Multi-sensor Finger Ring for Authentication Based on 3D Signatures

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Abstract. Traditional methods of authenticating a user, including password, a Personal Identification Number (PIN), or a more secure PIN entry method (A PIN entry method resilient against shoulder surfing [14]), can be stolen or accessed easily and, therefore, make the authentication unsecure. In this work, we present the usability of our multi-sensor based and standalone finger ring called Pingu in providing a highly secure access system. Specifically, Pingu allows users to make a 3D signature and record the temporal pattern of the signature via an advanced set of sensors. As a result, the user creates a 3D signature in air using his finger. Our approach has two main contributions: (1) Compared to other wearable devices, a finger ring is more socially acceptable, and (2) signatures created via a finger in the air or on a surface leaves no visible track and, thus, are extremely hard to forge. In other words, a 3D signature allows much higher flexibility in choosing a safe signature. Our experiment shows that the proposed hardware and methodology could result in a very high level of user authentication/identification performance.

Keywords: uman Computer Interaction (HCI), Touch less gestural interaction, Wearable device, Finger ring.

1 Introduction

Due to increased capability of a smartphone, users tend to store all of their personal information in their mobile devices. Smart technology, however, raises a serious threat to a user's credentials, unless the access to these devices is secured by information unique to each user. As an example, access to a user's smartphone may lead to his bank account, social security number, email accounts, or other personal information.

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Traditional methods used for authenticating a login include entering a password, Personal Identification Number (PIN). Previous research shows that it's not difficult to replicate this information, thereby making it insecure. A more robust solution will be to provide users with a unique way of interaction with their computing device. While a modern computing device easily fits a human hand, our world of interaction is not limited by the size of the device. With this motivation, we have developed a multi-sensor based framework called Pingu [1] that helps a user perform gestural signatures to access his computing device (e.g. smartphone). Pingu is calibrated in the form of a miniature, wearable finger ring that can perform sharp and tiny gestures. When the user performs his signature as a general gesture, sensor readings specific to each sensor are recorded, even if the device is not in the vicinity of the user. These sensor readings define the 3D trajectory of the ring and, therefore, are unique to each individual.

With wireless connectivity, feedback mechanism, and an advanced set of sensors, Pingu offers a wide range of applications. In addition, unlike previously proposed wearable devices (such as gloves, wristwatch [2, 6]), Pingu is a standalone device that does not require any extra hardware for interaction with a computing device and is also socially wearable. In this work, we explore the usability of Pingu in providing a secure authentication method for users to access their computing devices. To illustrate further, we conducted a user study with 24 participants, where each participant performs his signature in the form of a gesture and the sensor readings specific to the gesture are recorded. We show that the recorded sensor readings provide rich information specific to each gesture made by a user and with simple classification algorithms, the users can be authenticated based on their signatures with very high accuracy.

The rest of this paper is organized as follows. In Section 2, we review the related potential solutions for generating 3D signatures. Then in Section 3, we explain the architecture of the Pingu's hardware. In Experiments Section, the data collection and feature extraction via Pingu are explained. Section 5 presents our results of signature classification via different machine learning algorithms. In Section 6, further classification based on correlation and frequency features is illustrated. Finally, we conclude the paper in the Section 7.

2 Related Works

In recent years, different gestural recognition approaches are developed which are either used to generate 3D signatures such as MagiSign [5, 16], or can potentially be used to generate a 3D signature [2, 3, 4, 6, 7, 15].

In our previous work, MagiSign [5, 16], a 3D signature is created via influencing the magnetic field of a magnetic (compass) sensor embedded in mobile devices. However, the space of interaction is limited to the immediate 3D space around the device. Moreover, while Pingu can work with any computing device, MagiSign works only with smartphones (e.g., an iPhone). Finally, using multiple sensors in Pingu leads to a more precise gesture recognition in comparison to only one magnetic sensor in MagiSign.

In other approaches, which can potentially be used for 3D signature such as Acceleration Sensing Glove [2], a user has to wear additional gloves to interact with the computing device. The disadvantage of this approach is that they can be socially unacceptable or obtrusive. Other frameworks, such as Gesture Pendant [3] and SixthSense [4], require users to wear pendant and additional hat, respectively, which suffer from the same problems. Moreover, in approaches like SixthSense and Gesture Pendant, there is a need for an optical sensor (e.g., camera) which causes problem when performed gestures are not in the direct line of sight of the sensor.

Finger rings or wristwatches can be used to solve the problem of social awkwardness. Pinchwatch [6] uses a wristwatch for finger gesture recognition with the help of a camera. By performing sliding and dialing motions, some functions are invoked. However it still has the occlusion problem. More recently, Nenya [7], a magnetically-tracked finger ring, is developed which includes a permanent magnet in the form of a finger ring and worn-watch wireless tracking bracelet. The magnetometer is used to track the ring's position and a Bluetooth radio allows the bracelet to send ring input to the user's device. However, Nenya only supports 1D input in comparison to 3D inputs supported by Pingu. Furthermore, the IR Ring provides an innovative method which can be used for Authenticating users' touches on a multi touch display [13].

3 Design

Figure 1 shows the prototype for Pingu. Specifically, Pingu has four sensors: a tri-axis accelerometer, a tri-axis gyroscope, a tri-axis magnetometer, and proximity sensing plates with two channels. The accelerometer is used to detect the orientation and motion of the device along x, y, and z axes. A tri-axel gyroscope detects the angular rate of movement of the ring along the three axes x, y, and z. The deformation of magnetic fields is useful in recognizing coarse gestures made around the device. In addition, the proximity-sensing plates allow sensing the proximity of other fingers. The feature set obtained from one or more sensors can then be combined to form a feature vector specific to each gesture. Based on the movement of the ring, each of these sensors provides a feature set. Table 1 lists the details specific to three sensors and radio technology used in the design of Pingu.

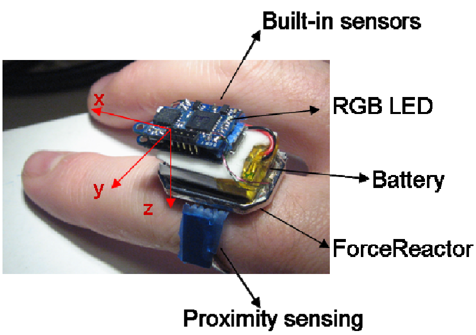

Fig. 1. Prototype for our multi-sensor based framework called Pingu

Table 1. Sensors used in the design of Pingu with their specifications.

Sensor	Description
Accelerometer	[-8g, 8g]
Magnetometer	[-2gauss, 2gauss]
Gyroscope	[-2000deg/s, 2000deg/s]
Bluetooth	Up to 2m

4 Experiment

To evaluate the usability of Pingu in secure authentication, we perform gestures defined as a signature. Since Pingu is worn on a finger, even sharp and tiny gestures can be used for the purpose of authentication. When the user performs a gesture, the associated sensor data is collected. The sensor readings define the temporal pattern of the signature and, thus, can be used in matching the signature for authentication. Our experiments were split into two categories:

1. Signature in the air and
2. Signature on the table

Setting the two medium of air and desk provides a variety of surfaces for gesturing. In this way, the methodology can be tested under more variable yet practical scenarios. The desk medium is a surface which is commonly available for users during the gesturing process. The air medium also provides the fantasy of writing in air for the user, when the two other mediums are not available.

Signatures for each user are recorded on two different mediums to evaluate Pingu for its dynamic usability. In other words, these two experiments ensure that the usability of Pingu in secure authentication is irrespective of the surface (or medium) of interaction. Each signature is first performed in the air and then on the table. Multiple templates per signature are collected. Specifically, when a signature is performed, the 3D trajectory of the ring is recorded in the form of sensor readings. For example, as the ring moves, the accelerometer, embedded in Pingu, measures the linear acceleration along three axes: x, y, and z.

Since Pingu performs sharp and tiny gestures, any general gesture can be used as a signature pattern. When a user performs a gesture, the sensor readings specific to the gesture are compared to the previously recorded signature pattern (template) for the user. The two patterns can be compared via Dynamic Time Warping (DTW) technique and if the difference between the two patterns is less than a pre-defined threshold, the signature is accepted. Next, we provide details on the datasets and the classifiers used to analyze signatures made by the users.

Fig. 2. An example of a 3D signature made in the air

4.1 Data Collection

Our dataset consists of six signatures, obtained from 24 users. Every user performs each of these six signatures 15 times. The sensor readings specific to each signature are captured via a Java desktop application. To classify the signatures based on the sensor readings captured, we extract an extended set of features, specific to every sensor reading captured for each signature performed by a user. To extract feature vector from the sensor readings, we use the following approach.

4.2 Feature Extraction

We mixed the data collected from all the 24 users and cross-validated. For this purpose, we formed a feature vector containing the data specific to each sensor. For example, the feature vector specific to accelerometer contains the following:

1. Mean and variance of the linear acceleration along x, y, and z axes (6 features),
2. Mean and variance of the Euclidian norm of the linear acceleration along x, y, and z axes (2 feature),

The feature vector from gyroscope is obtained in a similar manner. Feature vector for each sensor, therefore, contains 8 elements. Since multiple windows provide more detailed information in gesture classification, our results are based on 4 windows. Feature vectors obtained from each window are concatenated to form a new feature vector of 32 (=8x4) features.

5 Signature Classification

The feature vectors obtained for each sensor are then concatenated to form a large feature set that represents the features defining each signature. To classify users based on their signatures, we use a set of four classifiers: (a) Decision Tree (DT), a decision tool that uses graphs and model of decisions to derive the outcomes and consequences, (b) Multi-Layer Perceptron (MLP), a feedforward artificial neural network that models the relationship of inputs and outputs to find the patterns, (c) Naïve Bayes (NB), a probabilistic classifier that uses Bayes' theorem with strong independence assumptions, and (d) Support Vector Machines (SVM), which set hyperplanes in high dimensional space for using classification and regression. The current implementations available for these classifiers in Weka machine learning toolkit version 3.7.0 [11, 12] on Mac OS X are used. Tables 2-3 list the classification accuracy obtained for both sets of experiments. As shown, MLP and SVM outperform the other two classifiers (i.e., DT and NB). In addition, we note that using simple features (i.e., mean and variance of sensor readings) can enable us to classify users (based on their signature patterns) with an accuracy of about 99% in both experiment categories.

Table 2. Signature Classification for 24 Users in Signature in the air

Classifier	Accuracy
MLP	98.8889%
DT	82.2222%
NB	97.5%
SVM	99.1667%

Table 3. Signature Classification for 24 Users in Signature on the table

Classifier	Accuracy
MLP	99.1549%
DT	87.0423%
NB	97.4648%
SVM	99.4366%

6 Correlation and Energy Features

To illustrate the effect of a feature set on the accuracy of classification techniques, we extract piecewise correlation and frequency features of sensor readings. Frequency features measure the intensity in the movement of ring and are calculated as the sum of squared discrete FFT magnitudes. The correlation features, on the other hand, help differentiate between sharp and tiny gestures made by users. Together, these features help capture the periodicity in sensor readings. Thus, we performed another study of classifyingsignatures with a feature set that contains frequency and correlation features in addition to mean and variance extracted from each of the three sensors. Specifically,

1. Piecewise correlation between linear acceleration along x, y, and z axes (3 features), and
2. Frequency domain features along x, y, and z axes (3 features).

Feature vector for each sensor, therefore, contains 14 elements. With a window size of 4, the size of the feature set is 56 (=14x4). To classify, we again use the four classifiers listed earlier. Tables 4-5 present our results obtained for the experiments performed in air and on the table. The results indicate that with correlation and frequency features, the accuracy can be excelled to 100%.

Table 4. Signature Classification for 24 Users in Signature in the air (with Correlation and Frequency features)

Classifier	Accuracy
MLP	100%
DT	86.6667%
NB	98.3333%
SVM	100%

Table 5. Signature Classification for 24 Users in Signature on the table (with Correlation and Frequency features)

Classifier	Accuracy
MLP	100%
DT	86.6667%
NB	99.1549%
SVM	99.7183%

7 Conclusions

In this work, we have proposed a unique secure authentication solution and presented our results for this system using a standalone, miniature, and wearable finger ring called Pingu. Pingu is a socially wearable, small finger ring that is equipped with multiple sensors to provide rich information about the signatures made by a user. Our analysis for signature recognition is based on a large dataset of 24 users and we have shown that with simple classification algorithms, the signature performed by a user can be recognized with a very high accuracy. Therefore it can be a trustworthy authentication solution for many applications.

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