughout much of the literature on luminance gain control, but so far have received only little attention (Shapley and Enroth-Cugell 1984).

To construct the dynamic model of gain control, we will thus extend the steady-state model discussed in the previous chapter with three stages: (1) a fast mechanism that computes local luminance; (2) a fast mechanism that computes local contrast; (3) a slow adaptation mechanism inspired on the slow effects of luminance. While the first two stages are strongly constrained by the results discussed above, the third stage is by far the least constrained component of the model. We will then test the model and discuss its functioning by simulating the responses to many of the simple stimuli discussed throughout the previous chapters.

### 7.2 Model description

The dynamic model of gain control (Figure 7-1) is aimed at describing the responses of LGN neurons to arbitrary visual stimuli. The input to the model is an arbitrary luminance distribution $s(x,y,t)$ and its output is the time-varying firing rate $r(t)$. Unlike the steady state model described in Chapter 5, the dynamic model does not require the stimulus luminance and contrast as additional inputs; rather, luminance and contrast are computed directly from the stimulus $s(x,y,t)$. The mathematical implementation of the dynamic model is described in Appendix A.

The model consists of six consecutive stages: (1) the linear receptive field; (2) luminance gain control; (3) slow response adaptation; (4) contrast gain control; (5) temporal filtering; (6) noise and rectification.

As in all previous chapters, the receptive field has antagonistic center and surround. Both are modeled as 2d-Gaussians in space with biphasic impulse response in time. The output of the receptive field, $r_{rf}$, is the convolution between the stimulus and the receptive field. The parameters of the receptive field are fitted to the selectivity of an LGN neuron to spatial frequency, temporal frequency and location in visual space (Chapter 1).

The output of the receptive field is then shaped by luminance gain control. As in the steady state model (Chapter 5), luminance gain control is implemented as a series of RC-circuits (Figure 7-1A). Their conductance $g_L$ at a given instant in time is proportional to an estimate of local luminance (Figure 7-1C). We defined local luminance $L_{local}$ as the temporally low-pass filtered
version of the light intensity falling on the receptive field surround (Figure 7-1B). This definition in only partially consistent with the literature on luminance gain control (e.g., Enroth-Cugell and Shapley 1973b; Enroth-Cugell et al. 1975; Cleland and Freeman 1988). As we will explain in the discussion, this definition of local luminance was strongly constrained by its effects on the stages of the model that follow luminance gain control.

After luminance gain control, the signal is fed into a slow adaptation stage (Figure 7-1A). Slow adaptation operates by subtracting from the response at a given instant in time the average response over the recent past. This stage mimics some of the slow adaptation mechanisms that have been described in neurons in the early stages of visual processing (Lankheet et al. 1993b; Saito and Fukada 1986). For essentially all the stimuli discussed in this thesis, the slow adaptation stage has little direct effect on the responses of LGN neurons. However, it does affect the responses of the subunits used to compute local contrast, which indirectly affect the response of the neurons through contrast gain control. As a consequence of slow adaptation, the output of the pool of subunits (i.e. the signal driving contrast gain control) slowly decays to zero for any arbitrary light distribution that does not change over time.

The output of slow response adaptation, $r_{sub}$, is shaped by contrast gain control. Again, contrast gain control is implemented as a series of RC-circuits (Figure 7-1A). The conductance $g_c$ of the RC-circuits is related to local contrast through a power law (Figure 7-1E). Local contrast $C_{local}$ is computed from the output of a pool of subunits covering the receptive field (Figure 7-1D)(Shapley and Victor 1979; Enroth-Cugell and Jakiela 1980). The pool of subunits contains equal numbers of ON-center and OFF-center cells; for every ON-center subunit, there is an otherwise identical OFF-center cell in the pool. Local contrast is obtained by computing the square root of the rectified, squared and summed responses of all subunits. Thus, the computation of local contrast is similar to the computation of motion energy by complex cells in V1 (Watson and Ahumada 1985; Adelson and Bergen 1985), which are thought to integrate the rectified or squared responses of a pool of subunits (Hubel and Wiesel 1962; Movshon et al. 1978; Spitzer and Hochstein 1985).

The subunits of contrast gain control are in many ways similar to the LGN neuron itself. Unlike the model LGN neuron, however, they lack a stage performing contrast gain control as well as the subsequent temporal filtering stage. The subunits of a given LGN neuron have a receptive field that is, other than for its location in visual space, identical to that of the LGN neuron. The subunits cover the entire receptive field of the LGN neuron; the closer a subunit is to the center of the receptive field, the more it contributes to the computation of local contrast. After the convolution of the stimulus with a subunit’s receptive field, the response is shaped by luminance gain control and slow adaptation. In Figure 7-1D we illustrate the effect of luminance gain control as a luminance-dependent change in the impulse response of each subunit.

The computation of local contrast in the dynamic model is closely related to the usual definition of contrast as the standard deviation of the luminance distribution divided by its mean. First, as we have discussed at length in Chapter 5, the effect of luminance gain control is to divide the response of the subunits by the local luminance. Second, as we show in the Methods, the local contrast at time $t$ corresponds to the standard deviation of the distribution of subunit responses at
time \( t \). Unlike the simpler definition of contrast based on the luminance distribution falling on the receptive field, the definition of local contrast in the dynamic model predicts that (1) only a limited range of spatial and temporal frequencies contribute to the signal driving contrast gain control, and (2) as luminance is increased, the high temporal frequencies in the stimulus contribute progressively more to local contrast.

Figure 7-1. A model of dynamic gain control in LGN neurons. A: The model transforms the luminance distribution \( s(x,y,t) \) into firing rates \( r(t) \). It consists of 6 consecutive stages: the receptive field (RF); luminance gain control; slow adaptation; contrast gain control; temporal filtering; rectification. Only one of the RC-circuits performing luminance gain control and one performing contrast gain control are shown. B: Computation of local luminance. Local luminance is defined as the stimulus luminance falling onto the receptive-field surround, averaged over a short period of time in the past. C: The conductance of first RC-circuit, which performs luminance gain control, depends linearly on local luminance. D: Computation of local contrast. Local contrast is computed from the response of a pool of subunits covering the receptive field. Each subunit’s receptive field has center-surround organization. For clarity of the illustration, we plot only the center of the receptive-field for a subset of the subunits. Because of luminance gain control, the temporal impulse response of the subunits depends on local luminance. E: The conductance of second RC-circuit, which performs contrast gain control, is a saturating function of local contrast.

After contrast gain control, the responses are convolved with a fixed bandpass filter. The convolution of this bandpass filter with the impulse response of the receptive field roughly corresponds to the fixed filter in the steady state model (Figure 5-1). We included this additional temporal filter in the dynamic model to allow the temporal frequency selectivity of the LGN neuron to be different from the selectivity of the subunits of contrast gain control, which lack this additional filtering stage.
The last stage of the model, as in the previous chapters, is rectification, which occurs after the addition of Gaussian noise to the responses.

7.3 Results

We used the model to simulate the responses to four experiments that summarize many of the phenomena that have been ascribed to gain control. First, we simulate the response to steps in luminance and contrast (Chapter 2.2.1). Second, we simulate the response to temporal frequency sweeps of various luminance and contrast (Chapter 2.2.3). Third, we show that the model predicts contrast saturation and size tuning of the responses, as well as their dependency on temporal frequency (Chapter 6). Finally, we show that the model predicts the effects of masking obtained when two gratings are superimposed (Bonin 2005).

Whenever possible, we have used the responses of LGN neurons to constrain the parameters of the model. For some of the parameters we have used values obtained from the fits of the responses of one example neuron. For other parameters, we have averaged the fitted values over the entire population of neurons. For the remaining parameters, which were not constrained by any of the experiments we performed, we have used best guesses based the literature on gain control.

7.3.1 Steps in luminance and contrast

To illustrate how the different stages of the model contribute to the output of the dynamic model we start by simulating the responses to steps in luminance and steps in contrast. In these stimuli the contributions of the two gain control mechanisms can be very clearly discerned, as contrast or luminance are the only stimulus parameters varying over time.

Luminance step

The stimulus is a drifting grating of optimal spatial and temporal frequency. In the case of the luminance step (Figure 7-2), the contrast of the grating is fixed to 50% over the entire duration of the stimulus. During the first third of stimulus, the mean luminance of the grating is 19 cd/m², or 30% of the maximum luminance of the screen. At the end of the first third luminance is stepped to 60%, and then back to 30% at the end of the second third. The resulting luminance profile for one pixel of the stimulus is shown in Figure 7-2A.

Similarly to the response of LGN neurons (Figure 2-1), the response of the dynamic model is barely affected by the step in luminance (Figure 7-2B). Neither the increase in mean luminance nor the increase in the amplitude of the luminance modulation are reflected in the amplitude of the model response. Moreover, responses occur faster during when mean luminance is high (not shown), consistent with the experiments in LGN (Figure 2-1, inset).

The first step of the model is the spatial antagonism between the center and surround of the receptive field. In Figure 7-3A we show the spatial convolution between the stimulus and the center (thin line) and between the stimulus and the surround (thick line). For simplicity, in this simulation we imposed the center and surround to have the same strength.
Figure 7-2. Model response to a step in mean luminance. The stimulus is drifting grating of optimal spatial and temporal frequency. Mean luminance steps from 30% to 60% of the maximum after 1s and then back to 30%. The contrast of the grating is constant at 50%. A: The luminance profile for one pixel of the stimulus, located over the center \((x_0, y_0)\) of the receptive field. B: The model response to the step.

For both center and surround, the modulation amplitude and the mean of the response increase as the luminance of the stimulus is stepped up, reflecting the increase in mean and modulation amplitude in the stimulus. The mean response of the center and surround is the same, since the mean over the center and surround is the same. On the other hand, the modulation amplitude is larger for the center because the grating has optimal spatial frequency, which is poorly resolved by the surround.

The increase in modulation amplitude is reflected also in the difference \(r_{diff}\) between the responses of the center and the surround (Figure 7-3B). If the surround had been weaker than the center, the difference response would have been overall larger. However, the ratio between the modulation amplitude in the low and high luminance period would have been the same, independently of the strength of the surround.

The increase in mean luminance, on the other hand, is eliminated by the spatial antagonism in the receptive field. Indeed, the difference response has the same mean (i.e. the same baseline) throughout the stimulus, independently of its mean luminance. Had we chosen the surround to be weaker than the center, then the mean of the difference response would have differed from the one in Figure 7-3B in two ways. First, the mean response during both the low or high luminance period would have been larger than zero. Second, the mean response during the low luminance period would have been smaller than the mean during the high luminance period.

Even in the case of a weaker surround, however, the final, unrectified response of the model would contain almost no mean, independently of the mean luminance of the stimulus. Indeed, luminance gain control is most effective at low temporal frequencies, and thus it in particular it discards the contribution of zero temporal frequency, which corresponds to the mean luminance of the stimulus. Moreover, in situations when luminance gain control does not completely discard the mean (for instance when mean luminance over center and surround are different) the temporal filtering stages in the model tend to filter out the low temporal frequencies in the response.
Figure 7-3. Luminance step: contribution of the center-surround antagonism to the model response. A: The output of the spatial filtering of the stimulus by the receptive field. The result of the spatial filtering by the center (thin) and surround (thick) are plotted separately. The response of the center is larger, because the grating has optimal spatial frequency. B: The difference between the two curves plotted in A. Because of the spatial antagonism between center and surround, the mean response is zero throughout the stimulus.

In addition to filtering the stimulus in space, the receptive field performs filtering in time. This temporal filtering has little effect on the response to the luminance step, since the stimulus contains essentially only one temporal frequency and the mean luminance is filtered out by the spatial antagonism between center and surround. Thus, we do not separately show the result of the temporal filtering.

The output of the receptive field is fed into the series of RC-circuits performing luminance gain control (Figure 7-4). The conductance $g_L$ of the RC-circuits is proportional to a low-pass filtered version (Figure 7-4B) of the luminance falling on the surround (Figure 7-3A, thick line). In Figure 7-4B we normalized $g_L$ such that 100% luminance corresponds to $g_L = 1$. Before the onset of the stimulus, $g_L = 0.5$, since the luminance of the blank screen is 50% of the maximum. During the stimulus $g_L$ reflects the mean luminance at given instant in time. Sudden changes in mean luminance are reflected rapidly in the value of $g_L$, with a delay that reflects the time constant of the filter integrating mean luminance.

The conductance $g_L$ sets the gain and integration time of the RC-circuits. As $g_L$ is increased, gain and integration time are reduced (Chapter 5). When temporal frequency is small enough, as in Figure 7-4, gain is inversely proportional to $g_L$, and thus to mean luminance. This decrease in gain perfectly compensates for the increase of modulation amplitude in the stimulus. Thus, the amplitude of the response after luminance gain control, $r_{lum}$, is the same independently of the mean luminance of the stimulus. The amplitude $r_{lum}$ differs from its steady state value only shortly after the step to higher or to lower luminance.
Figure 7-4. Luminance step: contribution of luminance gain control to the model response. A: The response after the spatial antagonism between center and surround, replotted from Figure 7-3B. B: The conductance of luminance gain control. The conductance is proportional to local luminance, which in turn is a filtered version of the response of the surround (Figure 7-3A, thick). C: The response after light adaptation. It was obtained by filtering the trace in A with the fixed impulse response, followed by the luminance-gain filter, whose conductance is shown in B.

After luminance gain control, the response is shaped by slow response adaptation. Slow adaptation affects the responses only when the output of luminance gain control contains slow variations in mean. This is not the case for this stimulus and thus the response after slow adaptation is essentially identical to the response after luminance gain control (Figure 7-4C).

The response after slow adaptation, computed for a large number of subunits, is the basis for the computation of local contrast. The responses $r_{sub}$ of three example subunits are shown in Figure 7-5A. The three responses have different temporal phases, because different subunits cover different portions of visual space, but are otherwise similar to the response of the LGN neuron after luminance gain control (Figure 7-4C).

Local contrast corresponds to the square root of the rectified, squared and summed responses of all subunits. Different subunits contribute to the sum with different weights: the closer a subunit’s center is to the center of the receptive field, the larger is its weight. Rather then plotting local contrast, in Figure 7-5B we plot the conductance $g_C$ of the RC-circuits implementing contrast gain control. This conductance is related to local contrast through a power law, and is normalized such that on average $g_C = 0.5$ for a 50% contrast grating.

Before the onset of the stimulus the value of $g_C$ corresponds to its lower bound (see Methods), since the grating is preceded by a blank screen with no contrast. After the onset of the stimulus, $g_C$ rapidly increases up to 0.5, reflecting the contrast of the grating. The transition to the higher value is gradual, with a rising time that reflects the integration time of the subunits. After this initial transition, $g_C$ is approximately constant over the duration of the stimulus, with the exception of a short positive and negative deflection at the beginning and end of the luminance step.

Local contrast thus is not simply the instantaneous, spatial contrast of the stimulus. In particular, even though the spatial contrast is constant over time, local contrast is not. The
difference between these two measures of contrast is attributable to the impulse response of the
subunits, which enhances temporal variations in the stimulus.

Figure 7-5. Luminance step: computation of local contrast. A: The response of three example subunits. One
of the subunits is centered in the same location as the receptive field, and thus its response corresponds to
the response of the receptive field after luminance gain control (Figure 7-4C). The other two subunits are
displaced along the direction of motion of the grating. B: The conductance of contrast gain control. The
conductance is related by a power law to local contrast. Local contrast roughly corresponds to the envelope
of the rectified response of all subunits in the pool.

The conductance $g_C$ (Figure 7-5B) determines the gain and integration time of the RC-circuits
implementing contrast gain control. Because $g_C$ is constant throughout most of the stimulus,
contrast gain control has little effects on the response. However, it does affect the response at the
beginning and end of the luminance step, when $g_C$ differs from its steady state value. The
transient increase in response amplitude at the beginning of the step (Figure 7-5A) is almost
eliminated by contrast gain control (Figure 7-5C), since gain is reduced when $g_C$ is large.
Similarly, the increase in gain at the offset of the step compensates for the transient decrease in
response amplitude.

Finally, in the last step of the model, the response after contrast gain control, $r_{con}$, is added to
Gaussian noise and rectified. We already showed the output of this last stage in Figure 7-2B.

Figure 7-6. Luminance step: contribution of contrast gain control to the model response. A: The response
after luminance gain control, replotted from Figure 7-4C. B: The conductance of contrast gain control,
replotted from Figure 7-5B. C: The response after contrast gain control. It was obtained by convolving the response in A with the RC-circuits of contrast gain control.

**Contrast step**

The stimulus is again a drifting grating of optimal spatial and temporal frequency. The mean luminance of the grating is fixed to 50%, while contrast is stepped from 30 to 100% after the first third of the stimulus, and then back to 30%. The resulting luminance profile for pixel of the stimulus is shown in Figure 7-7A.

Similarly to the response of LGN neurons (Figure 2-2), the response of the dynamic model is barely affected by the step in contrast (Figure 7-7B). The amplitude of the response is weakly increased during the contrast step, though by much less than the factor of 3 expected from a linear neuron. This approximate invariance of the response amplitude reflects a reduction in the gain of the neuron, which is completed well within the duration of a cycle of the response. Moreover, the phase of the response at high contrast is advanced with respect to low contrast (not shown), similarly to what we observed in LGN neurons (Figure 2-2, inset).

Figure 7-7. Model response to a step in contrast. The stimulus is drifting grating of optimal spatial and temporal frequency. Contrast steps from 30% to 100% after 1s and then back to 30%. The mean luminance of the grating is fixed at 50%. A: The luminance profile for one pixel of the stimulus. B: The model response to the step.

The responses to the step in contrast and the step in luminance are thus very similar. In fact, also the stimuli are very similar. Both the step in luminance and the step in contrast cause an increase in the modulation amplitude of stimulus luminance (Figure 7-2A and Figure 7-7A). The only difference between the luminance profile for the two stimuli is that the baseline of the luminance modulation (i.e. the mean luminance of the stimulus) is increased during the luminance step, while it is constant during the contrast step. This small difference between the stimuli results in a very different response pattern across the various stages of the model.

We start again by looking at how the model response is affected by the spatial antagonism between center and surround (Figure 7-8). As in Figure 7-3A, the responses of the center (Figure 7-8A, thin line) and surround (Figure 7-8A, thick line) directly reflect the mean and the modulation amplitude in the stimulus. The difference response $r_{diff}$ to the contrast step (Figure 7-8B) is very similar to the difference response to the luminance step (Figure 7-3B): the modulation amplitude is increased during the step, while the mean response is zero throughout the stimulus.
Figure 7-8. Contrast step: contribution of the center-surround antagonism to the model response. A: The output of the spatial filtering of the stimulus by the receptive field. The result of the spatial filtering by the center (thin) and surround (thick) are plotted separately. The response of the center is larger, because the grating has optimal spatial frequency. B: The difference between the two curves plotted in A.

Given that mean luminance is constant throughout the stimulus, luminance gain control has little effects on the responses (Figure 7-9). The conductance of luminance gain (Figure 7-9B) is approximately constant at $g_L = 0.5$, corresponding to the lowpass filtered luminance falling on the surround. Thus, the response after luminance gain control $r_{lum}$ (Figure 7-9C) is simply the convolution between the difference response (Figure 7-9A) and two temporal filters, the impulse response of the receptive field and the approximately constant impulse response of the series of RC-circuits.

Figure 7-9. Contrast step: contribution of luminance gain control to the model response. A: The response after the spatial antagonism between center and surround, replotted from Figure 7-8B. B: The conductance of luminance gain control. The conductance is proportional to local luminance, which in turn is a filtered version of the response of the surround (Figure 7-8A, thick). C: The response after light adaptation. It was obtained by filtering the trace in A with the fixed impulse response, followed by the luminance-gain filter, whose conductance is shown in B.

As for the luminance step, slow response adaptation has no effect on the response. The response after slow adaptation is essentially the same as the response after luminance gain control (Figure 7-9C).

The responses $r_{sub}$ of the subunits are thus analogous to $r_{lum}$ (Figure 7-9C), with a different temporal phase that depends on the position of the subunit in visual space. The response of three
example subunits is shown in Figure 7-10A. The amplitude of the subunit responses, and thus local contrast, varies considerably over the duration of the stimulus, always reflecting the spatial contrast of the grating. For this simulation we have chosen the exponent of the power law relating local contrast to \( g_C \) to be \( \gamma = 0.9 \), and thus the value of \( g_C \) approximately corresponds to the spatial contrast of the stimulus (Figure 7-10B).

![Diagram](image)

**Figure 7-10. Contrast step: computation of local contrast.** A: The response of three example subunits. One of the subunits is centered in the same location as the receptive field, and thus its response corresponds to the response of the receptive field after luminance gain control (Figure 7-9C). The other two subunits are displaced along the direction of motion of the grating. B: The conductance of contrast gain control. The conductance is related by a power law to local contrast. Local contrast roughly corresponds to the envelope of the rectified response of all subunits in the pool.

Since local contrast, and thus \( g_C \), strongly vary throughout the stimulus, contrast gain control has strong effects on the responses (Figure 7-11). The large variation in the modulation amplitude of the response after luminance gain control (Figure 7-11A) is almost absent in the response after contrast gain control \( r_{con} \) (Figure 7-11C). Indeed, because \( g_C \) is very large during the high contrast step, gain is very small, and thus the increase in modulation amplitude is suppressed.

Finally, the response of the model (Figure 7-7B) is computed by adding noise and rectifying the response after contrast gain control Figure 7-11C.

![Diagram](image)

**Figure 7-11. Contrast step: contribution of contrast gain control to the model response.** A: The response after luminance gain control, replotted from Figure 7-9C. B: The conductance of contrast gain control, replotted from Figure 7-10B. C: The response after contrast gain control. It was obtained by convolving the response in A with the RC-circuits of contrast gain control.
7.3.2 Responses to sweeps

As a second example of the functioning of the dynamic model, we simulate the effects of luminance and contrast on the responses to temporal frequency sweeps. In the previous chapters we used these stimuli to estimate the temporal frequency selectivity and the impulse response of LGN neurons (Chapter 2).

As we have shown in Chapter 5, the effects of luminance and contrast on the temporal frequency selectivity can be explained with a simple, steady state model. In the steady state model (Figure 5-1), as in the dynamic model, luminance and contrast gain control are implemented with a series of RC-circuits. While in the dynamic model $g_L$ and $g_C$ are computed directly from the stimulus, in the steady state model they are functions of the mean luminance and the spatial contrast of the stimulus, with constitute additional inputs to the model. Thus, since mean luminance and spatial contrast are fixed throughout a stimulus, the conductances of the steady state model are also fixed as well.

In the dynamic model, on the other hand, the values of the conductances vary over the duration of a sweep. The values of $g_L$ and $g_C$ reflect the mean luminance and spatial contrast of the stimulus only on average. This is illustrated in Figure 7-12, where we show the values of $g_L$ and $g_C$, as well as the resulting responses of the model, for a sweep at 33% contrast and 50% luminance.

The conductance $g_L$ of luminance gain control is modulated around a baseline level at the instantaneous temporal frequency of the stimulus (Figure 7-12A, red). The baseline level corresponds to the mean luminance of the grating; as in the previous section, we normalized $g_L$ such that $g_L = 0.5$ when local luminance is 50%. The modulation is strongest at low temporal frequencies and reflects the response of the receptive field surround. The modulation is relatively small, since the grating has optimal spatial frequency and thus is poorly resolved by the surround. At high temporal frequencies $g_L$ is constant, because the modulation in the response of the surround is averaged out by the lowpass filtering transforming local luminance into conductance.

The conductance $g_C$ of contrast gain control, on the other hand, depends strongly on the temporal frequency of the stimulus (Figure 7-12B, red). The value of $g_C$ is small at very low or very high frequencies and peaks at intermediate frequencies. This dependency simply reflects the temporal frequency selectivity of the subunits contributing to the computation of local contrast. Since the response of the subunits varies throughout the stimulus, so does local contrast and thus $g_C$. Similarly, the transient increase in $g_C$ at the onset of the stimulus reflects a transient onset response in some of the subunits. The transient response occurs only in subunits that are displaced with respect to the LGN neuron along the direction of motion of the grating (not shown), since the phase of the grating was chosen to minimize the transient in the response of the LGN neuron.
To assess how these variations in conductance affect the response of the model, we compared predictions of the dynamic model (Figure 7-12C, red) to the predictions of a static model (blue), for which the conductances are fixed throughout the duration of the stimulus. In the static model, $g_L$ was fixed to the average value of $g_L$ in the dynamic model (Figure 7-12A, blue), while $g_C$ was fixed to the average value of $g_C$ between 4 and 5 Hz (Figure 7-12A, blue).

The differences between the predictions of the static model (Figure 7-12C, blue) and the predictions of the dynamic model (red) are driven mostly by contrast gain control. At times when the $g_C$ is smaller than average, the response of the dynamic model is larger than the response of the static model, and vice versa. The differences between the two models, however, are small and the predictions of the dynamic model closely resemble the measured responses (Figure 7-12C, gray).
Figure 7-13. Response to a temporal frequency sweep at low luminance. Mean luminance is 10%, contrast is 33%. A: The conductance of luminance gain control. B: The conductance of contrast gain control. C: Measured and predicted response. Same conventions as in Figure 7-12.

Decreasing the mean luminance of the stimulus (from 50% to 10%) while keeping contrast fixed has the largest effect on the conductance of luminance gain control (Figure 7-13A). Because $g_L$ is reduced, the gain is increased and integration time become longer. The resulting prediction closely matches the measured response (Figure 7-13, gray). To appreciate the effects of gain control, we also predicted the response using the static model, whose conductances (Figure 7-13A and B, blue) were fixed at the same values as in Figure 7-12. Because of the increase in gain, the response of the dynamic model (Figure 7-13C, red) is larger than the response of the static model (Figure 7-13C, blue). The largest differences occur at the low temporal frequencies, where gain is reduced the most. Moreover, because of the longer integration time, the phase in the responses of the dynamic model is advanced with respect to phase in the static model.

The decrease in conductance, however, also affects the conductance of contrast gain control. Indeed, the values of $g_C$ at high temporal frequencies are smaller in the low luminance case (Figure 7-13B, red) than in the high luminance case (Figure 7-12B). This is a consequence of luminance gain control, which affects the temporal frequency selectivity of the subunits and thus, indirectly, the measure of local contrast.
On the other hand, reducing the contrast of the stimulus (from 33% to 11%) while keeping mean luminance fixed has effects only on the conductance of contrast gain control (Figure 7-14). Throughout most of the stimulus the value of $g_c$ corresponds to its lower bound (Figure 7-14B) (see Methods). The corresponding increase in gain and integration time make the responses of the dynamic model (Figure 7-14C, red) larger and faster than those of the static model (Figure 7-14C, blue).

### 7.3.3 Contrast saturation and size tuning

As discussed in Chapter 6, we used similar methods to those described in the previous section (7.3.2) to study how contrast and size affect the responses of LGN neurons. In Chapter 6 we used temporal frequency sweeps to estimate the impulse response of the neurons and to understand how stimulus contrast and size, rather then contrast and luminance, affect the gain and integration time of LGN neurons. The finding that increasing the increasing the size of the stimulus has the same effects on the impulse response as increasing its contrast gave us important insights on how contrast is integrated over different locations in visual space. The definition of local contrast in the dynamic model is based directly on the results of these experiments.

Here we use the dynamic model to illustrate the effects of contrast and size in a different format than the one we used in Chapter 6. At several locations throughout the previous chapters we have made the point that gain control affects mostly the responses at low temporal frequencies, while the response at high temporal frequencies grow almost linearly with luminance and contrast. As a consequence, nonlinear behaviors like contrast saturation and size tuning occur at low but not at high frequencies. Even though we made that point qualitatively from the responses to temporal frequency sweeps at various contrasts and size (Figure 6-1) we were nevertheless not able to directly plot responses as a function of contrast or size for different...
temporal frequencies. Here, rather than running these experiments on real LGN neurons, we simply simulate them with the dynamic model. The parameters of the model are the same as those used throughout this chapter.

The effects of contrast on the simulated response to a drifting grating are shown in Figure 7-15A. The three curves correspond to three temporal frequencies, 2, 10 and 20 Hz, which lie well within the range of frequencies covered by the sweeps (i.e., 0.5 to 40 Hz). We plotted response as a function of linear contrast, to better appreciate the saturation in the responses.

As expected, the degree of contrast saturation depends strongly on the temporal frequency of the grating. At the lowest temporal frequency (Figure 7-15A, white) saturation is very strong and responses are almost constant over a large range of contrasts. On the other hand, at the highest temporal frequency (dark gray) saturation is very weak and responses grow almost linearly with contrast. The transition between these two extremes is gradual: intermediate temporal frequencies show intermediate degrees of contrast saturation (light gray).

Similarly, the degree of size tuning depends strongly on temporal frequency (Figure 7-15B). A common measure of size tuning is given by the ratio between the responses elicited by a grating of optimal size and the response to a grating that is far larger than the receptive field. According to this measure, at the lowest temporal frequency the model neuron is very size tuned (white) while at the highest frequency it is not size tuned at all (dark gray). Again, intermediate frequencies result in intermediate degrees of size tuning (light gray). Crucially, without contrast gain control the responses would not be size tuned, independently of temporal frequency. In fact, the shape of the predicted responses at the highest temporal frequency (dark gray) matches the predictions of the receptive field alone (not shown).

![Figure 7-15. The effects of temporal frequency on contrast saturation and size tuning. The stimuli are drifting gratings of optimal spatial frequency. Temporal frequency is 2, 10 or 20 Hz (see legend). Response is the amplitude of the first harmonic at the frequency of the grating. A: The effect of contrast on the response. The degree of contrast saturation depends on temporal frequency. Saturation is strongest at low temporal frequencies. B: The effect of size on the response. The degree of size tuning depends on temporal frequency. Like contrast saturation, size tuning is strongest at low temporal frequencies.](image-url)
7.3.4 Masking experiments

Finally, we present the simulations to a set of experiments that we did not discuss in the previous chapters, even though they provided crucial constraints for the design of the dynamic model (Bonin 2005). The response of LGN neurons measured in those experiments closely resemble the simulations discussed in this section (not shown).

The experiments involve stimuli usually referred to as “plaids”, which consist of the superposition of two gratings, a test and a mask. The attributes of the test are chosen to elicit optimal response in the neuron, and are kept fixed across all stimuli. The attributes of the mask, on the other hand, are varied across stimuli. In four separate experiments we varied either the contrast, size, spatial frequency or temporal frequency of the mask. If the test and the mask have incommensurate temporal frequencies, the plaid elicits two distinct response components (Bonds 1989): a test response that oscillates at the temporal frequency of the test, and a mask response that oscillated at the temporal frequency of the mask.

Figure 7-16. Effect of contrast and size of the mask on the test response. Test response is the amplitude of the first harmonic at the frequency of the test. Test and mask have temporal frequencies of 7.8 and 12.5 Hz. We simulated the response either with (gray) or without (white) contrast gain control. A: Test response as a function of mask contrast. B: Test response as a function of mask diameter. C: The conductance of contrast gain control as a function of mask contrast. D: The conductance of contrast gain control as a function of mask diameter. Conductance was averaged over the entire stimulus duration (2 seconds).

In the predictions of the dynamic model the mask has a strong, suppressive effect on the response to the mask (Figure 7-16 and Figure 7-17). For instance, the response to the test
becomes progressively smaller as the contrast (Figure 7-16A, gray) or the size (Figure 7-16B, gray) of the mask are increased. In particular, adding a large, high contrast mask to the test reduces the test response to less than half the response of the test alone.

The suppression of the response to the test is mediated by contrast gain control. In fact, increasing the contrast (Figure 7-16C, gray) or size (Figure 7-16D, gray) of the mask makes the conductance $g_C$ of contrast gain control larger, which in turn results in a smaller gain. When mask contrast is increased, the total power in each subunit’s response also increases. When mask diameter is increased, progressively more subunits are recruited. Therefore, both manipulations result in a larger local contrast and thus in a larger conductance.

To show that this reduction in gain alone is responsible for the suppression, we also simulated the response of the model for a fixed value of $g_C$ (Figure 7-16C and D, white symbols), a manipulation that effectively “turns off” contrast gain control. We fixed $g_C$ to its average value in the absence of a mask, and thus the two simulations predict the same response to test alone. We found that without contrast gain control the mask has indeed only minimal effects on the response to the test (Figure 7-16A and B, white symbols).

![Figure 7-17](image_url)

Figure 7-17. Effect of spatial and temporal frequency of the mask on the test response. Test and mask have temporal frequencies of 7.8 and 12.5 Hz or as indicated on the abscissa. Same conventions as in Figure 7-16. A: Test response as a function of mask spatial frequency. B: Test response as a function of mask temporal frequency. C: The conductance of contrast gain control as a function of mask spatial frequency. D: The conductance of contrast gain control as a function of mask temporal frequency.
The strength of suppression strongly depends also on the spatial (Figure 7-17A, gray) and temporal (Figure 7-17B, gray) frequency of the mask. In the case of spatial frequency, the strength of suppression closely reflects the subunits' selectivity for spatial frequency. Suppression is strongest at the optimal spatial frequency of the LGN neuron, since the receptive field of the subunits is identical to the receptive field of the LGN neuron.

Varying the temporal frequency of the mask, on the other hand, has more complicated effects on the response. First, the increase in the strength of suppression (i.e. the reduction in response in Figure 7-17B, gray) does not perfectly match the increase in the value of $g_C$ (Figure 7-17D, gray). In particular, the strongest suppression occurs for a mask frequency of 15.6 Hz, while $g_C$ peaks at 8.9 Hz. In fact, the response to the test depends on mask temporal frequency even when $g_C$ is fixed, i.e. when contrast gain control is turned off (Figure 7-17B and D, white).

The effects of mask temporal frequency in the absence of gain control can be accounted for by the rectification stage, which transforms membrane potential into firing rates. The effects of rectification tend to be large only if the duration of the stimulus is small compared to the duration of a cycle of the test or mask (i.e., for low temporal frequencies of the mask in Figure 7-17B) or if the temporal frequencies of test and mask are not incommensurate (i.e. when mask temporal frequency is 15.6 Hz, twice the frequency of the test).

7.4 Discussion

In this chapter we have presented a dynamic model of gain control in LGN neurons that can be used to predict the responses to arbitrary stimuli. The dynamic model captures all the effects of gain control that we have discussed in the previous chapters. We implemented very fast luminance and contrast gain control mechanisms, and thus the dynamic model predicts the rapid reductions in gain and integration time caused by a step in mean luminance or contrast (Chapter 2.2.1). Despite this fast dynamics, the model correctly predicts the temporal frequency selectivity of LGN neurons measured at steady state, when mean luminance and contrast are fixed over time (Chapter 2.2.2). Moreover, in the dynamic model local contrast is computed by integrating the response of subunits covering an extended region of visual space; thus the model also predicts the effects of size on the response, as well as their close relation to the effects of contrast (Chapter 6). Finally, we showed that the model correctly predicts that adding a mask grating to a test grating suppresses the response to the test, and how this suppression depends on various mask attributes (Bonin 2005).

Even though the dynamic model was designed to predict the responses of X-cells, it might represent an important step towards a model of Y-cell responses to arbitrary stimuli. Indeed, the response of a Y-cell consists of the sum of two components, one of which is driven by the receptive field and is thus analogous to the response of an X-cell. The second component has been modeled as the response of a pool of subunits covering the receptive field (Hochstein and Shapley 1976b; Victor and Shapley 1979b; Hochstein and Shapley 1976a; Enroth-Cugell and Freeman 1987). At least in retinal ganglion cells, the properties of these subunits are strikingly similar to the properties of the subunits computing local contrast, and thus the two kinds of subunits could correspond to the same population of retinal neurons (Shapley and Victor 1979;
One could thus imagine to extend the dynamic model to capture the responses of Y-cells by adding the output of the subunits of contrast gain control to the model response. The sum would have to occur before contrast gain control, since the gain and integration time of the subunits depend on contrast in the same way as the gain and integration time of the receptive field (Hochstein and Shapley 1976a; Victor and Shapley 1979a; Shapley and Victor 1980; Enroth-Cugell and Freeman 1987; although see Victor 1988).

7.4.1 Relation to previous models

As discussed in Chapter 5, our implementation of luminance gain control builds on a number of models proposed in the past (in particular, Fuortes and Hodgkin 1964; Sperling and Sondhi 1968; Baylor et al. 1974; Shapley and Enroth-Cugell 1984; Brodie et al. 1978). However, these models describe only the temporal aspects of luminance gain control and, unlike the dynamic model, cannot be used to predict the responses to an arbitrary stimulus.

Our implementation of luminance gain control differs from the one proposed in the only current model that implemented gain controls based on both luminance and contrast. van Hateren and collaborators (2002) proposed a model of retinal ganglion cells that describes responses to spatially uniform stimuli. These authors chose an implementation of luminance gain control that, by itself, correctly predicts the responses of horizontal cells (Smith et al. 2001). Thus, in their model the responses after luminance gain control do not follow Weber's law (Smith et al. 2001).

In the dynamic model, on the other hand, the stage of luminance gain control is designed to describe the responses of LGN neurons and, by itself, predicts responses that do follow Weber’s law. However, it is not clear whether this difference in the implementation of luminance gain control is reflected in the final output of the models. In fact, in the model by van Hateren et al. (2002) the gain control stages following luminance gain control might contribute to effects that in our model are implemented already at the level of luminance gain control. The study by van Hateren et al. (2002) gives no insights into these issues, as it falls short of validating their model with simple stimuli.

As discussed throughout this thesis, our implementation of contrast gain control is closely related to previous models. In particular, the most influential model of dynamic contrast gain control has been proposed by Victor (1987). Victor’s model is considered the “standard model” of dynamic contrast gain control (Meister and Berry 1999) and has inspired or resembles more recent models (van Hateren et al. 2002; Keat et al. 2001; Pillow et al. 2004). As in our implementation, in Victor’s model contrast gain control operates by modifying the impulse response of the neuron; when local contrast is large, gain and integration time are reduced. However, the two models differ in the way local contrast is computed. In our model, local contrast is the integrated output of a pool of subunits covering the receptive field of the neuron. In Victor’s model local contrast at a given instant in time is monotonically related to the response of the neuron at that time.

However, these two definitions are equivalent when considering the stimuli used by Victor (1987), namely static luminance distributions modulated in time. Such stimuli result in synchronized responses across the entire pool of subunits. Thus, because by definition all the
properties of the subunits, other than their position in visual space, are identical to those of the LGN neuron, the average response of all subunits is proportional to the response of the neuron itself. The equivalence between the two definitions is reassuring, given the remarkable power of Victor's model to predict responses to rather complex, dynamic visual stimuli.

However, Victor's model was designed to capture only the temporal properties of gain control and would fail to predict its spatial properties. For instance, it would not predict size tuning of the responses (Figure 6-1 and Figure 7-15B). As we have discussed in Chapter 6, size tuning occurs because increasing the size of a stimulus can have very different effects on local contrast and on the output of the receptive field. Indeed, when a stimulus has optimal spatial frequency, extending it beyond the limits of the center does not result in a larger response of the receptive field, while it does result in a larger local contrast by recruiting more subunits. Because a larger local contrast implies a smaller gain, the net effect is a reduction in response. On the other hand, in Victor's model a constant response in the receptive field results in a constant estimate of local contrast, and thus size tuning would not occur.

7.4.2 Implications of the model

The design of the dynamic model points to an important distinction to be made between the effects of contrast gain control and the properties of the signal driving these effects. We have shown that contrast gain control has its strongest effects (i.e. gain is reduced the most) at the low temporal frequencies, while the responses to high frequencies grow approximately linearly with contrast (Figure 7-15A). As a consequence, the temporal frequency selectivity of neurons in the LGN depends on contrast (Figure 2-4). On the other hand, the masking experiments discussed in this chapter (Figure 7-17B) demonstrate that the strongest contributions to the signal driving contrast gain control (i.e. to local contrast) originate from relatively high temporal frequencies. In the model, we account for this observation by computing local contrast from the response of subunits whose selectivity for temporal frequency is similar to that of LGN neurons. Thus, counter intuitively, the temporal frequencies that are affected the least by contrast gain control are those that contribute the most to local contrast.

The dynamic model makes a strong prediction on how mean luminance should affect the computation of local contrast. Since the responses of the subunits are shaped by luminance gain control, their selectivity for temporal frequency depends on mean luminance. In particular, at low luminance levels the highest temporal frequencies contribute little to the computation of local contrast. Thus, in the masking experiments discussed in section 7.3.4, the effects of mask temporal-frequency on the responses to the test (Figure 7-17B) should depend on the mean luminance of the stimuli in a way consistent with the effects of luminance gain control.

As we have discussed in Chapter 6 (6.3.3), the model also shows that studies that aim at comparing the effects of contrast and size across different visual areas are prone to a very basic confound. We have shown that contrast saturation (Figure 7-17A) as well as size tuning (Figure 7-17B) are strongly dependent on the temporal frequency of the stimulus. Both effects are strong at low temporal frequencies and virtually absent at high frequencies. A comparison between the
degree of contrast saturation and size tuning across visual areas is possible only if the experiments are performed at the same temporal frequencies.

Similarly, the simulations in Figure 7-17B show that temporal frequency also affects estimates of the size of the receptive field. Indeed, because size tuning becomes progressively stronger as temporal frequency is reduced, the receptive field appears progressively smaller (Figure 7-17B). These effects are closely related to the effects of contrast on the apparent size of the receptive field. At optimal temporal frequencies, size tuning becomes progressively stronger as contrast is increased and thus the receptive field appears progressively smaller both in LGN (Solomon et al. 2002; Bonin et al. 2004b) and in V1 (Sceniak et al. 1999; Cavanaugh et al. 2002a). These effects are a consequence of contrast gain control (Bonin et al. 2004b) and are also predicted by the dynamic model (not shown).

7.4.3 Shortcomings of the model

Even though our main effort went into building a model that predicts the properties of LGN neurons studied in our lab (this thesis and Bonin 2005) at the same time we have tried to incorporate into the model many properties of gain control previously described in the literature. However, we did not always achieve consistency between the predictions of the dynamic model and known properties of gain control. Because the design of the dynamic model in many ways summarizes and unifies past models of gain control, these inconsistencies might point to important gaps in our understanding of the computations performed by the early visual systems.

With respect to luminance gain control, the definition of local luminance seems to be only partially in agreement with experimental results in cat. In the model, local luminance is the average luminance falling onto the receptive field surround in the recent past (Figure 7-1B). Although the temporal extent of this averaging (~150 ms) is consistent with typical values from experiments in cat (Lankheet et al. 1993b; Saito and Fukada 1986; Enroth-Cugell and Shapley 1973a), its spatial extent is not. In fact, a number of studies have shown that the gain of the receptive field center is affected only by luminance falling onto a region of visual space that is roughly coextensive with (in X-cells) or smaller than (in Y-cells) the center itself (Harding 1977; Cleland and Enroth-cugell 1968; Enroth-Cugell et al. 1975; Cleland and Freeman 1988).

We found that the proposed design of the dynamic model (Figure 7-1) can hardly be reconciled with the responses of neurons in the LGN if the computation of local luminance is as local as the center of the receptive field. To illustrate the problems arising when luminance gain operates very locally, consider the responses to sweeps discussed in this chapter (Section 7.3.2). Throughout the sweeps, the conductance $g_L$ of luminance gain control is essentially constant, and corresponds to the mean luminance of the stimulus (see for example Figure 7-12A). As a consequence, the effect of luminance gain control in the dynamic model is approximately the same as in the steady state model of gain control (Figure 5-1).

If the integration of luminance were as local as the center, on the other hand, the two models would make very different predictions. Because a grating of optimal spatial frequency strongly modulates the center, local luminance would be strongly modulated at the temporal frequency of the stimulus. Especially at high contrasts, the resulting modulation in gain would strongly deform
the responses, as increments in luminance would be suppressed and decrements would be enhanced (as in Figure 4-6). Because of the finite integration time of luminance gain control, these effects would be strongest at low temporal frequencies. Thus, at low temporal frequencies the responses of the dynamic model would differ from those of the steady state model. For ON-center cells, which respond to luminance increments, the dynamic model would predict smaller responses, while for OFF-center cells, which respond to luminance decrements, it would predict larger responses. For high contrast stimuli the discrepancies between the two models would be very large and the dynamic model would not predict the measured responses even with a set of parameters different from that of the steady state model. To avoid these discrepancies, in the dynamic model we compute local luminance over a region of visual space larger than the center, in disagreement with the literature.

It is possible, however, that past studies of luminance gain control did not characterize the spatial properties of what we have been referring to as luminance gain control. In fact, the effects on gain observed in these studies could have occurred over much slower times scales than those of luminance gain control, since they were induced by relatively long periods of adaptation to a particular luminance level (Harding 1977; Cleland and Enroth-cugell 1968; Enroth-Cugell et al. 1975; Cleland and Freeman 1988). If this were the case, one could imagine such slow mechanisms to be regulated more locally than luminance gain control. Alternatively, the spatial extent of the computation of local luminance could depend on stimulus luminance, which in the above studies was typically lower than then ranges covered in our experiments.

However, even if our definition were not inconsistent with the literature, it does not completely eliminate the discrepancies between the dynamic model and the steady model; it just limits the range of stimulus parameters at which they occur. While for a very local mechanism discrepancies occur even for stimuli of optimal spatial frequency, in our implementation they occur only at very low spatial frequencies, which elicit little response in the receptive field.

With respect to contrast gain control, our definition of local contrast is only approximately consistent with the masking experiments performed in our lab (Section 7.3.4). In the dynamic model, local contrast is computed from a pool of subunits whose receptive field is identical to the receptive field of the LGN neuron. This definition makes the strong prediction that the suppression caused by the mask should depend on mask attributes in the same way as the response to the test depends on test attributes. For instance, the curve in Figure 7-17A, describing the spatial frequency selectivity of suppression, is symmetric to the spatial frequency selectivity of the responses of the LGN neuron. Our experiments, however, do not support this prediction. Typically, the spatial frequency selectivity of suppression is substantially more bandpass than the selectivity of LGN neurons (Bonin 2005). Thus, the putative subunits driving contrast gain control are likely to have a receptive field that, at least spatially, differs from the one of LGN neurons.

We chose a definition of local contrast that is only approximately consistent with these experimental results for reasons that are similar to those underlying our definition of local luminance. If the receptive field of the model subunits differed from that of the LGN neuron then

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contrast gain control would strongly distort the spatial frequency selectivity of the dynamic model.

To understand why that is the case, consider again the response of the dynamic model to a sweep at the optimal spatial frequency (Figure 7-12). The conductance of contrast gain control, \( g_c \), is a smooth function of time that reflects the temporal frequency selectivity of the subunits (Figure 7-12B). Crucially, \( g_c \) is only weakly modulated at the temporal frequency of the stimulus, since the response of different subunits have different temporal phases (see for example Figure 7-10). However, if we had simulated the response to a stimulus of low spatial frequency, \( g_c \) would strongly vary over time. In fact, for low spatial frequencies all the ON-center subunits respond with the same temporal phase, as do all OFF-center subunits. Since the two populations of subunits are exactly in anti-phase, the resulting local contrast oscillates at twice the stimulus temporal frequency.

When local contrast is strongly modulated, contrast gain control distorts the output of the receptive field. Contrast gain control can either enhance or suppress the response, depending on whether peaks in the response coincide with troughs or peaks in local contrast. If the LGN receptive field is kept fixed, then the relative phase between response and local contrast depends on the properties of the subunit receptive-field. Especially at large temporal frequencies, even a small change in the receptive field of the subunits results in a substantially different relative phase and thus in a very different response. Because of their sensitivity to variations in model parameters, these distortions add a high degree of complexity to the dynamic model. To avoid this complexity, and to insure consistency with Victor’s model of contrast gain control (1987), we imposed the receptive field of the subunits to be identical to that of the LGN neuron. This choice guarantees that peaks in the response always coincide with peaks in local contrast.

Alternatively, we could have chosen the receptive field of the LGN neuron to match the properties of the subunits inferred experimentally (Bonin 2005). However, in this case the dynamic model would not predict the spatial frequency selectivity of LGN neurons, since experimentally the subunits are found to have a weaker antagonistic surround than LGN neurons. This choice would thus require a second spatial-filtering stage operating after contrast gain control, analogous to the second temporal-filtering stage already included in the dynamic model for similar reasons.

It is likely, however, that the distortion caused by contrast gain control represent less of a problem for real neurons. First, they occur only when all the subunits respond with the same temporal phase, which is unlikely to happen with real subunits. Indeed, even neurons of a same type are likely to cover a substantial range of response latencies and thus a full field stimulus would elicit responses of different phases across the population of subunits. This scatter in the phase of the subunits would at least partly reduce the modulations in local contrast. Second, the distortions are a problem only when the receptive fields of the subunits differ from that of the model neuron. This is the case in a model of LGN neurons, since the selectivity of LGN neurons is very different from the selectivity of the putative subunits (Bonin 2005). However, as we have discussed in Chapter 6 (6.3.1), the effects of contrast gain control observed in the LGN might be
due entirely to mechanisms operating on retinal ganglion cells, whose selectivity for spatial frequency (Enroth-Cugell and Robson 1966) is similar to the selectivity of the subunits.
Chapter 8

Gain control in complex stimuli

8.1 Introduction

Finally, having built a dynamic model of gain control whose formulation is general enough to simulate the responses to arbitrary stimuli (Chapter 7) we can go back to the responses to natural movies that we described in Chapter 1 and test if the predictions of the dynamic model are better than those of the receptive field alone. By testing the dynamic model on the responses to natural movies, we will address two separate issues. First, we will subject the dynamic model to a much more stringent test than we did in the previous chapter. In fact, so far we have tested the dynamic model only on the very same responses that inspired and constrained its design. The natural movies, on the other hand, span a much higher-dimensional space than the simple stimuli we used in the previous chapter. There is no guarantee that the various stages of the model, and in particular our definitions of local luminance and local contrast, will be meaningful on these far more complex stimuli. Second, we will assess if luminance gain control and contrast gain control play any role at all in shaping the responses to natural movies. We anticipated such a role in Chapter 1, where we argued that the effects of gain control could account at least for some of the discrepancies between the measured responses and the predictions based on the receptive field (Figure 1-10).

As in previous chapters, we will use the responses to simple stimuli, rather than the responses to natural stimuli, to estimate the parameters of dynamic model and of the receptive field. In fact, the dynamic model has by far too many parameters to be constrained by the responses to our natural stimuli, which are very limited in duration. Moreover, by estimating the parameters on responses to simple stimuli, we will be able to compare the prediction of the dynamic model to those of the receptive field on an equal footing, despite the different complexity of the two models.

8.2 Results

As we have shown in Chapter 1 (Figure 1-8), the receptive field correctly predicts the timing of the measured responses to natural movies, but if often over- or underestimates the amplitude of the responses (Figure 8-1F, blue). We have argued that the effects of gain control might contribute to the differences between the measured and predicted responses. According to this hypothesis, the receptive field fails to predict response amplitude because the gain of the LGN neuron varies over time. For instance, at times when local luminance or local contrast are larger than average, gain control would reduce the gain of the neuron and thus the receptive field would overestimate response amplitude. Using the dynamic model of gain control developed in the previous chapter, we can now test if gain control plays a role in the responses to movies.
Gain control indeed seems to affect the responses to the movies, since the dynamic model (Figure 8-1F, red) predicts the amplitude of the measured responses better than the receptive field alone (blue). As expected, whenever the receptive field underestimates response amplitude, the dynamic model predicts larger responses, and vice versa. The differences between the two models can be substantial: at times during the movies the predicted amplitudes differ by more than a factor of two.

Crucially, the only difference between the two models lies in the values of the conductances of luminance gain control and contrast gain control, $g_L$ and $g_C$. In fact, when $g_L$ and $g_C$ are constant over time, the effects of luminance gain control and contrast gain control are linear and thus the response of the dynamic model reduces to the response of the receptive field alone. Since luminance gain control and contrast gain control shape the impulse response of the receptive field, the predictions of the receptive field depend strongly on the precise values of $g_L$ and $g_C$. In Figure 8-1 (blue) we plot the predictions of the best receptive field, obtained by fitting the values of $g_L$ and $g_C$ directly to the responses to movies.

To understand how the predictions of the two models are generated and why they differ from each other, in Figure 8-1 we plot the outputs of the most important stages in the models, together with the values of $g_L$ and $g_C$ over time. The different panels in Figure 8-1 represent the luminance falling on the center and surround of the receptive field (A), the value of $g_L$ (B), the response after luminance gain control (C), the value of $g_C$ (D), the response after contrast gain control (E), and the final response of the two models (F).

In both models the response is driven by differences in the luminance falling onto the center (Figure 8-1A, thin) and the surround (thick) of the receptive field. This difference signal is identical in the two models because they share the same spatial parameters. Since the impulse response of the receptive field selectively enhances temporal variations in the difference signal, even very small differences between center and surround can result in robust responses. In fact, filtering the difference signal with the impulse response is equivalent to first convolving it with a lowpass filter and then taking its temporal derivative (Simoncelli 1993).

After luminance gain control the responses of the two models differ from each other whenever local luminance differs from its average value over all movies (Figure 8-1C). This is the case during the Tarzan sequence shown in Figure 8-1 (left). Throughout the Tarzan sequence local luminance is approximately half as large as during the Catcam sequence (Figure 8-1, right). This difference in local luminance is reflected in the value of $g_L$ for the dynamic model (Figure 8-1B, red), while in the prediction of the best receptive field the value of $g_L$ is fixed across time and movies (blue). We normalized $g_L$ such that $g_L = 1$ corresponds to the maximal luminance of the screen. The fits of the best receptive field yielded $g_L \approx 0.5$, corresponding approximately to the average pixel luminance over the entire set of movies used for the example cell in Figure 8-1 (see Methods).

Thus, the value of $g_L$ in best receptive field corresponds approximately to the average value of $g_L$ in the dynamic model. During the Catcam sequence the instantaneous value of $g_L$ is very similar to its average value, and therefore the responses after luminance gain control are almost undistinguishable in the two models.
Figure 8-1. Responses to movies and predictions of the dynamic model of gain control. The predictions of the dynamic model (red) are compared to the predictions of the best receptive field (blue). The measured responses as well as the predictions of the best receptive field are replotted from Figure 1-8. A: Stimulus luminance falling on the center (thin) and surround (thick). B: The conductance of luminance gain control. C: The response after luminance gain control. D: The conductance of contrast gain control. E: The response after contrast gain control. F: Measured (gray) and predicted responses.

In the next stage of processing of the dynamic model local contrast is computed by integrating subunit responses similar to the output of luminance gain control in Figure 8-1C. In the dynamic model the value of local contrast is reflected in $g_C$, the conductance of contrast gain control (Figure 8-1D, red). In the prediction of the best receptive field, on the other hand, $g_C$ is fixed and corresponds approximately to its average value in the dynamic model. The value of $g_C$ tends to be large when the response after luminance gain control contains large positive or negative...
defections. However, $g_c$ varies substantially slower than the response of the LGN neuron, since subunits at various spatial locations and of both polarities contribute to local contrast. The prominent, fast modulation in $g_c$ corresponds to the original refresh rate of the movies, 30 Hz; at the refresh rate of the monitor (i.e. 125 Hz), only every 4th or 5th frame in a sequence is different from the preceding one.

The instantaneous value of $g_c$ determines the effects of contrast gain control on the predicted responses (Figure 8-1E). In the Tarzan sequence contrast gain control has mostly the effects of reducing the differences between the prediction of the dynamic model and those of the best receptive field. Indeed, the largest differences between the responses of the two models after luminance gain control (Figure 8-1C) occur when the values of $g_c$ in the dynamic model is larger than for the best receptive field (Figure 8-1D). The larger value in $g_c$ corresponds to a smaller gain, and thus contrast gain control suppresses the responses of the dynamic model more than those of the best receptive field. Intuitively, the responses in the Tarzan sequence occur mostly when local luminance and local luminance are respectively smaller and larger than average, and therefore the effects of contrast gain control partly cancel out the effects of luminance gain control. As in the Tarzan sequence, in the Catcam sequence the largest responses also occur when the value of $g_c$ in the dynamic model is larger than for the best receptive field. However, in the Catcam sequence contrast gain control enhances the difference between the responses of the two models (Figure 8-1E), which are virtually identical at the output of luminance gain control (Figure 8-1C).

In the last stages of the model the output of contrast gain control (Figure 8-1E) is filtered with a fixed bandpass filter, added to noise and rectified to obtain the predicted firing rate (Figure 8-1F). Since all the parameters of these stages are identical in the dynamic model and the best receptive field, they do not contribute to the differences between the predictions of two models.

![Figure 8-2](image)

**Figure 8-2.** Responses to movies and predictions of the low-contrast receptive field. We compare the measured responses (gray) to the predictions of the dynamic model (red) and the predictions of the low-contrast receptive field (blue). Same neuron as in Figure 8-1.

The comparison between the two models (Figure 8-1F) thus demonstrates that the predictions based on a fixed receptive field are worse than the prediction of the dynamic model. The choice of the fixed receptive field, however, is almost arbitrary. Indeed, has we have discussed throughout this thesis, the impulse response of the receptive field depends strongly on the
attributes of the stimulus (for instance Figure 2-7A). In Figure 8-1 we have chosen a very special impulse response, namely the one that best predicts the responses to the movies. We have argued that the best impulse response roughly corresponds to the average impulse response of the dynamic model. Thus, differences between the predictions of the two models occur only when the impulse response of the dynamic model differs from its average shape.

The average values of \( g_L \) and \( g_c \) in the movies (Figure 8-1B and D, blue) correspond approximately to the values we would have obtained in response to an optimal grating of 50% luminance (i.e. 32 cd/m²) and 40% contrast. Thus, the best receptive field would correctly predict the responses only to a grating of that particular luminance and contrast. For instance, for a grating of the same luminance but lower contrast it would predict responses that are too small and too fast (Figure 7-14C). Similarly, we expect that the impulse response that best predicts the responses to the low contrast grating would predict only poorly the response to the movies.

To demonstrate that the wrong choice of impulse response does result in bad predictions of the response to the movies, we also simulated the responses with the low-contrast receptive field (Figure 8-2, green) and compared them to the predictions of the dynamic model (red). The low-contrast receptive field was estimated at 50% luminance and 10% contrast. Thus, both the gain and integration time of the low-contrast receptive field are larger than their average values in the dynamic model. However, since we fitted the overall gain of the model directly to the responses to the movies (see Methods) the difference between the predictions of the dynamic model and the low-contrast receptive field reflect largely the differences in their integration times.

As expected, the low-contrast receptive field (Figure 8-2, green) predicts the timing of the responses worse than the dynamic model (red) or the best receptive field (not shown). Because the integration time of the low-contrast receptive field is too long, the predictions are delayed with respect to the measured response (gray).

Overall, the predictions of the low-contrast receptive field are substantially worse than those of the best receptive field. For the example cell of Figure 8-1 and Figure 8-2, the dynamic model explains 66% of the stimulus-driven variance, while the best receptive field and the low contrast receptive field explain 58% and 39% of the variance (Figure 8-3). Over the entire population of neurons (\( N = 24 \)) the medians for the three models are 51, 46, and 35%.

These values are substantially lower than those obtained from the fits of the dynamic model on the stimuli that we used to estimate the parameters of gain control. For the example cell of Figure 8-1, the dynamic model explains 87% of the stimulus-driven variance in the fitted responses. Three out of five stimuli used for the fits on the example cell are shown in Figure 7-12, Figure 7-13, Figure 7-14. Over the entire population of neurons discussed in this chapter (\( N = 24 \)), the dynamic model explain 78% (median) of the stimulus-driven variance in the fitted responses.
Figure 8-3. Quality of predictions, comparison between the models. Each symbol corresponds to a cell. The example cell in plotted in red. A: Comparison between the best receptive field and the dynamic model. B: Comparison between the low-contrast receptive field and the dynamic model.

Figure 8-4. Quality of predictions, population. A: Quality of predictions with the dynamic model. B: Quality of predictions with the best receptive field. C: Quality of predictions with the low-contrast receptive field.
8.3 Discussion

In this chapter we have tried to achieve two closely related goals. First, we wanted to test the dynamic model of gain control (Chapter 7) on the response to complex, naturalistic stimuli. Given that the design of the model is based on the responses to simple, laboratory stimuli, we had no guarantee that the various stages of the model, and in particular our definitions of local luminance and local contrast, would be meaningful for natural movies. Second, we wanted to demonstrate that gain control shapes the responses of LGN neurons to our set of natural movies. We had argued in Chapter 1 that the effects of gain control could account at least for some of the discrepancies between the predictions based on the receptive field and the measured responses (Figure 1-10).

Our first goal, testing the dynamic model, was complicated by the fact that the overall responsivity of LGN neurons can vary substantially over the long time spans (i.e. hours) needed for our recordings. Because of these slow drifts in responsivity, the overall gain of the model effectively varies throughout different experiments. Thus, we were unable to predict the responses to movies from parameters that were entirely estimated by fitting the responses to simple stimuli. Rather, we had to fit the overall gain of the model directly to the responses to movies, which deprived the dynamic model of its greatest strength, namely the ability to predict the gain of a neuron in response to an arbitrary stimulus.

Thus, rather then probing the ability of the dynamic model to predict the overall gain of the neurons in response to the movies, we tested whether it correctly predicts how gain varies within and across the movies. In fact, we expected such variations in gain to occur as a consequence of variations of local luminance and local contrast across their average values over all movies. If the gain of the dynamic model follows these variations, then it should predict responses better than a model in which gain is fixed. We thus compared its the predictions of the dynamic model to those obtained when its conductances of luminance gain control and contrast gain control were kept fixed throughout the movies. Since for fixed conductances the dynamic model is linear (up to the rectification stage), this amounts to comparing the predictions of the dynamic model to the predictions of the receptive field. Since we fitted the values of the fixed conductances directly to the measured responses to movies, we actually compared the dynamic model to the receptive field that best accounts for the measured responses.

We found that the dynamic model predicts the responses to movies better than the best receptive field. Therefore, the measures of local luminance and local contrast computed by the dynamic model are meaningful even in the responses to complex, natural stimuli, since variations in gain based on them improve the predictions. At the same time, by comparing the dynamic model to the best receptive field we also achieved our second goal, namely proving that gain control does affect the responses to the movies and thus accounts for some of the differences between the measured responses and the predictions of the receptive field.

The advantages of the dynamic model are even larger when it is compared to a receptive field whose impulse was not estimated at the average local luminance and local contrast found in the movies. Indeed, we showed important differences between the predictions of the dynamic model and those of the low-contrast receptive field. Since this comparison effectively reflected only
differences in the integration times of the two models, we expect even larger advantages for the
dynamic model when considering also differences in gain.

The improvements of the dynamic model over the predictions of the receptive field were
similar across cells types. However, given the small sample size used in this chapter, this
observation does not necessarily generalize to all relay cells in the LGN. In fact, the majority of
the neurons in our sample were On-center X-cells (N = 13). Far fewer neurons were Off-center
X-cells (N = 4), On-center Y-cells (N = 3) or Off-center Y-cells (N = 4). However, the effects of
gain control, as well as the spatial and temporal properties of the signal driving contrast gain
control, are similar in these four cell types (e.g., Figure 5-10, Figure 6-9, and \Bonin, In press
#2968). Thus, the conclusions of this chapter are unlikely to depend on our particular sample of
neurons.

8.3.1 Shortcomings of the model

However, even the dynamic model has obvious shortcomings. First, even though it predicts
the measured responses better than the receptive field, clearly it does not explain all the features
of the responses. Second, the quality of predictions on the movies is markedly lower than the
quality of fits on simpler stimuli. For several reasons, both of these shortcomings are not
surprising.

First, the movies form a much higher-dimensional stimulus space than the simple stimuli used
for the fits. As discussed in Chapter 1, many of the assumptions built into the dynamic model can
have a substantial impact in this high-dimensional space, even though they play little role for the
simple stimuli. For instance, we assume that the center and surround of the receptive field have
Gaussian profiles and that they have identical positions in visual space. In real neurons, however,
the receptive field might contain hotspots, have elliptical rather than circular contours, and the
positions of the center and surround do not necessarily match (Soodak et al. 1987; Dawis et al.
1984; Passaglia et al. 2002). These “imperfections” in the receptive field are averaged out in the
responses to the simple stimuli, but in the responses to the movies, which have a much richer
spatial structure.

Second, we kept many model parameters fixed across all neurons, without fitting them to the
responses of individual neurons. Indeed, some of the parameters were not constrained by our
experiments, and thus we had to resort to using values found in the literature on gain control. For
instance, as discussed in the previous chapter, this was the case for the time constants of
luminance gain control and contrast gain control. However, to simply the fitting procedure, we
also fixed the values of a number of parameters that would have been constrained by our
experiments. In particular, the parameters describing the computation of local contrast are fixed
to their average values over the entire population of neurons. All these fixed parameters have
little effect on the fitted responses, but might well play a more important role in the responses to
the movies.

Finally, the dynamic model does not include a number of mechanisms that are known to affect
the responses of LGN neurons. For instance, the dynamic model does not include a spike
generation mechanism. Since spike generation is not a Poisson process (Pillow et al. 2004), it
affects even the predictions of a model that predicts firing rates rather than spike trains (Pillow et al. 2004; Keat et al. 2001). Moreover, the dynamic model does not account for bursts of action potentials (Sherman 2001), which are a prominent feature of LGN responses to naturalistic stimuli (Denning and Reinagel 2005; Lesica and Stanley 2004). A bursting mechanism could be easily added to the model even without a spike generation mechanism (Smith et al. 2000) and would certainly improve model predictions (Lesica and Stanley 2004). Because of their nonlinear nature, both a spiking mechanism and a bursting mechanism could potentially enhance the differences between the predictions of the dynamic model and the predictions of the receptive field. Finally, the dynamic model does not include the slow contrast adaptation mechanisms that have been described in retina and LGN. Even though we found that slow contrast adaptation plays no role in the response to sweeps (Chapter 3) we can not exclude that it affects responses to the movies.

8.3.2 Relation to natural vision

Even a model that overcame the shortcomings of the dynamic model and predicted all the features in the responses to our movies would not necessarily describe LGN response during natural vision. In fact, it is not clear how well our movies approximate the luminance distributions falling onto the retina during natural vision. Moreover, the animal preparation used for our recordings, which involved anesthetized and paralyzed animals, is obviously far from natural.

The natural movies used in this study capture some but probably not all the relevant properties of the stimuli encountered during natural vision. The spatial properties of natural stimuli have been extensively studied (for a review see Simoncelli and Olshausen 2001). At least a subset of the movies used for our experiments capture these spatial properties (i.e. the Catcam movies, Betsch et al. 2004). The temporal properties of natural stimuli, on the other hand, are not well understood. It is likely that they are dominated by the effects of rapid gaze shifts caused either by saccades or by rapid head movements. However, other forms of gaze shift like smooth-pursuit movements (Lisberger et al. 1987) and fixational eye movements (Martinez-Conde et al. 2004) as well as the temporal luminance pattern generated by objects moving against their background are likely to make important and specific contributions to the temporal properties of natural stimuli. Even though we used rather complex movies, their temporal properties only approximately match those of natural images. For instance, the variations in local luminance in the movies (Figure 8-1A and B) are much less frequent and cover a smaller range than those encountered in natural vision (Frazor and Geisler 2004).

Similarly, the computations performed in the LGN during natural, active vision might be rather different than those we studied in anesthetized and paralyzed animals. In particular, the LGN is thought to be more than just a passive relay station between the retinas and cortex. One view sees the LGN, and the thalamus in general, as a gate whose state is controlled by a number of cortical and subcortical structures (Sherman and Guillery 2001; Sherman and Guillery 2002). In this view, the “tonic mode” and “bursting mode” of LGN neurons (Sherman 2001) are thought to be manifestations of two operational modes of the gate. Bursting is rare or absent from LGN responses in awake animals (Guido and Weyand 1995; Weyand et al. 2001; Ramcharan et al.
It is not surprising then that there is little evidence for a direct role of bursting in visual perception (Weyand et al. 2001; Guido and Weyand 1995; Martinez-Conde et al. 2002; Sary et al. 2001). On the other hand, bursting is prominent in anesthetized or sleeping animals, where it is involved in the generation of synchronized thalamo-cortical oscillations (Steriade et al. 1993). These observations do not exclude that other extraretinal influences on the LGN might have a direct role in visual perception. In fact, two hallmarks of active visual perception, spatial attention (O'Connor et al. 2002) and saccades (Lee and Malpeli 1998; Ramcharan et al. 2001; Reppas et al. 2002) have been shown to affect LGN responses.

Whatever their role in visual perception, any computations occurring in the LGN are likely to add to the effects of gain control even during natural, active vision. In fact, most likely the effects of gain control are largely a consequence of mechanisms operating already in the retina (Bonin), which does not receive extraretinal feedback. Thus, independently of the behavioral state of an animal, the effects of gain control will shape the input to the LGN.

8.4 Methods

8.4.1 Cell population

We recorded from 17 X-cells and 7 Y-cells in 5 adult cats. Of these 24 neurons, 17 were located in layer A and 7 in layer A1. We recorded from both On-center cells (16/24 neurons) and Off-center cells (8/24 neurons). The median eccentricity of the receptive field center over all neurons was 11.5 degrees; 20/24 neurons had receptive fields with eccentricities between 7.6 and 18.3 degrees (10th and 90th percentiles).

8.4.2 Fits of the dynamic model

The simulations with dynamic model are relatively slow, since each prediction involves simulating the responses of 169 subunits, covering a 13x13 square grid. Rather then fitting the parameters of the dynamic model directly to the responses, we thus separately fitted different components of the model in 5 subsequent steps:

1. We fitted the parameters of the receptive field to the responses to gratings of various spatial frequencies, temporal frequencies and positions in visual space, as discussed in Chapter 1. The estimated spatial profile of the receptive field, as well as the delay between center and surround were kept fixed throughout the subsequent steps.

2. We fitted the parameters of the steady state model to the responses to sweeps at various luminances and contrasts, as described in Chapter 5. From these fits we obtained the capacitance and the number of RC-circuits in the dynamic model.

3. Based on the fixed filter of the steady state model, \( f_0 \) (Figure 5-1, pink) we defined the impulse response of the receptive field, \( f_r \). By least squares fitting we obtained parameters of \( f_r \) such that \( f_0 \approx f_r \ast f_r \). The parameters of \( f_r \) were then kept fixed throughout the subsequent steps.

4. We computed local contrast \( C_{local}(t) \) for all sweep stimuli.
5. We fitted the remaining parameters of the dynamic model directly to the responses to sweeps, using the simulated $C_{\text{local}}(t)$ as an additional input to the dynamic model. These fits yielded estimates of the second bandpass filter, $f_{bp}$, as well as estimates of the strength of contrast gain control, $\beta$ and $\gamma$.

### 8.4.3 Predictions of the dynamic model

We used the parameters obtained from the fits (8.4.2) to predict the measured responses to movies. The predictions are almost parameter-free, in that only two parameters of the dynamic model were allowed to vary between the fits and the predictions. The two free parameters are the overall gain of the neuron and the resting potential (i.e., $r_{\text{max}}$ and the mean of $G_{\text{th}}$, see Appendix A). We found that both the gain and the resting potential were subject to slow drifts across different experiments. These drifts were of particular concern for the predictions discussed in this chapter, as the responses to movies were recorded up to two hours later than the responses used for the fits.

### 8.4.4 Predictions of the linear model

To assess the importance of dynamic gain control in the responses to movies, we compared the predictions of the dynamic model to the predictions of the receptive field alone. Since the receptive field of a neuron is not fixed, but rather depends on local luminance and local contrast, we had to fix its shape to one of the many possible shapes. We predicted the response based on two shapes of the receptive field, which call the best receptive field and the low-contrast receptive field.

We obtained the predictions of the two receptive fields by simulating the responses of the dynamic model for values of $g_L$ and $g_C$ that were constant over time and movies. Crucially, when $g_L$ and $g_C$ are constant luminance gain control and contrast gain control operate as linear filters.

To obtain predictions with the best receptive field, we fitted $g_L$ and $g_C$ directly to the response to movies, while all other parameters were fixed from the predictions with the dynamic model (8.4.3). Intuitively, the fits yielded values of $g_L$ and $g_C$ corresponding approximately to their average values in the predictions of the dynamic model.

To obtain predictions with the low-contrast receptive field, we fixed $g_L$ and $g_C$ to their average values in the response of the dynamic model to an optimal grating of 50% luminance and 10% contrast. We fitted the overall gain and the resting potential of the neuron directly from the responses to movies, since we fitted these two parameters also for the dynamic model. All other parameters were the same as in the predictions of the dynamic model.
Conclusions

We developed a model of LGN responses that implements the effects of both luminance gain control and contrast gain control and that is general enough to predict the responses to arbitrary stimuli. Unlike previous modeling efforts, our model accounts for both the spatial and temporal aspects of gain control. The model unifies a large number of observations that had been separately ascribed to gain control or other suppressive mechanisms. We have validated the model on the responses to natural stimuli, and found that it predicts the responses better than a model based on the receptive field alone.

The model promises to be a useful tool to assess the role of gain control in natural vision. In particular, there is little consensus about the function of contrast gain control. The prevalent opinion has been that contrast gain control matches the range of local contrast in natural images to the limited dynamic range of single neurons (Laughlin 1981; Ruderman 1994; Tadmor and Tolhurst 2000). However, there is also computational evidence that contrast gain control enhances faint contours in natural images (Ruderman 1994) and increases statistical independence (reduces the redundancy) across the population of neurons (Schwartz and Simoncelli 2001). So far, these different hypotheses have been validated only on static natural images. However, throughout the thesis we demonstrated that the effects of contrast gain control depend strongly on the temporal-frequency content of the stimulus. Thus, it is crucial to validate these hypotheses with stimuli that preserve the temporal structure of natural stimuli. We will be able to do exactly that by comparing responses to natural stimuli simulated with or without contrast gain control.

The model will be useful also to understand the computations performed in visual cortex. In particular, the model describes the feedforward input to neurons in V1. Knowing this input is a necessary step to understand the computations performed within V1. Moreover, mechanisms whose effects resemble those of contrast gain control in the LGN have been described in many different visual areas (Carandini et al. 1999; Simoncelli and Heeger 1998; Sundberg et al. 2005). The same formalism that describes the effects of contrast gain control in LGN (Bonin 2005) has been applied to describe the nonlinear properties of neurons in these higher visual areas. Thus, it might be possible to extend the model to captures also nonlinear effects observed beyond the LGN.

What is missing from the model?

Even though the model predicts the responses to natural stimuli better than the receptive field alone, clearly it does not capture all the features in the responses. Indeed, over the entire population of neurons, the model explains only 51% (median) of the stimulus driven variance in the responses. The obvious question then is: What accounts for the missing variance?

First, as we have argued several time throughout the thesis, the model is limited because it lacks mechanisms that generate bursts and spikes. The contribution of these mechanisms to the variance in the responses can be substantial. We quantified that contribution in Chapter 1, where
we measured the responses to drifting gratings of fixed temporal frequency. Even though the receptive field predicts 96% of the variance in the fundamental component of the responses to these gratings, it predicts only 73% of the variance in the firing rate responses. This difference can be attributed entirely to the transformation of the predicted, sinusoidal membrane potential into firing rates. While the predicted firing rates are rectified sinusoids, the measured firing rates are heavily deformed by bursting and spiking mechanisms. The strength of these deformations depends on stimulus attributes like temporal frequency, contrast, and size. For instance, bursting and spiking seem to play less of a role in the responses to the temporal frequency sweeps used in Chapter 2, since fits of the receptive field (i.e. of the descriptive model) explain 85% of the variance in the responses to those stimuli. Even though it would be difficult to precisely quantify the contribution of bursting and spiking to the responses to natural stimuli, the contribution is likely to be substantial (Lesica and Stanley 2004; Pillow et al. 2004).

Second, in many ways the model is only an approximate description of the computations performed by the neurons. For instance, in the steady-state model (Chapter 5) we describe the effects of luminance and contrast on the impulse response with only two parameters, the conductances of the RC-circuits of luminance gain control and contrast gain control. Even though this is a good approximation, the steady-state model predicts about 3% less variance in the responses than descriptive model. In the dynamic model we constrain the impulse responses even further (Chapter 7). We impose that one conductance is proportional to luminance and the other increases as a power of contrast. These relations are exactly true only for few cells and thus cause a further loss of predictions quality. Moreover, we impose separability in the effects of luminance and contrast (Chapter 4). With the optimal set of filters, the separable model is about 4% worse than the descriptive model. This differences is likely to be substantially larger with the filters of the dynamic model, which are only approximations of the optimal filters. Similarly, the receptive field of the model is only an approximation of the real receptive field, which is not exactly circularly symmetric, not exactly Gaussian, whose center and surround are not exactly concentric, and do not have exactly the same impulse response (1.3). These differences often play little role in the responses to simple stimuli, which span only a low-dimensional stimulus space. However, they are likely to play a more important role in the responses to the complex natural stimuli.

Third, even if the model faithfully described the computations performed by LGN neurons, we might not have estimated or chosen its parameters correctly. For instance, two very basic parameters that have a profound impact on the predictions are the horizontal and vertical position of the receptive field. Estimating the position of the receptive field can be difficult, because even in anesthetized cats the eyes can slowly drift over the several ours of experiments involving recordings from a single cell. These eye movements are particularly problematic for neurons that are close to the area centralis and thus have relatively small receptive fields. Bad estimates of the position of the receptive field, like the approximations in the model, affect the responses to natural stimuli more than the responses to simple stimuli. Moreover, many parameters of the model were not fitted directly to the responses of each neuron. Rather, we fixed their values to averages over the entire population of neurons. For instance, we fixed the spatial and temporal extent of the computations of local luminance and local contrast. We did so either to simplify the
fitting procedure or because we lacked experiments that would constrain these parameters. In many neurons, these choices are likely to result in suboptimal predictions.

These limitations of the model and of our methods to estimate its parameters could account for an important fraction of the missing variance. In principle, at least some of these limitations could be overcome. It would be relatively easy to add a mechanism that generates bursts (Lesica and Stanley 2004) or spikes (Pillow et al. 2004). Both mechanisms operate at the last stage of the model and could be fitted separately from the previous stages. Moreover, one could reduce the number of approximations in the model by using a more sophisticated description of the receptive field, or of the effects of luminance and contrast on the impulse response. However, a more complex model would require even more data to constrain its parameters. Thus, it would make the task of fitting its parameters even harder than it already is.

Of course, it is also possible that our model simply does not correctly capture the effects of gain control in the responses to natural stimuli. Our experiments allowed us to characterized only a limited number of properties of gain control. Some of the properties that we failed to characterize might be crucial in the responses to natural stimuli. In particular, we have relied heavily on past studies of gain control to define local luminance and local contrast, since we have characterized only the spatial aspects of the computation of local contrast. Unfortunately, the interpretation of past studies is sometimes problematic. For instance, past studies have often used ranges of stimulus luminances that differ from those we used. Thus, it is not clear if their results apply directly to our stimuli (7.4.1). Moreover, past studies have separately characterized the computations of local luminance and local contrast. In Chapter 4 we showed that at steady-state the effects of luminance and contrast on the impulse response are independent of each other. However, independence is not guaranteed to hold when luminance and contrast vary rapidly over time, as probably is the case in natural stimuli. Finally, past studies have separately characterized the spatial and temporal extent of the computation of local luminance. This complicates the interpretation of the results, since the fast and slow components of luminance gain control might well have different spatial footprints.

Therefore, the model will require further validation, since many of its components are not constrained by the results of past studies. Two kind of experiments will be crucial to validate the model. First, experiments with stimuli containing rapid variations in both luminance and contrast. These experiments will show if the effects of luminance and contrast are independent also under more “natural” conditions. However, teasing apart the effects of gain control during rapid variations of luminance and contrast will be difficult. In fact, rapid, localized variations in luminance (at least in our model) inevitably cause variations in contrast (e.g., Figure 7-5). Second, the model should be validated on the responses to spatially uniform stimuli whose luminance varies slowly over time. As we discussed in Chapter 7, the model predicts that luminance gain control strongly deforms the responses to such stimuli, especially when they have high contrast. The model predicts that the deformations should be very different for On-center and Off-center cells, in that luminance gain control should enhance the responses of Off-center cells, and suppress the responses of On-center cells (7.4.3).
**Did we use the right approach?**

The final goal of the work presented in this thesis was to build a model that accounts for the responses of LGN neurons to natural stimuli. We have designed the model to capture the responses of LGN neurons to large sets of simple stimuli, which we used to isolate and characterize the different mechanisms contributing to the responses. We then estimated the parameters of the model from the responses to simple stimuli and tested the model on the responses to natural stimuli. This approach yielded mixed results. On one hand, the model predicts the responses to natural stimuli better than the receptive field alone. On the other hand, it does by far not capture all the features in the responses. And as we argued above, even the predictions of a better, more sophisticated model are unlikely to capture all the variance in the responses. Does this mean that our goal was ill posed? Or did we choose the wrong approach to achieve it?

The appeal of simple stimuli is that they allow to isolate one particular nonlinear contribution to the responses of a neuron. Unfortunately, because they are nonlinear, these mechanisms might operate very differently in the responses to simple stimuli and in the responses to the much more complex natural stimuli (Olshausen and Field 2005). For this reason, any model that is based on the responses to simple stimuli in not guaranteed to describe the responses to natural stimuli. Thus, nonlinear models that are meant to be useful to understand natural vision have to be somehow validated with natural stimuli.

However, we have shown that designing a model that can be applied to arbitrary stimuli provides important insights by itself, independently of its success in predicting the responses to natural stimuli. In fact, the effort of designing the model revealed important gaps in our understanding of the effects of gain control. We have addressed two such gaps with experiments presented in this thesis. First, we showed that the effects of luminance gain control and contrast gain control are independent of each other. Second, we demonstrated that the suppressive field of LGN neurons is a manifestation of contrast gain control. Both findings were necessary steps towards a model of responses to arbitrary stimuli. Other questions that have arisen when designing the model still wait to be addressed experimentally. For instance, the model correctly predicts the responses to simple stimuli only if the computation of local luminance is somehow inconsistent with the results of previous studies (7.4.3). Thus, either the results of these experiments have been interpreted incorrectly or the model is wrong. Since the model incorporates much of the common wisdom about gain control, any inaccuracy in its design would question this wisdom.

A number of recent studies have attempted to infer the properties of visual neurons directly from the responses to natural stimuli. In particular, two arguments have been put forth in favor of this approach. First, since the visual system has evolved to process natural stimuli, these might engage nonlinear mechanisms that cannot be revealed with simple stimuli (Kayser et al. 2004; Machens et al. 2004; David et al. 2004). However, studies that addressed this issue have failed to demonstrate the existence of such nonlinear mechanisms. In fact, these studies have only succeeded in refining models that had been developed based on the responses to simple stimuli (Touryan et al. 2005; Touryan et al. 2002; Lau et al. 2002). A second argument that favors natural
stimuli over simple stimuli is that the latter elicit strong responses only in early visual areas. In higher visual areas neurons respond to mostly unknown features, which possibly could be inferred from the responses to natural or otherwise complex stimuli (Touryan and Dan 2001). So far, this approach has not been proven to work. Responses to appropriate simple stimuli, on the other hand, have provided insights into the computations performed by neurons even in higher visual areas (Pasupathy and Connor 2001; Tanaka et al. 1991; Tsunoda et al. 2001). Thus, natural stimuli might be useful to estimate the parameters of a model, or to refine its design. Simple stimuli, though, still seem the most powerful tool to understand the computations performed by neurons and to inspire models of these computations.

However, the validation of a model might not necessarily require predicting the full responses to natural stimuli, as in Chapter 8. One could imagine to modify the natural stimuli along a dimension that selectively engages only one or few components of the model. Rather then using the model to predict the responses to these stimuli, one could use it to predict how responses vary when the stimuli are varied along the modified dimension. We have used this approach in a very crude form in Chapter 1, when we compared the responses to movies that differed only in their contrast. Since the effects of increasing the contrast of the movie were qualitatively similar to those expected by contrast gain control, we concluded that contrast gain control shapes the responses to natural stimuli. Similarly, other studies have qualitatively compared the effects of varying the spatial extent of natural stimuli to the effects expected from surround suppression (Vinje and Gallant 2000; Guo et al. 2005). This approach could be made much more quantitative with the use a model that can actually predict the responses to these complex stimuli. Moreover, the stimuli could be modified along dimensions that are particularly informative to validate the various stages of the model. These stimuli would retain many of the complex and singular properties of natural images while at the same time offering the advantages that make simple stimuli so appealing.
Appendix A

The dynamic model

The model (Figure 7-1) is aimed at describing the responses of LGN neurons to arbitrary visual stimuli. Many of the different stages in the model correspond to computations that most likely occur already in the retina.

The input to the model is an arbitrary luminance distribution $s(x,y,t)$ and its output is the time-varying firing rate $r(t)$. The model consists of six consecutive stages: (1) the linear receptive field; (2) luminance gain control; (3) slow response adaptation; (4) contrast gain control; (5) temporal filtering; (6) rectification.

Some of the parameters are fitted individually for each neuron from the responses to simple stimuli. The other parameters are fixed to be consistent with the published literature.

A.1 Receptive field

The first stage of the model (Figure 7-1A) is the convolution between the linear receptive field $h_r(x,y,t)$ and the stimulus $s(x,y,t)$:

$$ r_f(t) = [h_r * s](x_0,y_0,t), $$

where $x_0, y_0$ are coordinates of the receptive field center. The receptive field $h(x,y,t)$ has center-surround organization:

$$ h_r(x,y,t) = G_c(x,y) f_r(t) - G_s(x,y) f_r(t - \delta) $$

where $G_c$ and $G_s$ are Gaussian spatial profiles for center and surround, $\delta$ is the delay between center and surround, and $f_r(t)$ is the temporal band-pass filter. The latter is identical for center and surround, and is given by a difference of Gamma functions $g_j(t)$:

$$ f_r(t) = p \left[ g_1(t) - kg_2(t) \right], \quad k \geq 0 $$

where $p$ sets the gain of the receptive field and

$$ g_j(t) = \left[ t - \tau_j \right]^{\alpha_j} \exp \left( \frac{t - \tau_j}{\phi_j} \right) $$

with $j = 1,2$, and $\left[ \right]$ indicating rectification.

A.2 Luminance gain control

The second stage of the model (Figure 7-1A) is luminance gain control, which we implement as the effects of $n_L$ resistor-capacitor (RC) circuits in series.
Consider first the case when \( n_L = 1 \) (as illustrated in Figure 7-1A). The response after luminance gain control is then obtained by feeding the output of the receptive field into an RC-circuit of capacitance \( C_L \) and conductance \( g_L \). While \( C_L \) is fixed for a given neuron, \( g_L \) is proportional to a measure of local luminance \( L_{\text{Local}} \) (Figure 7-1C):

\[
g_L(t) = \alpha L_{\text{Local}}(t). \tag{12}
\]

At steady state, i.e. when \( L_{\text{Local}} \) is constant over time, the RC-circuit acts as a linear filter that is completely characterized by its impulse response \( f_L(t) \):

\[
f_L(t) = \frac{1}{C_L} e^{-\frac{t}{\tau_L}}, \quad \tau_L = \frac{C_L}{g_L}, \tag{13}
\]

where \( 1/g_L \) is the gain and \( \tau_L \) the time constant of the RC-circuit. The response after luminance gain control can be obtained by just convolving \( f_L(t) \) with \( r_f(t) \):

\[
r_{\text{Lum}}(t) = \left[ f_L * r_f \right](t). \tag{14}
\]

Equation (14) can be used to describe steady state responses also when \( n_L > 1 \). In that case, \( f_L \) is the net impulse response of the series of \( n_L \) RC-circuits:

\[
f_L(t) = \left[ f_L^1 \cdots f_L^n \right](t). \tag{15}
\]

The RC-circuits all have the same time constant \( \tau_L \), but differ in their conductances: the conductance of the first RC-circuit is given by eq. (12), while for all other RC-circuits \( g_L = 1 \).

The effects of luminance gain control at steady state can be understood best by looking at the net transfer function of the RC-circuits [i.e., the Fourier transform of eq. (15)]:

\[
F_L(\omega) = \frac{1}{g_L} \left( \frac{1}{1-i\omega \tau_L} \right)^{n_L}. \tag{16}
\]

The transfer function describes how the effects of luminance gain control depend on the temporal frequency \( \omega \) of the stimulus. For \( \omega \ll 1 \), equation (16) approximates to:

\[
F_L(\omega) \approx \frac{1}{g_L},
\]

and therefore the amplitude of low temporal frequency responses is progressively reduced for increasing luminance, while their phase is unchanged. On the other hand, for \( \omega \gg 1 \), equation (16) approximates to:

\[
F_L(\omega) \approx \left( \frac{1}{-i\omega C_L} \right)^{n_L},
\]

and therefore the amplitude of high temporal frequency responses is unchanged by luminance gain control, while their phase is progressively advanced for increasing luminance. At
intermediate temporal frequencies, both the gain and phase of the response are affected by luminance gain control.

Consider now the case when \( L_{local} \) varies over time. The net impulse response of the RC-circuits, rather than being fixed, varies over time as well, as described by eq. (16). In this case, we compute \( r_{\text{lum}} \) by approximating a solution to the differential equation describing the RC-circuits. For \( n_L = 1 \), the differential equation is:

\[
\frac{d}{dt} r_{\text{lum}}(t) = \frac{1}{C_L} \left( r_{\text{rf}}(t) - g_L(t) r_{\text{lum}}(t) \right),
\]

This equation can be solved by integrating the corresponding difference equation:

\[
r_{\text{lum}}(t + dt) = r_{\text{lum}}(t) + \frac{dt}{C_L} \left[ r_{\text{rf}}(t) - g_L(t) r_{\text{lum}}(t) \right].
\]

For \( n_L > 1 \), we obtain \( r_{\text{lum}} \) by integrating equation (17) \( n_L \) times, with the appropriate choices for \( g_L \) and \( C_L \).

**Computation of local luminance**

We define local luminance as the stimulus luminance falling onto the receptive field surround, averaged over a short period of time in the past (Figure 7-1B):

\[
L_{\text{Local}}(t) = \left[ h_{\text{local}} \ast s \right](x_0, y_0, t),
\]

where

\[
h_{\text{local}}(x, y, t) = G_r(x, y) f_{L_{\text{local}}}(t),
\]

and the temporal profile of the filter is a Gamma function:

\[
f_{L_{\text{local}}}(t) = \left[ t \right]^\alpha \exp \left( -\frac{t}{\phi_L} \right)
\]

with \( \phi_L = 35\text{ms} \) for all neurons.

**Response to uniform, steady illumination**

Both the receptive field and luminance gain control operate on very fast time scales. Therefore, after the onset of a stimulus whose spatial luminance distribution does not change over time, \( r_{\text{lum}}(t) \) rapidly converges to a constant response \( r_{\text{lum}}^0 \). In particular, when the stimulus is a uniform screen of luminance \( L \), the response of the receptive field is \( \text{Eq. (10)} \):

\[
r_{\text{rf}}(t) = L \int h_{\text{rf}}(x_0, y_0, t) \, dx \, dy \, dt = L r_0.
\]

After luminance gain control this becomes \( \text{Eq. (12), (16) and (18)} \):
For simplicity, we can thus modify the definition of \( r_{\text{lum}}(t) \) such that after luminance gain control the steady state response to a uniform screen is zero. The response after luminance gain control then becomes:

\[
r_{\text{lum}}^*(t) = r_{\text{lum}}(t) - r_{\text{lum}}^0.
\]  

As will become clear from the following sections, this definition guarantees that the membrane potential obtained in response to a steady, uniform screen is also zero, which greatly simplifies the transformation of the membrane potential into firing rates. Indeed, this transformation then depends essentially on a single parameter, namely on the distance between the membrane potential obtained at steady state and the spiking threshold. Without the definition made in eq. (20), this distance would not be an independent parameter in the model, but rather would depend on the computations of the other stages of the model.

**A.3 Slow response adaptation**

The output of luminance gain control is modified by a slow adaptation stage. The adaptation operates on time scales that are substantially slower than those of luminance and contrast gain control. Although slow adaptation plays little role in the responses of the receptive field, it can affect the responses of the subunits used to compute local contrast (see below).

Unlike luminance and contrast gain control, slow adaptation does not affect the dynamics of the responses. Its only function is to regulate the steady state response to a stimulus that does not change over time.

As we have shown in the previous section, luminance gain control removes any response to a steady stimulus of uniform luminance [eq. (20)]. However, the steady state response after luminance gain control is not guaranteed to be zero for a non-uniform luminance distribution. In the case of the receptive field, most of this residual response is removed by the temporal filtering (Section A.5). However, this is not the case for the subunits, because the temporal filtering occurs after contrast gain control (Figure 7-1).

Slow adaptation removes any residual response to a steady stimulus that has not been removed by luminance gain control. It operates by subtracting the average response over the recent past from the response at a given time \( t \):

\[
r_{\text{sub}}(t) = r_{\text{lum}}^*(t) - \left[ f_{\text{sub}} * r_{\text{lum}}^*(t) \right](t).
\]

Responses are averaged with a Gamma function:
\[ f_{\text{sub}}(t) = \left[ t \right]^n \exp \left( -\frac{t}{\phi_{\text{sub}}} \right) \]

with \( \phi_{\text{sub}} = 200\text{ms} \) for all neurons.

Because of slow adaptation, at steady state the local contrast (i.e. the signal driving contrast gain control) is zero for a stimulus that does not change over time.

### A.4 Contrast gain control

The implementation of contrast gain control is essentially identical to that of luminance gain control. The responses are fed into a series of RC-circuits with fixed capacitance \( C_c \) and variable conductance \( g_c \). Here conductance depends on a measure of local contrast (Figure 7-1E):

\[ g_c(t) = \left[ \beta C_{\text{Local}}(t) \right]^n. \]

At steady state, i.e. when local contrast does not change over time, the effects of contrast gain control are captured by the net transfer function of the RC-circuits:

\[ F_c(\omega) = \frac{1}{g_c} \left( \frac{1}{1 - i\omega\tau_c} \right)^{n_c}, \quad \tau_c = \frac{C_c}{g_c}. \]

This equation is analogous to eq. (16), and therefore the effects of contrast gain control on gain and phase of the responses depend on temporal frequency in the same way as the effects of luminance gain control.

As for \( r_{\text{lum}} \), we find the response \( r_{\text{con}} \) after contrast gain control by integrating the corresponding difference equations. For example, when \( n_c = 1 \) the equation is:

\[ r_{\text{con}}(t + dt) = r_{\text{con}}(t) + \frac{dt}{C_c} \left[ r_{\text{sub}}(t) - g_c(t) r_{\text{con}}(t) \right]. \tag{21} \]

For \( n_c > 1 \), we obtain \( r_{\text{lum}} \) by integrating equation (21) \( n_c \) times, with the appropriate choices for \( g_c \) and \( C_c \).

### Computation of local contrast

We obtain a measure of local contrast from the responses of a large population of subunits covering the receptive field of the LGN neuron (Figure 7-1D). Each subunit’s receptive field is centered in a different position, but is otherwise identical to the receptive field of the LGN neuron. The output of the receptive field of the \( i \)-th subunit is:

\[ r_{ij}(t) = \left[ h_f * s \right](x_i, y_i, t), \quad i \in [1, N], \]

where \( N \) is the total number of subunits. The subunit centers are chosen to uniformly cover the receptive field of the LGN neuron. The distance \( \Delta x_{su} \) between neighboring subunits is:
\[ \Delta x_{su} = \frac{\pi \sigma_c}{2}, \]

where \( 2\sigma_c \) is the standard deviation of the receptive field center \( G_c \).

For each subunit we compute the response after luminance gain control, \( r'_{\text{lum}}(t) \), and the response after subtractive adaptation, \( r_{\text{sub}}(t) \), in the same way as we compute them for the LGN neuron. Local contrast is then defined as:

\[ C_{\text{local}}(t) = \sqrt{\sum_{i=1}^{N} G_{su}(x_i, y_i) \left( \left[ r'_{\text{sub}}(t) \right]^2 + \left[ -r_{\text{sub}}(t) \right]^2 \right)^{-1}}, \]

where the two terms in the summand correspond to a population of ON-center cells and a population of OFF-center cells. The subunits are weighted by a Gaussian \( G_{su} \) centered on the LGN receptive field. The size of \( G_{su} \) is twice the size of the receptive field center.

Thus, local contrast at time \( t \) corresponds to the standard deviation of the distribution of all subunit responses \( r_{\text{sub}}(t) \). This follows from the observation that the average response over all subunits is zero, since in the average the response of each ON-center cell is cancelled out by the response of the identical OFF-center cell in the pool.

We conservatively imposed \( C_{\text{local}} \) to have a lower bound:

\[ C_{\text{local}}(t) \geq C_{\text{min}}, \]

where for any given neuron \( C_{\text{min}} \) is the smallest contrast at which we estimated the impulse response of the neuron.

**A.5 Temporal filtering**

After contrast gain control, the responses are convolved with a second band pass filter (Figure 7-1A):

\[ r_{bp}(t) = f_{bp} * r_{\text{con}}(t), \]

where \( f_{bp}(t) \) is a difference of Gamma functions [eq. (11)].

Because of this second bandpass filter, the selectivity for temporal frequency of the LGN neuron is different from the selectivity of the subunits computing local contrast.

**A.6 Rectification**

Finally, we obtain firing rates by first adding Gaussian noise \( n(t) \) of fixed mean \( r_0 \) and variance \( \sigma \) to the response and then rectifying (Carandini 2004):

\[ r(t) = r_{\text{max}} \left[ r_{bp}(t) + n(t) \right]. \]
where $r_{\text{max}}$ sets the overall gain of the neuron and $r_0$ is the difference between the spiking-threshold and the resting potential.
Appendix B

General Methods

B.1 Physiological Experiments

All procedures were approved by the Veterinary Office of Canton Zurich and by the Animal Care and Use Committee of the Smith-Kettlewell Eye Research Institute.

B.1.1 Pre-operative preparation

In the morning of the experiment the animal receives an intramuscular injection of a mixture of sedative and anesthetic (Ketamine 20-24 mg/kg i/m + Xylazine 1.0-1.2 mg/kg i/m) (Flecknell 1996). This initial anesthesia is meant to last about 30-45 min, the time usually needed to perform the initial surgery and move on to the steady anesthesia regime; additional doses are given when necessary. An anticholinergic, atropine sulfate (0.04-0.06 mg/kg, i/m), is administered intramuscularly as salivary and bronchial secretion may interfere with respiration. This administration is repeated daily for the duration of the experiment.

B.1.2 Initial Surgery

To be able to continuously and securely deliver anesthetics and other liquids intravenously, we place a catheter in the saphenous vein of each leg. We make a small incision in the skin over the vein, we isolate the vein through gentle blunt dissection of the overlying fascia, we make a small cut in the vein using microscissors, we insert an appropriate cannula and we tie the cannula to the vein.

To be able to artificially respirate the animal and to monitor the end-tidal CO₂ output of the respiratory system we place a cannula in the trachea. We perform a standard tracheotomy, insert an appropriately sized cannula and secure the cannula to the trachea with ligatures.

Once the first catheter is inserted into a vein, anesthesia is continued with a loading dose of Thiopental Sodium (Pentothal, 10-15 mg/kg i/v) (Flecknell 1996).

B.1.3 Neurosurgery

After these simple surgical procedures the animal is moved a few feet to the experiment area. This area contains a stereotactic apparatus set on a vibration isolation table. These devices ensure maximal stability and allow precise placement of microelectrodes (for electrical recordings), and of a high-performance camera (for optical recordings). A respiration pump and injection pumps for syringes are located adjacent to this equipment.

In the experiment area we provide continuous infusion of barbiturate anesthetic, Thiopental Sodium (Pentothal, 0.5-4 mg/kg/hr, i/v) (Kara et al. 2002; Thompson et al. 2003; Gillespie et al. 2001; Martinez et al. 2002). We enhance the analgesic effect of the barbiturate with additional
inhalation of nitrous oxide (N₂O) mixed with oxygen (O₂) in concentration of commonly 50% to 70% (Hammond 1978; Hikasa et al. 1997).

Rate of barbiturate infusion needs to be adjusted for each animal, and greatly depends on the proportion of body fat. Fat tissues absorb barbiturates and release them slowly over an extended period. Infusion rate, thus, must be progressively decreased. Infusion rate is thus determined by monitoring the depth of anesthesia and by an estimate of lean body mass, i.e. the body weight minus the estimated proportion of fat tissues (Flecknell 1996).

The pupils are dilated and accommodation paralyzed with topical atropine (drops). The nictitating membranes are pharmacologically retracted with phenylephrine (drops). The corneas are protected with contact lenses.

We employ standard neurosurgical techniques to expose a piece of the brain. As is common during neurosurgery, the head of the animal is fixed to the stereotactic apparatus. Contact points are first sprayed with local anesthetic (Lidocaine, 10 mg/spray). The cranium is then exposed and appropriate electrodes inserted to monitor the electro-encephalogram (EEG). From now on the EEG is continuously monitored to detect possible signs of arousal (Rampil 1998). A small craniotomy is performed over the area of the relevant brain structures, and the dura mater is opened to allow the insertion of microelectrodes or the imaging of brain activity. To improve stability and to prevent drying of the exposed regions, the craniotomy is covered with 3-4% agar in saline solution.

After neurosurgery, the animal is given an infusion of muscle relaxants to minimize eye movements (described in a later section).

The animal receives constant fluid replenishment. Fluid balance is maintained by continuous intravenous infusion of replacement-type solutions such as 0.9% NaCl or Normosol-R. Rate is 5-10 ml/kg/hr during the initial surgery and 2-5 ml/kg/hr later, to compensate for insensible loss (Muir 2000). The bladder is periodically expressed to relieve urine accumulation.

The animal receives periodic administration of antibiotic to prevent possible infections (Cephazolin, 18-22 mg/kg IM, twice daily), and anti-edematic agents that prevent brain swelling (Dexamethasone, 0.3-0.5 mg/kg daily). The animal is periodically massaged to stimulate circulation.

B.1.4 Paralysis

After neurosurgery, the animal is given an infusion of muscle relaxants to minimize eye movements (pancuronium bromide, 0.20-0.40 mg/kg loading dose, 0.10-0.20 mg/kg/hr maintenance dose, in balanced solution). This infusion occurs through the second I/V line. The animal is artificially respirated with the mixture of Oxygen and Nitrous Oxide. End-tidal CO₂ is continuously monitored and maintained close to the physiological value of 32-34 mmHg by manipulation of the respiratory rate or volume.

During experiments, in the presence of muscle relaxants, the EEG constitutes the primary source of information on depth of anesthesia. The ideal depth of anesthesia is one in which activity is synchronized in the low-frequency range (2-10 Hz) and occasionally breaks into high-
amplitude, low-frequency spindle episodes typical of sleep. Indeed, in human surgery the accepted standard for assessing the depth of anesthesia is now the Bispectral Index, which is entirely based on the EEG (Sigl and Chamoun 1994).

B.1.5 Post-operative monitoring

The physiological state is continuously monitored and the depth of anesthesia is maintained in a surgical plane by adjusting the rate of delivery of the anesthetic agents.

- We measure temperature, which is kept at a comfortable 38.5 degrees Celsius through the thermostat.
- We measure heart rate, which is commonly between 120 and 190 beats per minute, but becomes higher under Penthotal anesthesia.
- We measure the electrocardiogram (ECG) waveform to detect possible problems with cardiac activity.
- We measure the electrical resistance of the chest to know the respiration rate. This rate is variable during anesthesia, and when we attach the respirator we set its rate to 20-40 breaths per minute, depending on body weight.
- We measure the saturation of oxygen in the blood (SPO2) using an optical sensor. When the signal is sufficiently strong to get a reading, we commonly observe normal values in the range of 97-99%.
- We measure the maximal end-tidal CO₂ content of expired air, and adjust the respiration rate and volume to maintain it around the physiological value of 32-34 mmHg.
- We measure lung pressure to detect possible obstructions in the airway. Reference values are taken at the beginning of the experiment, and subsequent measurements are evaluated on the basis of the reference values.
- We measure the electro-encephalogram (EEG) to know the depth of anesthesia (see below).

During the brief surgical procedures at the beginning of the experiment, surgical plane of anesthesia is assessed with classic measures (Brown 1994). We test for the absence of jaw tone and of reflex reactions to toe pinch or to outer eye stimulation. Corollary evidence on the depth of anesthesia is also provided by respiration rate and heart rate. As soon as it becomes available, we correlate these observations with the EEG.

B.1.6 Euthanasia

The duration of the experiments is determined by the general physiological state and in particular by the responsiveness of the brain, which we monitor continuously. When the physiological state deteriorates there is an overall decrease of responsiveness to visual stimulation. We end the experiment after 120 hours or earlier if the quality of the data deteriorates.
At the end of the experiment, while they are still under surgical anesthesia, the animals are euthanized through an overdose of anesthetic (Thiopental Sodium, >100 mg/kg).

**B.2 Recordings**

For recordings in LGN, a craniotomy was performed above the right LGN (Horsley-Clarke, A6L9). Electrodes were lowered vertically until visual responses were observed. The location of LGN was determined from the sequence of ocular dominance changes during penetration. Nearly all cells were located either in the first contra-lateral layer (presumably lamina A) or in the first ipsi-lateral layer (presumably lamina A1). Less than 10% of the cells were located in subsequent layers.

Eyes were mapped on tangential screen by illuminating the back of the eye. Location of blind spot and area centralis were marked.

**B.3 Visual stimulation**

Once a neuron with well isolated spikes has been identified, we mapped its receptive field was mapped on a tangential semi-reflective screen.

Visual stimuli were displayed using the Psychophysics Toolbox (Brainard 1997; Pelli 1997) and presented monocularly on a calibrated monitor with mean luminance of 32 cd/m² and refresh rate of 124 Hz. Typically, the distance between the screen and the cat’s eyes was 57 cm. However, when recording from neurons with particularly small receptive fields, we reduced screen distance to as little as 35 cm. All stimuli were monochromatic.

Stimuli lasted 1–17 s and were presented in blocks of 3-15 repeats. Stimuli within blocks were presented in randomized order. Each block included one or more blank stimuli.

**B.4 Data acquisition**

Extracellular signals were recorded with Quartz-coated Platinum/Tungsten Microelectrodes (Thomas Recordings), sampled at 12 kHz with a National Instruments data acquisition board, and stored for offline analysis using custom software.

Spike discrimination and data analysis was performed with custom software. Candidate spikes were identified by thresholding the extracellular signals.

**B.5 Data analysis**

All data analysis was performed with MATLAB (The Mathworks, Cambridge, MA).

**B.5.1 Firing rates**

We computed firing rates by convolving the spike trains with a Gaussian running window with a width of 5 ms (standard deviation). We then averaged the firing rates across the different stimulus presentations.
B.5.2 Model fits

Unless otherwise stated, fits minimize square error between measured responses and model predictions. Square error is given by \( \sum_{ij} (r_{ij} - m_{ij})^2 \) where \( r_{ij} \) denote the observed response to trial \( i \) of stimulus \( j \), and \( m_{ij} \) represent the response predicted by the model.

B.5.3 Quality of predictions

To quantify how well the model predictions \( r_t \) capture the measured responses \( s_t \) (both consisting of \( t = 1, ..., M \) samples) we estimated the fraction of stimulus driven variance in the responses accounted for by the model (Machens et al. 2004; Sahani and Linden 2003):

\[
\beta = \frac{\sigma_s^2 - \sigma_e^2}{\sigma_s^2 - \sigma_n^2}
\]

where:

\[
\sigma_s^2 = \left\langle \frac{1}{M} \sum_t s_t^2 \right\rangle
\]

is the variance in the response,

\[
\sigma_e^2 = \left\langle \frac{1}{M} \sum_t (r_t - s_t)^2 \right\rangle
\]

is the mean square distance between data and model and

\[
\sigma_n^2 = \frac{d}{d-1} \left[ \left\langle \frac{1}{M} \sum_t s_t^2 \right\rangle - \frac{1}{M} \sum_t \left\langle s_t^2 \right\rangle \right], \quad (22)
\]

where angular brackets indicate the average over \( d \) presentations of the same stimulus. Here we assumed that the predicted and measured response have zero mean.

Equation (22) follows from a simple additive model of response and noise and yields an estimate of the variance in \( s_t \) that is due to noise, \( \sigma_n^2 \) (Sahani and Linden 2003).

B.5.4 Cell classification

We classified neurons into On-center and Off-center by reconstructing the receptive field from responses to rapid sequences of flashed gratings (Ringach et al. 1997). We classified neurons into X-type and Y-type based on standard criteria (Hochstein and Shapley 1976b). Most units encountered were of X type, consistent the known layeral distribution of LGN cells (Wilson et al. 1976). We did not attempt to identify the so-called W cells (Enroth-Cugell et al. 1983), as these form a very heterogeneous class (Rodieck et al. 1993; Wassle 2004; Callaway 2005) and are largely confined to layer C of the LGN (Wilson et al. 1976).
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Appendix C

Companion data CD

As required by the Swiss Federal Institute of Technology Zurich, we have compiled all original data and code that led to the results described in this thesis onto a single compact disc (CD). All data files and analysis scripts can be inspected and executed using the Release 14 of MATLAB (The Mathworks Inc, Natick, MA).

The CD is organized as follows. The directory \Data contains one file for every unit used in this thesis. Each file is a MATLAB structure, whose fields correspond to different experiments performed on that unit. For each experiment we saved the recorded spike times (in the field .unit), the parameters of the corresponding visual stimuli (.protocol), and the settings of the computer monitor used to display the stimuli (.myscreen). The directory \Code contains MATLAB code used to perform the experiments (in the subdirectory \experiments), general purpose data-analysis toolboxes developed in the lab (\analysis), and the code used to generate the fits presented in this thesis (\virtual lab).
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