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iGesture: A Java Framework for the Development and Deployment of Stroke-Based Online Gesture Recognition Algorithms

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ABSTRACT
Existing gesture recognition tools and frameworks tend to focus on specific settings, gesture sets or algorithms. Further, they are often designed to support the developers of either applications or algorithms, but not both. Our goal was to develop a general and extensible framework that provides an integrated platform for the design and evaluation of algorithms, as well as for their deployment to a wide audience. The presented iGesture framework supports the definition and evaluation of new gesture sets. Furthermore, our gesture recognition framework enables an easy integration of new forms of input devices. We present the iGesture framework, show how it has been used to support the development of two new gesture recognition algorithms—an extension of Rubine called E-Rubine and SiGrid—and finally provide an evaluation of these algorithms.

General Terms
Algorithms, design, experimentation

Keywords
Gesture recognition algorithms, gesture recognition framework, pen-based input

1. INTRODUCTION
Emerging technologies for mobile and ubiquitous computing have led to increased interest in the use of gestures as a means of interacting with applications. Thus, in addition to traditional uses of gesture-based interaction in desktop environments, an increasing number of applications are using pen-based gesture recognition for not only PDAs and tablet PCs, but also interactive paper [13]. At the same time, the use of gestures is being widely investigated in the fields of pervasive and wearable computing to interact with applications based on either the movement of physical objects or parts of the body.

As a result, there has been a lot of research not only on the development of gesture recognition algorithms but also tools and frameworks to support the development of applications based on these algorithms. However, existing systems tend to either focus on specific settings—such as screen-based input—or on specific gesture sets and/or algorithms. Our goal was to develop a general and extensible gesture recognition framework that would support both application developers and the developers of new algorithms. The resulting iGesture framework [9] provides a simple gesture recognition application programming interface (API) that allows iGesture results to either be used directly or through an event manager that executes commands based on recognised gestures.

To facilitate the development of new algorithms as well as the evaluation of existing algorithms, the Java-based iGesture framework also supports the creation and management of gesture sets. A test bench enables the manual testing of algorithms and special functionality is provided to create the test data. We provide tools to evaluate different gesture recognition algorithms and their configurations in batch mode and visualise the results. Note that these evaluation tools can not only be used to analyse existing or new gesture recognition algorithms but also for verifying new gesture classes. For example, the result an evaluation will reveal if two gesture classes look too similar and therefore cannot be classified correctly by the recognition algorithm. This information helps designers of new gesture sets to define unambiguous gesture sets resulting in better gesture recognition performance.

In this paper, we present the iGesture framework and, as a demonstration of its effectiveness in supporting the development and evaluation of new gesture recognition algorithms, we describe two new algorithms that were developed and tested using the framework. The first one is an extension of the well-known Rubine algorithm, called E-Rubine, to handle single-stroke as well as multi-stroke features. The second algorithm is a simple grid-based signature algorithm called SiGrid that our evaluations have shown to be simple but effective in some application settings. We present these algorithms and also report on comparative evaluations generated using the iGesture test bench.

We start with an outline of related work and the requirements of a general gesture recognition framework in Section 2. The architecture and some implementation details of our iGesture framework are presented in Section 3. In Section 4 we then go on to present the algorithms currently supported by the gesture recognition framework, including our two new algorithms, and provide an initial evaluation of these algorithms in Section 5. Concluding remarks are given in Section 6.

2. BACKGROUND
A number of tools and frameworks for gesture recognition have been developed and we review the main ones in this section in order to highlight the benefits and requirements of a general, integrated framework.

GRANDMA (Gesture Recognizers Automated in a Novel Direct Manipulation Architecture) is an object-oriented toolkit for rapidly
adding gestures to direct manipulation interfaces that was proposed by Rubine in 1991 [12]. It introduced a specific classification algorithm, now commonly referred to as the Rubine algorithm, that uses statistical single-stroke gesture recognition based on 13 different features. New gestures could be introduced by specifying a set of sample gestures, thereby enabling application developers to easily design their own gesture-based interfaces without having to program the corresponding recognition algorithms.

Hong and Landay later developed SATIN [8], a toolkit for informal ink-based applications that uses the Rubine algorithm in its recognition process. SATIN is a powerful toolkit targeted at pen-based applications and a major part of the framework deals with the interpretation and beautification of stroke data to build ink-based graphical Java Swing applications. A feature of SATIN was the introduction of pie menus to replace common pop-up menus.

SwingGestures [15] is another framework designed to support gestures in Java Swing applications. In this case, eight basic gestures (up, down, left, right and the four diagonals) are hard-coded and other gestures can only be constructed based on these eight gestures. This severely limits the kinds of gestures that can be supported as it is nearly impossible to model curving gestures using only these basic gestures. Furthermore, the framework was not designed to support different recognition algorithms. While the tool is useful for simple Swing-based applications, it does not seem to scale well in terms of the number of supported gestures.

Microsoft also provides a gesture recognition tool in the form of the Microsoft Tablet PC SDK [4] that distinguishes between system and application gestures. Microsoft provides a recommended interpretation of their gestures that developers should follow to avoid confusion. Unfortunately, the recogniser of the Microsoft Tablet PC SDK is limited to a predefined set of gestures and new gestures can only be integrated by implementing new recognition algorithms. Further, the Microsoft Tablet PC SDK was designed for screen-based applications and is implemented on the .NET platform.

A problem of developing gesture-based user interfaces is often the similarity of specific gestures which makes it difficult to develop robust gesture recognisers. quill [10] is a gesture design toolkit that addresses this problem by providing active feedback to the gesture designers when there is an ambiguity between different gestures. It introduced a specific classification algorithm, now commonly referred to as the Rubine algorithm, that addresses this problem by providing active feedback to the gesture designers when there is an ambiguity between different gestures. In such cases, it also assists them with textual advice to enable them to create more reliable gesture sets. A computational model based on geometric gesture features is used to measure the similarity of gestures.

From the above outline of existing systems, we can see that existing toolkits and frameworks tend to focus on specific settings and tasks. None of them supports the entire process of designing new gesture recognition algorithms, including deployment to a wide audience. The development of new algorithms should be supported by providing benchmarking and parameter optimisation tools. A gesture recognition framework should also provide tools to define new gestures and to efficiently capture gesture samples for testing. It should also be possible to work with different input devices and to easily integrate new devices to cater for emerging technologies and new modes of interaction. Last, but not least, the framework should offer an easy-to-use interface that enables application programmers to fully exploit the potential of gesture-based interfaces and latest developments in gesture recognition algorithms. Based on these requirements, we have developed a Java-based gesture recognition framework to support an integrated solution for the use and development of gesture recognition algorithms with a focus on extensibility and cross-application reusability.

3. iGESTURE FRAMEWORK

The iGesture framework is based on a set of modular components and some common data structures as shown in Figure 1. We will start with a description of the common data structures and then go on to describe each of the components in turn, starting with the recogniser and then going on to describe the management console and evaluation tools.

![Figure 1: Architecture overview](image)

The representation of gestures within the iGesture framework was a fundamental design decision since it had implications on all components. One requirement for the data structure was that it should be possible to represent single gestures as well as groups of gestures. Furthermore, it was clear that different algorithms need different descriptions of a gesture. Therefore, it is important that the model classes do not make any assumptions about a specific algorithm or provide algorithm-specific data. The UML class diagram of our general gesture data structure is shown in Figure 2.

![Figure 2: Gesture representation](image)

The GestureClass class represents an abstract gesture characterised by its name and a list of descriptors. For example, to cope with circles as a specific gesture, we instantiate a new GestureClass and set its name to ‘Circle’. Note that the class itself does not contain any information about what the gesture looks like and needs at least one descriptor specifying the circle as a graphical object. A set of gesture classes is grouped in a GestureSet which can then be used to initialise an algorithm. The Descriptor interface has to be implemented by any gesture descriptor. For example, we provide the SampleDescriptor class describing
gestures by samples which is used by training-based algorithms. A single GestureSample is an instance of a gesture and contains the note captured by an input device. In addition to the sample descriptor, we provide a textual description of the directions between characteristic points of a gesture as well as a digital descriptor describing the gesture in terms of a digital image. Note that the digital descriptor is not used in the recognition process but rather acts as a visualisation for a recognised gesture to be used, for example, in graphical user interfaces.

In addition, we need a mechanism to persistently store any gesture samples for later retrieval. Again, our goal was to be flexible and not to rely on a single mechanism for storing data objects. The iGesture storage manager encapsulates any access to persistent data objects and uses a specific implementation of a storage engine to interact with the data source. We decided to use db4objects [7], an open source object database for Java, as the primary storage container. However, we also implemented a second storage engine that simply serialises the data objects into an XML document based on the x-stream Java library [17].

An iGesture recogniser is a general component that can be configured to use different recognition algorithms. To provide maximal flexibility in the design and use of algorithms, we decided to provide a compact interface as highlighted in Figure 3. The Algorithm interface provides methods for the initialisation, the recognition process, the registration of an event manager and for retrieving optional parameters and their default values.

An algorithm always has to be initialised with an instance of the Configuration class containing gesture sets, an optional event manager and algorithm-specific parameters which are managed in a key/value collection. This configuration object can be created using the Java API or by importing the data from an XML document. The framework further offers an algorithm factory class [5] to instantiate algorithms based on information handled by a configuration instance.

While the algorithm interface is mainly used by the designer of new recognition algorithms, the application developer has access to the framework’s recogniser component—configured with one or more recognition algorithms—based on a single Recogniser class (facade pattern) shown in Figure 4.

Note that multiple algorithms may be specified in a single configuration. The Recogniser class provides two methods with different behaviours depending on whether a single or multiple algorithms have been specified. The recognise(Note note) method goes through the algorithms in sequential order and terminates the recognition process as soon as an algorithm returns a valid result whereas the recognise(Note note, boolean recogniseAll) method combines the results returned by all of the algorithms. A Note represents our data structure for storing information captured by an input device. Each Note contains one or more strokes consisting of a list of timestamped positions. The Recogniser always returns a result set which is either empty or contains an ordered list of result objects. We decided to return a set of potential result objects instead of a single one to enable specific applications to use any additional contextual information in the selection process.

The iGesture framework’s management console has been implemented as a Java Swing application providing support for testing and defining gestures as well as creating test sets as represented by the Test Bench, Admin, Test Data and Batch Processing tab components. The test bench tab, shown in Figure 5, provides functionality to acquire a single gesture from an input device and execute the recogniser with the chosen gesture set and algorithm. This enables a simple and quick manual testing of specific gestures. The entire collection of gesture sets of the currently opened persistent storage container are available and any registered algorithm may be used. This manual testing of gestures is relevant to get initial feedback about the quality of a specific algorithm’s recognition rate.

The admin tab is used to manage gesture sets, gesture classes and the corresponding descriptors as illustrated in Figure 6. New gestures are captured with the aid of the input device and shown in the Input Area. From there they can, for example, be added to the sample descriptor of a given gesture class.
The results of a batch process containing the key figures for each run and gesture class, such as precision, recall and F-measure, as well as the configuration of the parameters, are collected in a test result data structure which is stored in an XML document. We also provide some XSLT templates to render the results as an HTML document and sort the data based on specific key figures. This allows the designer of a new recognition algorithm to easily identify the most promising parameter settings for a given algorithm and test set.

The algorithm designer also has to provide a configuration stored in a file which can be used by the application developer to instantiate the recogniser with a given algorithm and parameter set. Note that the settings stored in the configuration file may be a direct result of previous batch process evaluations. The code snippet in Figure 8 shows how easy it is for the application programmer to use the gesture recognition engine.

```java
Recogniser recogniser = new Recogniser(ConfigurationTool.importXML("config.xml"));
ResultSet result = recogniser.recognise(note);
if (!result.isEmpty())
    logger.log(result.getResult(i.getName()));
```

Figure 8: Recogniser

In addition to the explicit handling of the results by the client application, iGesture also provides an event manager where a client can register actions to be triggered when a specific gesture class has been recognised.

We mainly use the digital pen and paper technology provided by the Swedish company Anoto [1] as an input device for the iGesture framework. However, since the iGesture framework should not depend on a specific hardware technology, all the components work on an abstract input device interface. This makes it easy to integrate new devices and use them for capturing new gesture sets as well as controlling specific applications. So far we support different Anoto digital pens as well as the standard computer mouse as a gesture input device. Furthermore, we are currently integrating the Wintab tablet API [16] to also acquire data from arbitrary graphics tablet solutions.

To simplify the time-consuming process of capturing gesture samples from different users, we provide a component to generate interactive gesture capture paper forms as shown in Figure 9. After a set of gesture classes has been defined, the corresponding interactive paper forms can be generated automatically and printed out with the position encoding pattern provided by Anoto.
Each row of the form contains a sample of the gesture to be captured and some empty fields that the user has to fill in with the digital pen. The pen data is continuously streamed to the iGesture application and stored in the corresponding gesture sample set. To enable the exchange of gesture sets with other applications, we further provide support for importing and exporting documents in Ink Markup Language (InkML) [3] format.

4. ALGORITHMS
In this section, we introduce four different gesture recognition algorithms that we have implemented so far for the iGesture framework. These include two existing solutions—the Rubine algorithm for specifying gestures by example [12] and the Simple Gesture Recogniser (SiGeR) algorithm developed by Swigart [14]. In addition we have implemented two new algorithms which we also present in this section. E-Rubine is an extended version of the Rubine algorithm dealing with additional single and multi-stroke features while SiGrid is a new signature-based algorithm that classifies gestures based on distance functions. Note that the implementations of the different gesture recognition algorithms presented in this section conform to the Algorithm interface introduced earlier.

4.1 Rubine Algorithm
The Rubine algorithm represents one of the first algorithms published for the recognition of mouse and pen-based gestures. The gestures are not described programmatically but instead learnt by examples. With the appropriate tools, such as the iGesture management console, it is easy to create new gestures and add them to the gesture recognition engine. In our implementation of the Rubine algorithm, we use the equations described in the original Rubine paper [12]. We now present the main features of the algorithm and show some of the equations involved in order that the reader can obtain not only an understanding of the algorithm, but also how it is integrated into iGesture and how we extended it in E-Rubine.

Features are extracted from gestures which consist of timestamped points and then used in the recognition process. In Rubine’s paper 13 features are described to be used in the recognition process. This includes the cosine and sine of the initial angle with respect to the x-axis (f₁ and f₂), the length of the bounding box diagonal (f₃), the angle of the bounding box (f₄), the distance between the first and last point (f₅), the cosine and sine of the angle between the first and last point (f₆ and f₇), the total gesture length (f₈), the total traversed angle (f₉, f₁₀, and f₁₁), the maximum speed squared (f₁₂) and the stroke duration (f₁₃). For the implementation of the standard Rubine algorithm evaluated later in this paper, we implemented these 13 features.

The classification does not depend on specific features which allows us to use it for different recognition tasks as long as the classifiable objects can be described by feature vectors. In a first step, the feature vector \( f_{esi} \) is computed for each gesture \( e \) for \( 0 \leq i < P \), where \( P \) is the number of selected features. These vectors are then summarised in a mean vector for each gesture class \( c \), where \( E_c \) represents the number of training examples for gesture class \( c \). The mean vector \( f_c \) is simply the average of the sample feature vectors for a given gesture class as illustrated in Equation 1.

\[
\hat{f}_c = \frac{1}{E_c} \sum_{e=0}^{E_c-1} f_{esi}
\]  

Based on these feature vectors, the covariance matrix \( M_c \) shown in Equation 2 is computed.

\[
M_{cij} = \sum_{e=0}^{E_c-1} (f_{esi} - \hat{f}_c) (f_{esi} - \hat{f}_c) = \sum_{e=0}^{E_c-1} f_{esi} f_{esi}
\]  

For each gesture class and the covariance matrices are averaged to a single covariance matrix \( M \) as shown in Equation 3, with \( C \) representing the number of gesture classes.

\[
M_{ij} = \frac{\sum_{c=0}^{C-1} M_{cij}}{M} = \frac{\sum_{c=0}^{C-1} M_{cij}}{C + \sum_{e=0}^{C-1} E_c}
\]  

The single covariance matrix allows us to estimate the weights \( \omega_{cij} \) of the vector components shown in Equation 4 and the initial weight \( \omega_{c0} \) for each gesture class as illustrated in Equation 5.

\[
\omega_{cij} = \frac{\sum_{i=1}^{F} (M^{-1})_{ij} \hat{f}_c}{\sum_{i=1}^{F} (M^{-1})_{ij} \hat{f}_c}
\]  

\[
\omega_{c0} = \frac{1}{2} \sum_{i=1}^{F} \omega_{c0, i} \hat{f}_c
\]  

Note that all these steps can be accomplished in the algorithm’s initialisation phase and the weights computed for each gesture class will not change during classifications. The classification itself is realised with the linear function shown in Equation 6. For an input gesture, the feature vector with the same features is computed and each component of the vector is multiplied with the corresponding gesture class weight. The classified gesture is denoted by the gesture class yielding the maximal value.

\[
u_c = \omega_{c0} + \sum_{i=1}^{F} \omega_{ci} f_i
\]  

This kind of classification has the drawback that a result will always be returned even if an input gesture does not have any similarities with a trained example gesture. Therefore, Rubine proposed a mechanism for rejecting gestures which are not similar to the trained ones and also the ones which are ambiguous. In our implementation a threshold can be set through an AMBIGUITY parameter to reject gestures which are too close to multiple gesture classes. Furthermore, to detect outliers the Mahalanobis distance [11] introduced in Equation 7 is used.

\[
\delta^2 = \sum_{j=1}^{P} \sum_{k=1}^{P} (M^{-1})_{jk} (f_j - \hat{f}_c) (f_k - \hat{f}_c)
\]
In addition to the AMBIGUITY parameter introduced earlier, in our implementation of the Rubine algorithm, other parameters can be specified. The MIN\_DISTANCE denotes the minimal distance between two succeeding points of a gesture. This enables us to automatically filter points that are too close together and could have a negative impact in the computation of specific features. A feature of our Rubine implementation has to conform to the Feature\_interface. The FEATURE\_LIST parameter holds a list of comma-separated fully qualified class names of feature objects that will be instantiated in the algorithm’s initialisation phase using dynamic class loading. Finally, the maximal distance for outliers can be defined by the MAHALANOBIS\_DISTANCE parameter. For further details about Rubine’s algorithm and feature definitions please refer to [12].

4.2 E-Rubine Algorithm

For our extended version of the Rubine algorithm, we developed new single-stroke and multi-stroke features. Our E-Rubine algorithm uses the core of the Rubine implementation presented in the previous section together with the new features presented in this section. We first introduce the single stroke features ($f_{14}$ to $f_{19}$) and then present an extension for multi-stroke gestures ($f_{20}$ to $f_{24}$). Note that some of our new features contain references to the original Rubine features ($f_{1}$ to $f_{13}$).

4.2.1 Single-Stroke Features

A single-stroke gesture $S$ can be defined as a totally ordered set of points $p_i = (x_i, y_i)$, where $1 \leq i \leq n$.

$$S = \{p_1, \ldots, p_n\}$$  

(8)

The $x$ and $y$ coordinates of any given point $p_i$ can be accessed by the $x$ and $y$ operators. Furthermore, we define a function $\varphi$ always returning the last point of a given list of points.

If $S = \{p_1, \ldots, p_n\}$, then $\varphi(S) = p_n$  

(9)

The distance $\delta$ between two points $p_i$ and $p_j$ can then be defined as

$$\delta(p_i, p_j) = \sqrt{(p_j.x - p_i.x)^2 + (p_j.y - p_i.y)^2}$$  

(10)

**Number of stop points**

Our first new single stroke feature $f_{14}$ is the number of so-called stop points within a gesture. A stop point occurs when the drawing speed falls below a specific lower bound threshold value. The average speed for the entire gesture is computed and the lower bound value is set to one third of the average speed. The speed between two points is then always compared to this lower bound value. Finally, the number of stop points is defined by the number of sequences having a speed below the specified lower bound. Stop points typically occur on directional changes and at the end of strokes. If $StopPoints$ is the set of all stop points, then

$$f_{14} = |StopPoints|$$  

(11)

**Distance from start to centre point in relation to the diagonal**

This feature measures whether the first or second part of the gesture is more winding. An integer division is used to access the centre point $S[n/2]$ in the computation of the distance $d_1$ from the start point to the centre point as shown in Figure 10.

$$d_1 = \delta(S[1], S[n/2])$$  

(12)

$$f_{15} = \frac{d_1}{f_3}$$  

(13)

**Direction of the first half of the stroke**

Feature $f_{16}$ measures the general direction of the first part of the stroke based on the sine of the angle between $d_1$ and the $x$-axis.

$$f_{16} = \sin \alpha = \frac{S[n/2].y - S[1].y}{d_1}$$  

(14)

**Direction of the second half of the stroke**

The cosine of the angle between the straight line $d_2$ from the centre point to the end point of the single-stroke gesture and the $x$-axis is used to compute $f_{17}$.

$$d_2 = \delta(S[n/2], S[n])$$  

(15)

$$f_{17} = \cos \gamma = \frac{S[n].x - S[n/2].x}{d_2}$$  

(16)

**Angle between the first and the second half of the stroke**

The cosine between $d_1$ and $d_2$ is used to compute this feature describing the change of direction with respect to the gesture’s centre point.
\[ f_{18} = \cos \beta = \frac{d_1^2 + d_2^2 - f_s^2}{2d_1d_2} \] (17)

**Distance from start to end point in relation to the diagonal**

Our last single stroke feature \( f_{19} \) is a gesture size-independent replacement of Rubine’s original feature \( f_5 \).

\[ f_{19} = \frac{f_5}{f_3} \] (18)

### 4.2.2 Multi-Stroke Features

To improve the performance of the original Rubine algorithm for new multi-stroke gestures, we designed and implemented five additional multi-stroke features. Note that these features are used in combination with the single stroke features. A multi-stroke gesture is defined as a totally ordered set of points \( M \) of \( m \) strokes \( S_1, \ldots, S_m \).

\[ M = \{S_1, \ldots, S_m\} \] (19)

Each stroke \( S_i \) is thereby defined as a totally ordered set of points \( p_j = (x_j, y_j) \), where \( 1 \leq j \leq |S_i| \).

\[ S_i = \{p_1, \ldots, p_{|S_i|}\} \] (20)

#### Number of strokes

This feature takes into account the number of strokes that a gesture contains. Note that if most of the strokes to be recognised contain the same number of strokes, feature \( f_{20} \) may not be a good classifier.

\[ f_{20} = |M| \] (21)

#### Straightness

The straightness of a multi-stroke gesture is represented by our new feature \( f_{21} \), dividing the sum of each stroke’s distance from the start to its end point \( \Delta(S_i) \) by the sum of the stroke lengths \( l(S_i) \).

\[ \Delta(S_i) = \delta(S_i[1], \varphi(S_i)) \] (22)

\[ l(S_i) = \sum_{j=1}^{|S_i| - 1} \delta(S_i[j], S_i[j + 1]) \] (23)

\[ f_{21} = \frac{\sum_{i=1}^{|M|} l(S_i)}{\sum_{i=1}^{|M|} \Delta(S_i)} \] (24)

#### Total distance between strokes

Feature \( f_{22} \) sums up the distances between the strokes and thereby provides information about their distribution. In order to make the feature size-independent, the sum is divided by the diagonal of the gesture’s bounding box.

\[ f_{22} = \frac{1}{|M| - 1} \sum_{i=1}^{|M| - 1} \delta(\varphi(S_i), S_{i+1}[1]) \] (25)

#### Angle between strokes

Feature \( f_{23} \) sums up the angles between the different strokes. The angle for each stroke, represented by the angle between the straight line from its start point to its end point and the x-axis, is computed and subtracted from the previous stroke’s angle.

\[ f_{23} = \sum_{i=1}^{|M| - 1} \text{Angle between Strokes } S_i \text{ and } S_{i+1} \] (26)

#### Stroke distances in relation to each other

Last but not least, feature \( f_{24} \) puts the stroke distances \( \Delta(S_i) \) in relation to each other.

\[ f_{24} = \Delta(S_1) \prod_{i=2}^{|M|} \frac{1}{\Delta(S_i)} \] (27)

Clearly, there was a lot of experimentation to test the effectiveness of proposed new features and compare the performance of the extended algorithm to that of the original Rubine algorithm and also other algorithms. The iGesture test bench gave us a lot of support for these experiments and enabled us to quickly arrive at an extension that yields promising results as reported in Section 5.

### 4.3 SiGeR Algorithm

The third algorithm that we have implemented with the help of the iGesture framework is the SiGeR algorithm that classifies gestures based on regular expressions [14]. Gestures are described with the eight cardinal points \( (N, NE, E, SE, S, SW, W, NW) \) and some statistical information. Out of such a description, a regular expression is created. These regular expressions are then applied to input gestures and, in the case that a class description matches the input string, the corresponding gesture class is returned as a result. Therefore the classification is binary and it is not possible to rate different results.

For example, the gesture shown in Figure 11 starting at the red dot is described by the following character string: \( E, N, S, \). Out of these characters, the regular expression \( (E) + (N) + (W) + (S) \) can be created. Because hand-drawn lines may not always be straight, Swigart proposed a more general form of a regular expression which also accepts neighboring distances. The extended regular expression for our example gesture would be \( (NE | E | SE) + (NW | N | NE) + (SW | W | NW) + (SE | S | SW) \).

The input gesture is transformed into a character string and the distance between two points is described by the directions corresponding to the cardinal points. Additionally, statistical information is
extracted out of the input gesture. Therefore, each direction is counted and information about the proportions of the directions provided. The proximity of the start and end points and the number of stop points is further counted to enable a more reliable description of gestures.

The description of gesture classes may impose constraints concerning this statistical information. For example, for a circle, we can define the constraints that there has to be an equal number of straight and diagonal elements and that the gesture’s start and end point have to be close to each other.

Our implementation of the algorithm differs in some points from the original SiGeR version. The most important change is the possibility to describe gesture classes in textual form using some keywords to describe the directions and also to make use of the statistical information. This allows us to use the existing text descriptor for gesture classes. In our implementation of the SiGeR algorithm, gestures are described using the language shown in Figure 12.

description = directions [";" constraints];
directions = direction ["," directions];
direction = "N" | "NE" | "E" | "SE" |
          | "S" | "SW" | "W" | "NW"; constraints = constraint ["AND" constraints];
constraint = operand operator (operand | real); operator = "EQ" | "NEQ" | "GT" | "GTE" |
            | "LT" | "LTE"; operand = "N" | "NE" | "E" | "SE" |
            | "S" | "SW" | "W" | "NW" | "DIAGONAL" | "STRAIGHT" |
            | "PROXIMITY" | "STOPPOINTS";
real = digit {digit} "." {digit}; digit = "0" | ".1" | ".2" | ".3" | ".4" |
      | ".5" | ".6" | ".7" | ".8" | ".9";

Figure 12: SiGeR description language

Using our new description language, the rectangle presented earlier would, for example, be described as E;N;W;S;STRAIGHT GT 0.8 AND PROXIMITY LT 0.2. The part before the semicolon describes the form of the rectangle with the directions. The two constraints define that at least 80% of the directions have to be straight and that the distance between the start and end point should be less than 20% of the gesture diagonal’s length. The algorithm’s Configuration object supports the definition of a MIN_DISTANCE parameter denoting the minimal distance between two succeeding points of a gesture.

4.4 SiGrid Algorithm

The SiGrid algorithm is a new algorithm that we developed that approximates gestures with a grid-based signature. The signature of a gesture class is computed based on sample gestures as done in the Rubine algorithm. These signatures are then compared to input gestures based on distance functions resulting in a classification of the gestures. To create the signatures for our new SiGrid algorithm, we use a grid consisting of equally sized squares. Each square has its unique bit string identifier and the identifier of two neighbouring squares always differs in exactly one bit.

During the preprocessing phase, the gestures are stretched to a uniform size and mapped to the grid. Each point of the gesture can now be represented with the bit string of its related square as shown in Figure 13. The full gesture signature consists of the concatenation of these bit strings.

Due to the limited resolution of the grid, the mapping of the gesture positions to points in the grid deliberately introduces some fuzziness into the gesture representation. The fuzziness is increased further by removing succeeding points that are mapped to the same grid square. In this way, we can guarantee that only significant points remain. In addition, our SiGrid algorithm applies a mechanism to remove points which do not change the signature significantly. A point is seen as irrelevant if the angle of the direction remains within a defined range.

We implemented two distance functions, the Hamming Distance and the Levenshtein Distance, for comparing different signatures and these can be selected by a parameter. Additional functions can be added by implementing the DistanceFunction interface. The Hamming Distance counts the number of bits which have to be flipped to make two signatures equal. The drawback of this function is that a displacement may trigger a lot of after-effects which may produce bad results. The Levenshtein distance is a generalisation of the Hamming distance. In addition to the flipping of bits, this measure is also able to add or remove bits to achieve the smallest possible distance between two bit strings. Based on this, after-effects can be minimised. The drawback of this function is that signatures might be changed drastically and so the result of the recognition is falsified. For each example gesture, the signature is created and an input gesture is compared with all the signatures. The accuracy of the result denotes the number of coinciding bytes.
5. EVALUATION

We now provide initial results of the evaluation of the four algorithms presented. The three algorithms based on sample descriptors (i.e., Rubine, E-Rubine and SiGrid) and the textual descriptor-based SiGeR have been tested with three different kinds of gesture sets: the Palm Graffiti letters and numbers, the Microsoft Application Gestures and a customised set of multi-stroke gestures. Note that the preliminary experiments were used to evaluate the algorithms as well as to validate the iGesture framework’s batch processing functionality.

5.1 Key Figures

An input can be classified in one of three different result categories by an algorithm. First, the algorithm may correctly recognise an input as the gesture it actually represents. We name this category Correct. The Error category contains incorrectly recognised gestures. In this case, the algorithm returns a wrong result which may lead to unintentionally triggered actions. The third category contains the rejected gestures Reject which have been returned as unclassifiable by the algorithm. Note that the test sets that we used for our experiments contained only classifiable gestures and therefore as few gestures as possible should be rejected. We evaluated the algorithms using the notions of Precision and Recall which we defined as follows.

**Precision**

The Precision shown in Equation 28 denotes the proportion of correct results versus all results. A value of 1 means that all recognised gestures are identified correctly and the result contains no errors.

\[
\text{Precision} = \frac{|\text{Correct}|}{|\text{Correct}| + |\text{Error}|} \quad (28)
\]

**Recall**

The Recall illustrated in Equation 29 provides information about the fraction of gestures which can be classified out of all classifiable gestures.

\[
\text{Recall} = \frac{|\text{Correct}| + |\text{Error}|}{|\text{Correct}| + |\text{Error}| + |\text{Reject}|} \quad (29)
\]

**F-Measure**

The F-Measure shown in Equation 30 is the weighted harmonic mean of the precision and the recall value. We decided to weight precision and recall equally.

\[
\text{F-Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (30)
\]

5.2 Palm Graffiti

We ran five experiments using the 26 letters and 10 numbers of the Palm Graffiti alphabet [6] as a gesture set. They cannot be combined into a single gesture set because several gestures in the number set are similar to letters. Overall, we collected training and test data from four persons which provides for a more objective estimation than with a single user.

5.2.1 Experiment 1: Graffiti Numbers

Experiment 1 used the Graffiti numbers as the gesture set trained with 15 examples for each gesture class by one person. The test set had a size of 150 valid samples and was collected by three different persons. To test the SiGeR algorithm, a textual description of the numbers was constructed manually. Table 1 shows the results for the best configuration of each algorithm defined as the one with the maximal F-Measure. This means that the configuration should have a low error rate as well as a high number of correctly recognised gestures.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
<th>SiGeR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>140</td>
<td>135</td>
<td>130</td>
<td>129</td>
</tr>
<tr>
<td>Error</td>
<td>9</td>
<td>15</td>
<td>15</td>
<td>8</td>
</tr>
<tr>
<td>Reject</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>Precision</td>
<td>0.940</td>
<td>0.899</td>
<td>0.898</td>
<td>0.942</td>
</tr>
<tr>
<td>Recall</td>
<td>0.993</td>
<td>0.993</td>
<td>0.980</td>
<td>0.913</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.966</td>
<td>0.944</td>
<td>0.937</td>
<td>0.927</td>
</tr>
</tbody>
</table>

Table 1: Graffiti numbers

Although the example-based algorithms were trained by only one person, nearly all algorithms reached a Precision of at least 90%. The result shows that the new features used in our extended version of the Rubine algorithm significantly improve the recognition quality. Even the simple SiGrid algorithm has almost the same precision as the original implementation of the Rubine algorithm. The SiGeR algorithm also has good test results, but since the textual description of the gesture classes were done on the basis of the test set, it should be noted that they were optimised for this specific experiment.

5.2.2 Experiment 2: Graffiti Numbers

The Graffiti numbers were again used as the gesture set but the training data was collected from four different persons. We trained each gesture class with 4 times 4 examples and the test set has a size of 140 samples collected from a single person. We compared only sample-based algorithms and so the SiGeR algorithm is not taken into account. Again the test set contains only valid samples which should all be recognised.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>140</td>
<td>135</td>
<td>130</td>
</tr>
<tr>
<td>Error</td>
<td>0</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td>Reject</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Precision</td>
<td>1</td>
<td>0.971</td>
<td>0.929</td>
</tr>
<tr>
<td>Recall</td>
<td>1</td>
<td>0.993</td>
<td>1</td>
</tr>
<tr>
<td>F-Measure</td>
<td>1</td>
<td>0.982</td>
<td>0.963</td>
</tr>
</tbody>
</table>

Table 2: Graffiti numbers

The Rubine algorithm provides better key figures than in experiment 1 as shown in Table 2. The extended Rubine algorithm achieved a perfect result whereas the Signature algorithm has a
higher error rate than the original Rubine algorithm. It can be assumed that the Rubine algorithm works significantly better with a broader variety of training data.

5.2.3 Experiment 3: Graffiti Letters
The 26 Graffiti letters were used as the gesture set and, as for Experiment 1, the training data was collected from a single person and the algorithms trained with 15 examples per gesture class. The test set has a size of 390 samples collected from three different persons. Again the test set contains only valid data.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>335</td>
<td>280</td>
<td>274</td>
</tr>
<tr>
<td>Error</td>
<td>52</td>
<td>107</td>
<td>113</td>
</tr>
<tr>
<td>Reject</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Precision</td>
<td>0.866</td>
<td>0.724</td>
<td>0.708</td>
</tr>
<tr>
<td>Recall</td>
<td>0.992</td>
<td>0.992</td>
<td>0.992</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.925</td>
<td>0.837</td>
<td>0.826</td>
</tr>
</tbody>
</table>

Table 3: Graffiti letters

The figures shown in Table 3 are significantly worse than those for Experiment 1. The reason is the size of the gesture set which is 2.5 times larger while the size of the training data is the same. These results highlight that the number of samples has to grow with the size of the gesture set. We note that several letters had a very high error rate whereas others were recognised perfectly. The reason for this behaviour is that the training data was collected by a single person. Better results would be expected using training data from different users.

5.2.4 Experiment 4: Graffiti Letters
As in Experiment 2, each gesture class was trained with 4 times 4 examples from different users. The test set had a size of 363 samples and was produced by the same persons used for the training of the algorithm. Again the test set contains only valid gestures.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>195</td>
<td>178</td>
<td>164</td>
</tr>
<tr>
<td>Error</td>
<td>4</td>
<td>19</td>
<td>34</td>
</tr>
<tr>
<td>Reject</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Precision</td>
<td>0.980</td>
<td>0.904</td>
<td>0.828</td>
</tr>
<tr>
<td>Recall</td>
<td>0.995</td>
<td>0.983</td>
<td>0.990</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.987</td>
<td>0.943</td>
<td>0.902</td>
</tr>
</tbody>
</table>

Table 4: Graffiti letters

Although this experiment was clearly not realistic because the training data and the test data were produced by the same person, it still shows that with the extended Rubine algorithm good performance even though the amount of training data used was relatively small compared to the size of the gesture set.

5.3 MS Application Gestures
The next set of experiments used the Microsoft Application Gestures [2] as the gesture set. Originally this set consisted of 42 gestures but two of them which represent mouse- or pen-clicks cannot be recognised with our feature-based algorithm because the gesture consists of only one or two points and does not provide enough input for computing the different features. Therefore the set used in the evaluation has a size of 40 gestures.

5.3.1 Experiment 5: MS Application Gestures
The 40 gestures were trained with 15 examples for each gesture class by one person and tested with 5 instances of each gesture class provided by the same person. Again the test set contains only valid gestures. Table 5 highlights that the extended Rubine algorithm had good performance even though the amount of training data used was relatively small compared to the size of the gesture set.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>343</td>
<td>305</td>
<td>297</td>
</tr>
<tr>
<td>Error</td>
<td>18</td>
<td>48</td>
<td>66</td>
</tr>
<tr>
<td>Reject</td>
<td>2</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>Precision</td>
<td>0.950</td>
<td>0.864</td>
<td>0.818</td>
</tr>
<tr>
<td>Recall</td>
<td>0.994</td>
<td>0.972</td>
<td>1</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.972</td>
<td>0.915</td>
<td>0.900</td>
</tr>
</tbody>
</table>

Table 4: Graffiti letters

Although this experiment was clearly not realistic because the training data and the test data were produced by the same person, it still shows that with the extended Rubine algorithm good results can be achieved even with a small amount of training data if the coverage is good.

5.4 Multi-Stroke Gestures
We defined a set of 15 multi-stroke gestures shown in Figure 14. Two of them consist of a single stroke only and are prefixes of other multi-stroke gestures in the set. The set is quite small but it should be a proof of concept that also multi-stroke gestures can be recognised by the implemented algorithms.
5.4.1 Experiment 6: Multi-Stroke Gestures
The algorithms were trained with 15 examples collected from one person and tested with 5 samples for each gesture class collected from the same person. The results shown in Table 6 are good with algorithms having a precision higher than 96%. However, again good results were expected due to the algorithm being trained and tested by the same person. Furthermore, the relatively high number of training-examples for each gesture class has a positive effect.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>75</td>
<td>72</td>
<td>73</td>
</tr>
<tr>
<td>Error</td>
<td>0</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Reject</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Precision</td>
<td>1</td>
<td>0.960</td>
<td>0.973</td>
</tr>
<tr>
<td>Recall</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>F-Measure</td>
<td>1</td>
<td>0.980</td>
<td>0.986</td>
</tr>
</tbody>
</table>

Table 6: Multi-stroke gestures

5.4.2 Experiment 7: Multi-Stroke Gestures
In this experiment the algorithms were trained with 20 examples collected from one person and tested with 5 samples for each gesture class collected from another person. As shown in Table 7, all algorithms achieved nearly the same high level of results as in the previous experiment. This is probably due to the high number of training samples compared to the size of the gesture set and also the kind of gestures we used since they were quite distinct from each other.

<table>
<thead>
<tr>
<th></th>
<th>E-Rubine</th>
<th>Rubine</th>
<th>SiGrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>74</td>
<td>73</td>
<td>75</td>
</tr>
<tr>
<td>Error</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Reject</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Precision</td>
<td>0.987</td>
<td>0.986</td>
<td>1</td>
</tr>
<tr>
<td>Recall</td>
<td>1</td>
<td>0.987</td>
<td>1</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.993</td>
<td>0.987</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 7: Multi-stroke gestures

The experiments have shown the behaviour of the chosen algorithms in different setups. These initial results show that only the extended Rubine algorithm seems to be good enough for general practical usage. However, the other algorithms may be useful in particular settings. Simple geometric figures in a small gesture set could also be recognised effectively with the SiGeR algorithm without having to create a large amount of example data and this in turn has the advantage of allowing gesture sets to be easily extended. The SiGrid algorithm also yielded good results when both the gesture set and the example sets were relatively small. In this setting, it may even be superior to the Rubine algorithm since it needs several examples per gesture class to compute the weights. If the number of gesture examples is too small, it is actually possible that the Rubine algorithm cannot be instantiated because the determinant of the covariance matrix is zero and therefore the inverse cannot be computed. In the future we plan to conduct further experiments with larger test sets.

6. CONCLUSION
We have presented a general and flexible framework for gesture recognition and described how we implemented two existing gesture recognition algorithms and also developed two new algorithms using the framework. In addition to providing interfaces that made it very simple to implement these algorithms and also use them in various applications, the iGesture framework supported the experimentation and evaluation processes. The fact that batch tests for different algorithms and parameter settings could easily be run against the same captured test sets greatly simplified the task of carrying out comparative evaluations and refinements of the algorithms. We believe that the fact that we were able to develop two new algorithms with very promising evaluation results within a short period of time can largely be attributed to the availability of the iGesture framework.

7. REFERENCES
[5] E. Gamma, R. Helm, R. Johnson, and J. Vlissides. Design Patterns: Elements of Reusable Object-Oriented Software. Addison-Wesley, 1995.