



Report

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Emergence of Complex Spiking Behavior from Noise-driven Neocortical Interaction

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Project

Statistical mechanics and dynamical systems aspects of biological neural networks. Poster highlights central set of problems on our attempts to solving them. The intent is to give an overview on our work. We operate on a mathematically exact mesoscopic level of description. Our approach fills the gap between

- approaches starting from detailed biologically motivated simulations but fail to make mathematically exact global predictions and
- approaches that are able to make exact investigations only on levels that are remote from biology.

Questions:

- 1) Is there a generic neuron model usable for network simulations?
- 2) What are generic network outputs, produced by this network?
- 3) In what terms information is coded?
- 4) Can „generic“ networks solve perceptive tasks?
- 5) Is there experimental evidence for the validity of our approach?

Solution: A New Neuronal Concept

We propose **noise-driven neocortical interaction**, based on the distinction of different levels of synaptic input:

- **Small-scale noisy input** (e.g., from remote synapses) drives the neuron towards regular spiking with well-defined periodicity
- **Strong input** from next neighbors (neurons or a group of synchronized neurons) arrives at the neuron as a simple, ideally periodic, structure in time
- **Medium-size interactions** that may reflect specific conditions in the neighborhood of the neuron, transmitted most likely by interneurons

We assume **quasistatic network** conditions, meaning that waves of neural excitation are excluded. Under this restriction, only **phase-coded transmission of information** is possible.

1. Generic Binary Interaction Neurons

Experiments I: Slices of rat neocortex prepared for **in vitro** recording. Measured is effect of periodic synaptic input onto periodically spiking neuron (binary neuron coupling). Reyes & Fetz [7] described similar experiments, to which our approach is a theoretical extension.

New theory: Response of a regular spiking neuron upon a synaptic perturbation is captured by a **phase-return function** (typical form of a **circle-map**):

$$f_{\Omega} := \phi_1 + \Omega + g(\phi_1), \text{ mod } 1, \quad (1)$$

Ω : inverse quotient of the intrinsic interspike time T_0 of the targeted neuron divided by the interspike time T_1 of the targeting neuron [4].

3. Cortical learning

Cortical learning is linked to pattern discrimination and pattern recognition. Task cannot be achieved by a network of locally coupled oscillators alone. Inclusion of **medium-size interaction** extends our model of cortical activity to a **coupled-map lattice approach with diffusive coupling**. For the site maps, we chose binary excitatory and inhibitory interaction maps with Ω at random and K random from intervals that monitor massive packages of transmitted information.

Results:

In quasistatic networks, pattern discrimination and recognition is possible, provided **Hebbian-type learning** is applied to connection strengths between lattice sites. Different input patterns are represented by changes in localized, input-specific coding-sites (Fig. 4), where phase is changed. This converts input information to phase-coded information with feature binding properties and avoiding representation catastrophe.

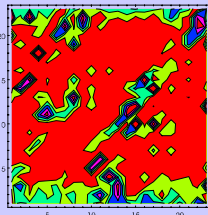


Fig. 4 Coding sites in red sea. Phase picture, 23x23 network.

2. Efficient Arnold'd coding of cortical activity

The coding scheme of cortical activity is basically unknown. **Arnold'd tongues** intrinsically provide a coding, able to describe frequency- and phase-coding.

$$\text{Coding scheme: } \{f_i, f_j\} \rightarrow \{f_i, p\}, \quad (3)$$

where f_i is the unperturbed frequency of the targeted neuron and p labels the emerging periodicity.

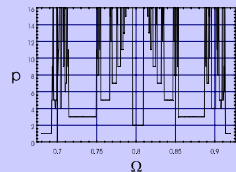


Fig. 3 Code generated at $K=0.9$ by changing Ω (frequency-coding).

Results: Code properties worth emphasizing

- largely independent of adaptation and relaxation processes
- independent of the excitability level in homogeneously excited area, in the sense that $\Omega = T_1 / T_0$ remains fixed, but responds to local gradients of the noise level
- is optimal in that the highest probability is assigned the lowest periodicity (like-wise to the Huffman code).

$g(\theta)$: measures the lengthening / shortening due to perturbation applied at phase θ , relative to unperturbed interspike interval, can experimentally be measured, for different stimulation strengths K . Dependence on K [6]:

$$g_{\Omega K}(\theta) = g_{\Omega K_0}(\theta-1) K + 1 \quad (2)$$

(reference curve $g_{\Omega K_0}$ measured at 75 % of maximal perturbation effect. Physical stimulation strength, to reasonable accuracy, proportional to perturbation of g , expressed by means of K).

Results:

A) Emerging periodicities p of binary neuron systems are organized along Arnold'd tongue structures [8], s. Fig. 1. For each periodicity p there are different Arnold'd tongues which comprise areas in $\{\Omega, K\}$ -parameter space. All periodicities appear, but with ever smaller basins of attraction.

B) Stability properties measured by Lyapunov exponents $\lambda_i(\Omega, K)$ [9], reveal that for inhibition, chaotic behavior is possible ($\lambda_i(\Omega, K) > 0$) at least numerically. However, large input strengths are needed. Analytic investigations prove that chaotic behavior indeed occurs on of non-zero Lebesgue measure in $\{\Omega, K\}$ -space [6].

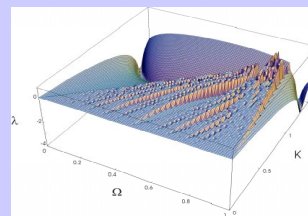


Fig. 1 Lyapunov exponents for binary inhibition, on $\{\Omega, K\}$ -space.

4. Long-tail spike interval distribution

Mesoscopic experimental access is mostly via interspike intervals. Comparison model predictions / experimental results? Common expectation: Poissonian probability distribution interspike interval histograms. However: Equilibrium states of the brain activity plausibly have marginally stable states, predicting Levy-type probability laws and long-tailed distributions, with superimposed self-similar structures (visible for large local K -values).

Results: Confirmation of predictions (see Fig. 5).

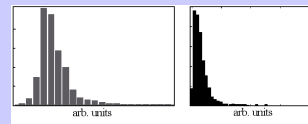


Fig. 5 Interspike interval distribution. Upper left): Interspike distribution from the model, upper right and following): from cut recordings. Lower left): fit measure in log-log-scale (base 2), almost perfect power-law. Lower right): power-law coefficients of region extending to given bin number. "Second frequency" barely visible (low values of K).

C) Generic behavior of noise-driven cortical networks:

- **Locally, low-periodic spiking behavior is abundant, by interaction of otherwise freely spiking neurons. This periodic response is organized along Arnold'd tongues and obeys the circle-map class universality.**

- **Network is able to respond locally with any desired periodicity. For weak local interaction: local spiking behavior dominated by wealth of different periodicities. For stronger interaction: tendency to settle towards more simple and more stable spiking patterns.**

- **For very strong inhibitory interaction: chaos is observable, or that systems could be tuned to this state.. However: chaos requires strong stimulations and only occupies a small portion of the parameter space.**

- **Universality principles of circle-map class show that experimental observations and theoretical conclusions do not depend on artificial system**

preparation, but are "generic".

We propose that in less ideal networks the described behavior plays a role similar to the unstable periodic orbits in chaotic systems. They provide the **backbone** for the complex structure hidden in the seemingly intractable chaotic motion. Figure 2 indicates the complexity of the emerging spiking patterns

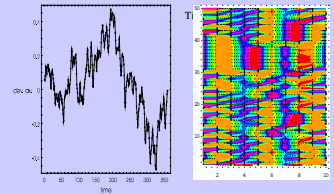


Fig.2 Emerging complexity in spiking patterns. Left): single neuron, deviation from mean spiking. Right): network of 10 neurons, phase description.

5. Preliminary Project Conclusions

- **A generic quasistatic cortical network model can be based on experimentally measured phase-response functions. This network model allows the inclusion of information-processing features that result in an efficient description of feature binding.**

- **For inhibitory binary interaction among neurons, chaotic response emerges on a nonzero measure of the parameter space for high excitation. This tells us that in the brain, chaotic behavior is already introduced on a local level. Detailed simulations show that inhibitory connections contribute most to a coherent network reaction. Possible chaotic behavior does not desynchronize, but tends to synchronize the network. Synchronization of neurons in the brain requires generically strong dynamical sources of driving. For quasistatic networks, synchronization is only possible for strong constant inhibition. Globally, the natural state of brain activity is chaotic, due to strong stable local oscillator interaction and second-order perturbation by medium-size input.**

- **Arnold tongues provide an efficient coding scheme for cortical activity. This coding unifies frequency-coding with phase-coding. This code is optimal in an information-theoretic sense and avoids the representation catastrophe.**

- **Interspike distributions of spiking neurons cannot be expected to be typically of Poissonian type. They more accurately described by long-tailed Levy [2] distributions.**

6. Epilog

Apart from our genuine interest in understanding the brain, in the future our insights also may become useful for a large number of on first sight seemingly uncorrelated applied problems, like pattern recognition in complex systems containing a large number of subsystems. Even more important applications are in the medical domain, like optimal usage of sensory aids for handicapped (as required, for example, for high-quality hearing aids).

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