BioPrivacy: Development of a Keystroke Dynamics Continuous Authentication System

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Abstract. Session authentication schemes establish the identity of the user only at the beginning of the session, so they are vulnerable to attacks that tamper with communications after the establishment of the authenticated session. Moreover, smartphones themselves are used as authentication means, especially in two-factor authentication schemes, which are often required by several services. Whether the smartphone is in the hands of the legitimate user constitutes a great concern, and correspondingly whether the legitimate user is the one who uses the services. In response to these concerns, Behavioral Biometrics (BB) Continuous Authentication (CA) technologies have been proposed on a large corpus of literature. This paper presents a research on the development and validation of a BBCA system (named BioPrivacy), that is based on the user's keystroke dynamics, using a Multi-Layer Perceptron (MLP). Also, we introduce a new behavioral biometrics collection tool, and we propose a methodology for the selection of an appropriate set of behavioral biometrics. Our system achieved 97.18% Accuracy, 0.02% Equal Error Rate (EER), 97.2% True Acceptance Rate (TAR) and 0.02% False Acceptance Rate (FAR).

Keywords: Machine Learning · Behavioral Biometrics · Continuous Authentication · Mobile Devices · Multi-Layer Perceptron (MLP).

1   Introduction

User authentication technology plays a critical role in securing access to online services. Authentication systems identify users only when the session is initiated (entry point authentication model), thus leaving them exposed to attacks that take place after the initial authentication process [1, 7, 8, 9, 10, 39, 41]. These systems defend themselves against such attacks by performing an additional authentication step at critical points in the session but are not popular with users due to the inconvenience caused by repetitive authentications. Also, smartphones are used as authentication means, especially in two-factor authentication schemes, which are often required by several electronic services. Whether the smartphone is in the hands of the legitimate user constitutes a great concern, and correspondingly whether the legitimate user is the one who uses the services. In addition, mobile devices are vulnerable to smudge attacks [40], i.e., the mark of the fingerprints left by our finger on the screen, as it is easy to reveal the touch pattern or the PIN of the device. Thus, stealing a device carries the risk of granting full access to personal data and crucial applications. Moreover, smartphone users are unaware of privacy and security threats and keep large amounts of private information including PINs, credit card numbers, etc., stored in their mobile devices [1].

For the above reasons, Behavioral Biometrics (BBs) and Continuous Authentication (CA) are employed by a new method of user authentication which is also based on the "something that the user is" paradigm [2, 3, 4, 5, 6, 7, 9]. The technological advancement of mobile devices has led to the efficient capture of user behavior via their incorporated sensors, thus enabling the authentication of users based on their behavioral biometrics [11, 12, 13, 14, 15]. The incorporated sensors of mobile devices are used to enroll BB templates [7, 14, 16]. The BBs that may be employed are walking gait, touch gestures, keystroke dynamics, hand waving, user profile, and power consumption. The advantage of BBs is that they use some characteristic feature of a single individual and provide continuous authentication [7]. Alongside the initial login process CA technology represents an extra security mechanism since it monitors user behavior and re-authenticates continuously the user's identity throughout a session [5, 17, 18, 19, 20]. Finally, the work of [10, 22, 23, 49] showed the eagerness of users to adopt biometric authentication methods in order to protect their privacy.

This paper presents a research on the development and validation of a keystroke dynamics Continuous Authentication System, named BioPrivacy. We aim at building a system that will continuously authenticate the user of a smartphone. We start with an experimental biometric data collection process via mobile smartphones. The main objective is to propose a methodology and a data collection tool (BioPrivacy Collection Tool) for the selection of an appropriate set of behavioral biometrics. In this experiment, we recorded users' keystroke dynamics. Also, the present research aims to designing and evaluating new approaches to Continuous Authentication (CA) by developing and using a Multi-Layer Perceptron (MLP).

2   Background

In this section, we present an overview of the keystroke dynamics, the Multi-Layer perceptron (MLP) and the evaluation metrics.

2.1   Keystroke dynamics

The procedure of recording the typing keyboard inputs of an individual on a mobile device and the effort to identify him via an analysis based on his tapping habits is called keystroke dynamics [7]. Some researchers on keystroke dynamics collect data from predefined texts, for example during the typing of a text message, or during the log-in session when entering passwords. Others conduct their research by collecting data not restricted on predefined sentences or passwords. In both cases the results are of high accuracy [7].

2.2   Multi-Layer perceptron (MLP)

Artificial Neural Networks (ANNs) are structures inspired by human brains' function. These networks can estimate model functions and handle linear/nonlinear functions by learning from data associations and generalizing to previously unknown scenarios. Multi-Layered perceptron (MLP) is a widely used Artificial Neural Network approach (ANNs) [46]. Specifically, a feedforward artificial neural network called a Multi-Layer Perceptron (MLP) is a type of Feedforward Artificial Neural Network (FANN). Each unit in an MLP neural network performs a biased weighted sum of its inputs and then passes this activation level through a transfer function to generate output.

MLP networks typically include three layers: input, hidden, and output. The number of neurons in the input layer is equal to the number of parameters affecting the problem. Almost all problems can be solved with just one hidden layer. The number of neurons in the hidden layer or layers should be arbitrarily chosen [47]. This is a powerful modeling tool that employs a supervised training procedure with data examples with known outputs. Training for the MLP approach is accomplished in two steps. In the first step, the training data set is fed by a randomly picked input vector. The activated neurons output is subsequently propagated from hidden layer(s) to the output layer. The back propagation step, begins by calculating the gradient descent error and then propagates it backwards to each neuron in the output layer, followed by the hidden layer. The neural network's weights and biases are recomputed at the end of the second step. These two steps are repeated until the network's total error is less than a predetermined rate or the maximum number of epochs is reached [47]. Although, MLP network is a widely-used ANN approach, the MLP network still has certain limitations, such as time-consuming issues in reaching a solution [48].

2.3   Evaluation metrics

The basic metrics applied to evaluate an authentication system depend on the error rates. Following, we discuss some basic metrics used to calculate authentication errors [7, 31, 32, 33]:

- True Acceptance Rate (TAR) is the conditional probability of a pattern to be classified in the class "Genuine" given that it belongs to it. TAR is given by the formula:

$$TAR=TA/(TA+FR) \qquad (1)$$

- False Acceptance Rate (FAR) is the conditional probability a pattern to be classified in the class "Genuine" given that it does not belong to it. FAR is given by the formula:

$$FAR=FA/(FA+TR). \qquad (2)$$

- False Reject Rate (FRR) is the conditional probability a pattern not to be classified in the class "Genuine" given that it belongs to it. FRR is given by the formula:

$$FRR=FR/(FR+TA) \qquad (3)$$

- Accuracy is defined as the probability of correct classification of a pattern. Accuracy is given by the formula:

$$Accuracy = (TA+TR)/(TA+TR+FA+FR) \qquad (4)$$

- Equal Error Rate (EER) is the error rate that is achieved by tuning the detection threshold of the system such that FAR and FRR are equal [28].

3   Related Work

In this section we present a recent state-of-the-art literature review focusing on keystroke dynamics. The majority of keystroke dynamics methods are restricted to using a specific context with a prearranged text. In the work of Clark and Furnell [24], the authors employed the typing patterns of users when entering telephone numbers and text messages, to authenticate them. They used Multi-Layer Perceptron (MLP), Radial Basis Functions (RBF), and General Regression Neural Network (GRNN) classifiers. The best results achieved were 12.8% average EER with the Multi-Layer Perceptron (MLP) classifier.

In the work of Draffin et al. [4], the authors conducted a real-world study and collected 86000 keystrokes from 13 participants in three weeks. Keystrokes were not restricted to the use of prearranged text or passwords. They used Feed Forward Neural Network for classification and achieved 86% accuracy after 15 keypresses with 2.2% FRR, and 14% FAR.

In the work of Darren and Inguanez [25], they collected typing data while users were entering 15 prearranged text sentences during four different scenarios, namely, One-Handed stationery, Two-handed stationery, One-Handed moving, and Two-handed moving. The participants were free to choose one of the four scenarios, while the smartphone owner had to complete all 4 activities. The authors used a Least Squares SVM classifier with RBF kernel and the one-handed scenario achieved the best results, namely, 0.44% EER, 100% accuracy, 0% FAR, and 1% FRR, while all their results achieved around 1% EER.

In the work of Krishnamoorthy [26], the classification of users was based on keystroke dynamics, by applying concepts of machine learning. The participants of this study were asked to type a specific password and their typing characteristics were recorded. Krishnamoorthy effectively identified each one of the 94 users and achieved 98.44% identification accuracy with the Random Forest classifier.

In Table 1, we present the performance of machine learning models on keystroke dynamics. For each system, there is at least one of the five basic metrics, namely FAR, TAR, FRR, EER, and Accuracy.

Table 1: A literature review

| Method | Works | Platform | Classifi-cation | Performance (%) | | | | |
				FAR	TAR	Accu-racy	FRR	EER
Keystroke Dynamics	[24] in 2006	Smartphone	MLP					12.8
	[4] in 2013	Smartphone	FFNN	14		86.0		22
	[4] in 2013	Smartphone	SVM	0		100	1	0.44
	[25] in 2018	Smartphone	Random Forest			98.44		2.2

As we can see in Table 1, RF and SVM classifiers have achieved very good results while the performance of the MLP and the FFNN is relatively low. We believe that further research is necessary to see if FFNN and MLP can have better performance. By applying a new design approach to MLP, using the BioPrivacy collection tool dataset, we will see if we have an improvement in the performance. In case a high performance is achieved, we will apply MLP in our system.

4   Experimental setup

In this part we present the BioPrivacy System Architecture. Specifically, we present the biometrics collection architecture by which we can collect the biometric data of the users, and the data preparation for introduction to machine learning algorithms.

4.1   Bioprivacy's collection tool

Bioprivacy's collection tool is an Android application for collecting cell phone keystroke dynamics values [7, 34]. The BioPrivacy Application sends the data to an API

endpoint that stores the data in an online MySQL database. This API is an online application running continuously. It is built to retrieve data from the application and store it in the online database. Each operation is performed on different files so that if one file has an error it will not affect the other. Each of the files receives different input parameters. The online database is designed to allow multiple users to store their sensor data at any time. Thus, there is no concern about data separation and synchronization. The application also handles any probable communication malfunctions. A software system must be sustainable and scalable. For this reason, the structure of the application follows an architecture that accommodates possible software modifications and expansions. The application was developed in Android Studio.

When a user types on the BioPrivacy's keyboard, the inputs are recorded and analyzed in order to identify him based on his tapping habits [7, 34]. The BioPrivacy application extracts the duration and latency of the pressure on keys and the location points of fingers as described [7, 29, 35, 36, 37]:

- *Duration*: is the time period between pressing and releasing a key.
- *Latency*: is the time period between releasing a pressed key until pressing the next key.
- *Pressure*: is the pressure on a key.
- *Location*: are the location points (xi, yi) of the finger on the screen.

In fig. 1 we see the keystroke recording interface.

Fig. 1. Bioprivacy's keystroke interface

4.2 BioPrivacy system architecture

The registration process, which is the first step of the BioPrivacy system, involves collecting the biometric sample, processing the biometric data to extract the reference

sample, and storing it for further use (see fig. 2). The efficiency and accuracy of a biometric system are directly dependent on the registration process. During the life cycle of a biometric, it is sometimes necessary to re-record, taking into account the normal as well as the unexpected change or evolution of biometric characteristics. There is a set of basic modules included in the BioPrivacy system which are as follows [7, 38]:

1. *Data acquisition:* Sample acquisition: To acquire biometric data we must use the appropriate sensor.
2. *Feature extraction:* The raw data must be preprocessed before extracting the distinctive features. More specifically, we must identify and extract outliers and improve the quality of data, especially in cases where data are collected in uncontrolled environments from uncooperative users. The set of discriminative features are extracted once the data is cleaned and processed.
3. *Feature templates:* This is a repository database containing a concatenation of the extracted feature vectors for a particular user (i.e., the device owner). It is created during the enrollment phase and used during the recognition phase to be compared with the captured feature sample and verify the claimed identity.
4. *Decision-making:* This is used only during the recognition process. This step compares the template that is currently being extracted with the saved template to generate a matching score and make a decision. The decision validates the claimed identity to see if it is done by the legitimate user (genuine) or an impostor.
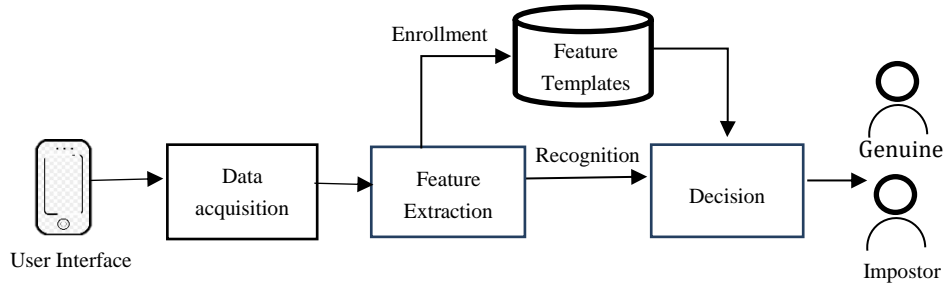

Fig. 2. BioPrivacy system architecture.

5   Methodology

In this section, we present the data collection process, via mobile smartphones and the BioPrivacy collection tool, by which we recorded users keystrokes. We have a sample of 39 individuals. All the participants are smartphone owners and familiar with the experimental part of the process. The data collection process consists of 16 sessions in total and each session lasts 2 minutes approximately. During the sessions, a predefined sentence or a sequence of numbers were displayed on the screen and participants had to either memorize and input them or input them immediately after they were displayed. In this way, we have two kinds of inputs, one that the participants must read, memorize,

and then write and another that the participants must read and then immediately write. We select one individual from the 39 participants of our sample as Genuine user and the rest 38 as impostors. Finally, we will evaluate our system which is based on a Multi-Layer Perceptron (MLP).

6 Results

In this section we present the results of our research. Firstly, we present the results from the bioprivacy's collection tool. In Table 2 we see records in the database regarding keystroke dynamics. The features are duration, latency, the pressure on keys, and the location points (x, y) of the finger. The data received from the database were in accordance and consistent with the theoretical framework presented in Section 4.1.

Table 2. Keystroke dynamics data

Sensor	Key	Duration	Latency	Pressure	X_value	Y_value
TouchScreen (Keyboard)	p	134	189	1.0	943.0	404.0
	u	96	176	1.0	637.0	417.0
	f	57	358	0.50	339.0	243.0

From the data collected with the bioprivacy collection tool, we created a dataset that consists of 39 individuals and 1488 Instances. We separated the users into 2 classes (Genuine – impostor), one individual as a Genuine user and the rest 38 individuals as impostors. We also inserted a data preprocessing step by applying Normalize with scale 1.0.

We applied the MLP classifier with the following configurations: L 0.3 -M 0.2 -N 500 -H 3. The learning rate (L) is set to 0.3, the Momentum to 0.2, the training time (N) to 500, and we used 3 hidden layers (H). Our system achieved 97.18% Accuracy and 0.02% Equal Error Rate. In Table 3, we summarize the accuracy and EER.

Table 3: Accuracy and EER

Accuracy	Equal Error Rate
97.18%	0.02%

In Table 4, we present the detailed results by class. In the class Impostor, we achieved 94.5% True Acceptance Rate (TAR) while we have 0% False Acceptance Rate (FAR). In the class Genuine, we achieved 100% True Acceptance Rate (TAR) while the False Acceptance Rate (FAR) is 0.05%. Finally, in the Weighted Average, we have 97.2% TAR and 0.02% FAR.

Table 4: Detailed results By Class

Classifier	TA Rate	FA Rate	Class
MLP	94.5%	0%	Impostor
	100%	0.05%	Genuine
Weighted Avg.	97.2%	0.02%	

7 Discussion

This paper presents our research on the development and validation of a BBCA system (BioPrivacy) that is based on the user's keystroke dynamics using Multi-Layer Perceptron (MLP). Also, we introduce a new biometrics collection tool of the BioPrivacy system. We applied an experimental procedure of biometrics data collection where 39 individuals participated and completed the process. We received positive feedback on the application and users stated that they enjoyed the procedure. The data received from the database were in accordance and consistent with the analysis presented in the section 4.1 of the present paper.

Regarding the challenges of the keystroke dynamics collection methodology, they are based on something that the user must recall from his/her memory, like a password, and something that the user sees and types, like a captcha. In this way, we have two kinds of inputs, one that the participants must read, memorize, and then write and another that the participants must read and then immediately write. We created a dataset that consists of 39 individuals and 1488 Instances and 2 classes (Genuine – impostor). One individual as a Genuine user and the rest 38 individuals as impostors.

By applying a new design approach of the MLP and the BioPrivacy dataset we achieved an improved performance in relation to the literature. In [4] the performance of the FFNN is relatively low achieving FAR 14%, Accuracy 86% and EER 22%. In [24] the MLP achieved 12.8% EER. Our approach achieved Accuracy 97.18%, EER 0.02%, TAR 97.2% and FAR 0.02%.

7.1 Contribution

The principal contributions of this paper are as follows:
- **A new behavioral biometrics collection tool.** We develop a new BB collection tool, named BioPrivacy Collection Tool, by which we can collect behavioral biometrics of users on mobile devices.
- **We propose a methodology for the selection of an appropriate set of behavioral biometrics.** We present a methodology for the collection of behavioral biometrics.
- **We developed a BBCA System.** We present the development of a BBCA system based on MLP.

7.2 Limitations

As suggested by Stylios et al. [7], CA systems need to be evaluated under the high effort approaches to see the actual performance of machine learning and deep learning models under the spectrum of today's possible threats. Therefore, our system should be evaluated against the Frog-Boiling attack [27], the Algorithmic attack [42], the Mimic attacks [43, 44], and the Snoop-forge-replay attack [45]. Finally, our system was tested in a sample of 39 individuals and we plan to evaluate it in a larger sample of users.

8 Conclusions and further research

Smartphones are used as a mean to authenticate individuals, particularly in two-factor authentication schemes, which are often obligatory by several electronic services. Whether the legitimate user possesses the smartphone constitutes a great concern, and correspondingly whether the services are used by the legitimate user. In this paper, we presented our research on the development and validation of a keystroke dynamics Continuous Authentication System, named BioPrivacy. In our paper, we present a new behavioral biometrics collection tool, named BioPrivacy Collection Tool and we propose a methodology for the selection of an appropriate set of behavioral biometrics. We applied an experimental test to examine the consistency of the collected data with the theoretical framework presented in section 4.1. Our results showed that the collected data are consistent and in accordance with the theoretical framework. In the present research we developed a BBCA system based on MLP. Our system achieved Accuracy 97.18%, EER 0.02%, TAR 97.2% and FAR 0.02%.

Our future research focuses on the extension of the BioPrivacy Collection Tool to include more behavioral modalities. Also, we will collect data from a larger population to create a dataset that will be publicly available. Finally, we will evaluate our model against possible attacks vectors and highlight relevant countermeasures.

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