# Towards a Secured Authentication Based on an Online Double Serial Adaptive Mechanism of Users' Keystroke Dynamics

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Abir Mhenni*‡, Estelle Cherrier†, Christophe Rosenberger† and Najoua Essoukri Ben Amara‡
*ENIT, University of Tunis El Manar, BP 94 Rommana 1068 Tunis, Tunisia
Email: abirmhenni@gmail.com
†Normandie Univ, UNICAEN, ENSICAEN, CNRS, GREYC, 14000 Caen, France
Email: estelle.cherrier@ensicaen.fr
Email: christophe.rosenberger@ensicaen.fr
‡LATIS- Laboratory of Advanced Technology and Intelligent Systems, ENISo
University of Sousse, BP 526 4002 Sousse, Tunisia
Email: najoua.benamara@eniso.rnu.tn

***Abstract*—Password based applications are commonly used in our daily lives such as the social networks, e-mails, e-commerce, and e-banking. Given the increasing number of hacker attacks, the only use of passwords is not enough to protect personal data and does not meet usability requirements. Keystroke dynamics is a promising solution that decreases the vulnerability of passwords to guessing attacks by analyzing the typing manner of the user. Despite its efficiency in the discrimination between users, it remains non-industrialized essentially due to the tedious learning phase and the intra-class variation of the users' characteristics. In this paper, we propose a double serial mechanism to adapt the user's model over time. An important property of the proposed solution relies in its usability as we only use a single sample as user's reference during the account creation. We demonstrate that the proposed method offers competitive performances while keeping a high usability.**

***Keywords–Passwords; Authentication; Password security; Keystroke dynamics; Adaptive strategy.***

## I. Introduction

Numerous applications used in daily life are based on password authentication. However, these passwords might be easily forgotten. That is why we generally opt for a unique password or simplified ones to remember all of them. But this strategy, although widespread, increases the vulnerability of passwords to guessing attacks. Besides, password composition policies calculate the complexity of the used passwords and advise users to combine symbols, numbers and letters to make them more complex and unguessable so as to avoid hacking attacks [1], [2]. Moreover, many studies explored the passwords length to evaluate their security [3].

Keystroke dynamics consists in analyzing the user's way of typing to decide if he/she is genuine or not. It is an interesting solution which enhances the security of password-based applications [4] regardless of the size and complexity of the password. In addition to the use of a syntactic verification of the password, the way of typing it must be similar to the legitimate user. Keystroke dynamics belongs to behavioral biometric modalities that vary over time. The characteristics describing the users' typing rhythms are mainly extracted from the latencies between the pressing and releasing moments of two successive keys.

Even if this modality has proved its efficiency in several scientific research, it is still not fully adopted in industrialized applications, unlike other morphological modalities such as the fingerprint (*e.g.*, fingerprint scanner, Touch ID, ...) and the face (*e.g.*, FaceSentinel ...). This is basically owing to the need of several typing captures during the enrollment phase to create the reference template that describes the typing rhythm of the users. It is not the case for real applications for which the password is usually requested only once, when creating an account. In [4], the reader can find a recent state of art on keystroke dynamics. As shown in Table I, for all the published research papers, the learning phase requires a large number of samples which generally exceeds 20 according to [5].

TABLE I. Number of samples required for enrollment phase for some systems in literature.

| References | [6] | [7] | [8] | [9] | [10] |
|---|---|---|---|---|---|
| Number of samples | 15 | 40 | 50 | 112 | 200 |

Besides the problem of the tedious enrollment phase, keystroke dynamics particularly suffers from large intra-class variation, as well as other behavioral modalities. In fact, the typing manner of the users is affected by different parameters [11]–[13] like emotional state, activeness, acquisition conditions, and keyboard changing.

Adaptive strategies [14], [15] are a promising solution in order to solve these problems. Indeed, they aim to update the reference template during the use of the authentication system. Therefore, they take into account the variations in the typing manner of users as time elapses. In this paper, we put forward an adaptive strategy based on a single sample for the enrollment phase of the initial reference template. The reference template is enriched thanks to the proposed adaptive strategy. The maximum size of the adapted reference template is set to ten samples. The proposed method makes possible the general use of keystroke dynamics on Internet as an efficient and usable logical access control to Web services. We demonstrate the benefit of the proposed approach on different datasets from the state of the art.

The remainder of this paper is organized as follows. Section II presents the literature work on the adaptation strategies applied to the keystroke dynamics modality. Section III describes the proposed methodology and the contributions of this paper. Section IV details the experimental protocol, the used databases and the obtained results. Section V presents the main conclusion of this work and some perspectives.

## II. Related work

The literature has shown that the adaptive strategy is one of the most suitable solutions to cope with intra-class variation, which is inherent to the keystroke dynamics modality. This strategy generally depends on five parameters according to [16]:

- Reference modeling: It consists of choosing the representation of the biometric reference. The reference template is generally composed of several samples. In this case, it is referred to as a gallery. To our knowledge, no work considers a single sample as reference for keystroke dynamics.
- Adaptive criteria: The adaptation process is initiated only if this criterion is verified. Different criteria have been proposed in the literature. We can cite the double threshold [17], the quality index [18], the context-sensitive [19], and the temporal errors distribution [20].
- Adaptive mode: It defines how to label the presented queries. It can be done in a supervised way or in a semi-supervised one.
- Adaptive periodicity: It details how often to apply the adaptation process, either immediately after the query acceptance, or after having collected a specific number of samples.
- Adaptive mechanism: It concerns how to modify the reference to update it. Different mechanisms have been suggested, like the additive mechanisms [21], the replacement mechanisms [22], [23] and the combined ones [24], [25].

Let us discuss some adaptive mechanisms given they belong to the most interesting step for the whole strategy. In fact, among the additive mechanisms, the growing window [26] is well known and frequently used [27]. The process consists in adding each accepted query to the reference gallery. Concerning the replacement mechanisms, the sliding window [26] is also commonly employed. It consists in replacing the oldest sample by the newly accepted query. Moreover, both of these mechanisms are generally combined to operate together. For example in [28], three combined mechanisms were proposed. All of them are based on two sub-references. These sub-references are managed as follows:

1) Parallel sliding: One biometric sub-reference is never updated, and the other one is updated with the sliding window.
2) Parallel growing: One biometric sub-reference is never updated, and the other one is updated with the growing window.
3) Double parallel: One biometric sub-reference is updated using the sliding window, and the other one is updated using the growing window. Later, Pisani et al [27] proposed an improved double parallel that limits the size of the sub-reference adapted with the growing window based on a statistical classifier.

According to [28], after 5 adaptation sessions the parallel growing, parallel sliding and double parallel mechanisms present respectively an Error Equal Rate (EER) higher than 20%, 15% and 10%.

As a main contribution, we combine two mechanisms, namely growing and sliding. The novelty lies in the fact that they are applied to a unique reference and they operate sequentially: The growing window is firstly applied, then the sliding window occurs. The obtained results show that this approach actually enhanced the performances.

## III. Proposed approach

In this paper, we put forward a novel keystroke dynamics authentication method that fits the industrial application conditions such as to secure the logical access control to a service on Internet. The main interest is to consider only the password sample introduced when creating an account. Furthermore, thanks to our adaptation strategy, the intra-class variation is taken into account over the use of the system in a transparent way. In what follows, we describe the main steps of our approach: enrollment, verification and adaptation. Fig. 1 represents the overall scheme of the suggested approach.

### A. Enrollment phase

In this work, the initial user's reference template $\mathcal{G}_j$ of the user $j$ is composed of a single typing capture, the one introduced to save the user's password. A simple JavaScript code embedded in the service provider login page is sufficient for this task. From this single sample, we extract four characteristics which are time information between two successive keys:

- Time duration between two successive pressure events
- Time duration between two successive release events
- Time duration between one key press event and the successive key release event
- Time duration between one key release event and the successive key press event

These characteristics are commonly used and provided by the majority of available public databases of keystroke dynamics [29]–[31].

### B. Verification phase

The classification is ensured with the K Nearest Neighbor (KNN) classifier. It is one of the most used classifiers for the keystroke dynamics modality that demonstrates good performances [32]. Knowing that the KNN classifier can be used with different distance metrics, we propose to evaluate its performances with different metrics described below:

- Statistical distance: It is based on extracting statistical values from each retained biometric feature (mean and standard deviation). This distance is well known for its competitive performances and its calculation speed while being used for the keystroke dynamics authentication [33].

$$D_{STAT} = 1 - \frac{1}{n}\sum_{i=1}^{n} e^{-\frac{|\ q_i\ -\ \mu_i\ |}{\sigma_i}} \tag{1}$$

- Hamming distance: It consists in calculating the percentage of different coordinates between the novel query and the reference samples.

$$D_{HAMMING} = (\#(q_j \neq \mathcal{G}_j(i))/n) \tag{2}$$

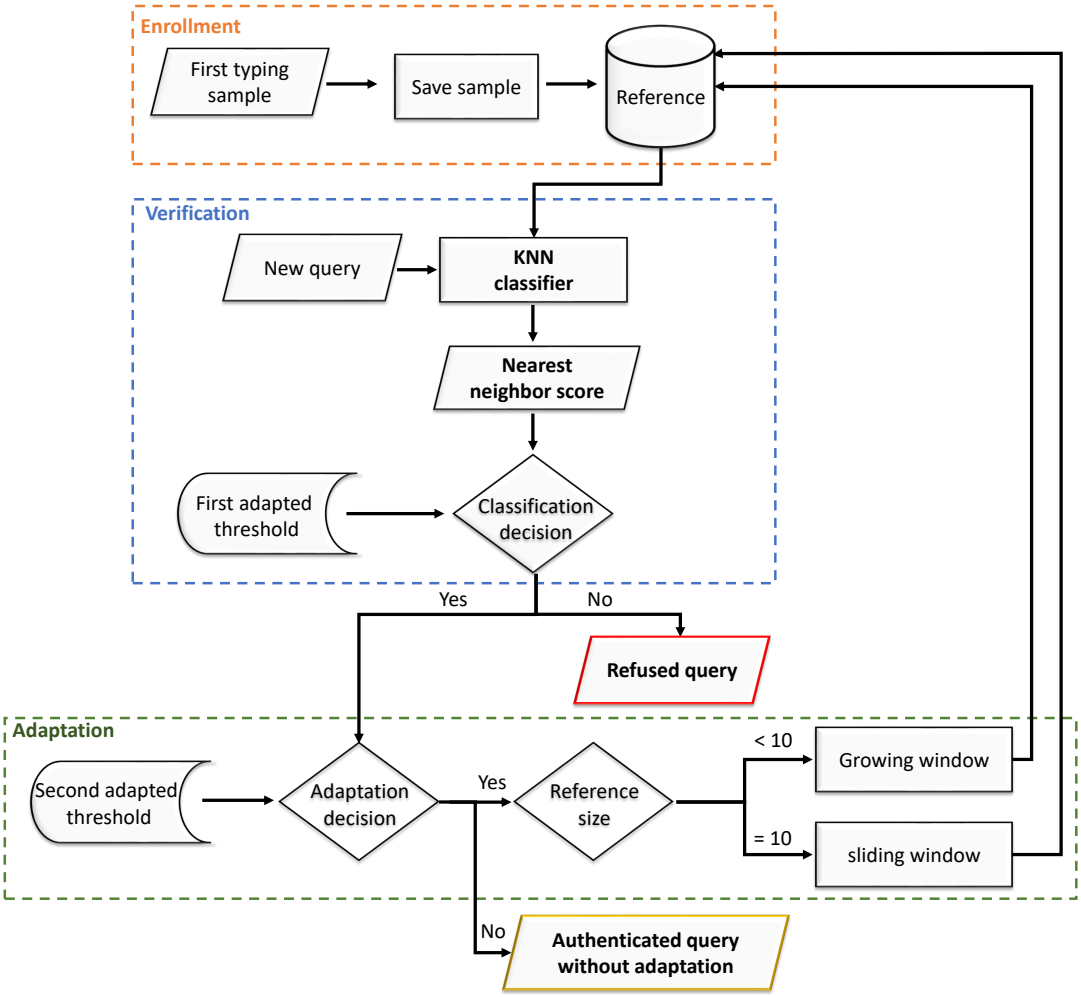



Figure 1. Description of the keystroke authentication process

- Euclidean distance: It is a simple distance metric usually used with the KNN classifier.

$$D_{EUCLIDEAN} = \sqrt{\sum_{i=1}^{n} (q_j - \mathcal{G}_j(i))^2} \quad (3)$$

- Manhattan distance: It calculates the sum of the differences of the corresponding components of the new query and the reference samples.

$$D_{MANHATTAN} = \sum_{i=1}^{n} |q_j - \mathcal{G}_j(i)| \quad (4)$$

where:
$q_j$ is the claimed query of the user $j$, $\mathcal{G}_j$ is the reference of the user $j$, $\mu$ is the mean vector of the reference, and $\sigma$ is the standard deviation vector of the user reference.

### C. Adaptation phase

The adaptation phase is required to remedy the problems of intra-class variation. It is ensured during the use of the authentication system to enhance its performances. For the proposed approach, we opt for the following choices:

- Reference modeling: To facilitate the enrollment phase task, the user is asked to only type the password once. This is a gread advantage in term of usability. Thus, the user's gallery is initially composed of a single sample. Each accepted query is therefore added to the gallery, to enrich the typing manner description. The maximum size of the gallery is equal to ten. We chose not to enlarge the reference, to facilitate the communication of the web server with the database.

- Adaptation criterion: The decision to update the reference is taken according to the adapted thresholds criterion which has already been proposed in [34]. It is based on the double threshold criterion [17]. Two thresholds are considered: The first one decides whether to accept or to reject the query, while the second one decides to use the accepted query whether to update the reference or not. All studies implementing the double threshold criterion, have generally used fixed thresholds [5], [28]. For our adaptation criterion, the thresholds are updated during the use of the system according to Equation (5):

$$T_j^{i+1} = T_j^i - e^{-\frac{\mu_j}{\sigma_j}} \quad (5)$$

where $\mu_j$ and $\sigma_j$ are respectively the mean and standard deviation vectors of the reference of the user $j$, and $T_j^i$ is the threshold of the user $j$ in the adaptation step $i$.

- Adaptation mode: The chosen mode for the suggested method is the semi-supervised one. The labels are assigned thanks to the KNN classifier. We apply it combined with different distance metrics to choose the optimal distance (best performances).
- Adaptation periodicity: The adaptation is performed online whenever a query is accepted by the adapted thresholds criterion.
- Adaptation mechanism: We propose the double-serial mechanism for our experimentations. At the beginning, the growing window mechanism is applied. Actually, each accepted query is added to the reference as long as the size of the gallery $\mathcal{G}_j$ is less than 10 samples. Once the size of the reference reaches 10 samples, the sliding window mechanism is launched to replace the oldest sample in the reference gallery with the last accepted query. The adaptation mechanism continues by updating the reference without any supervision by simply and efficiently considering the temporal variations in the keystroke dynamics.

As a consequence, once the decision criterion is verified, we update both the reference and the thresholds in a real time way. Thanks to the double-serial mechanism, the growing window mechanism serves to enrich the modeling of the keystroke dynamics of the users, whereas the sliding window is subsequently used to track the intra-class variation of the user's typing manner.

## IV. Experiments and results

We validate our adaptation approach of the keystroke dynamics on two public databases. The evaluation is done based on two commonly used metrics: the Error Equal Rate (EER) and the Area Under Curve (AUC) performance metrics. The experimentations and the achieved results are presented in the following.

### A. Datasets

We choose the *GREYC 2009* [30] and *Web GREYC* [29] databases for the validation of the proposed method. In GREYC 2009, 133 users participated in the creation of this database. We are interested in only 100 users, those who participated in five acquisition sessions during 2 months and provided 60 samples per user. For the Web GREYC, 118 users were involved in its creation. Only 45 among them participated in five sessions and provided 60 patterns. For both databases, we only consider users who provided 60 samples.

### B. Experimental methodology

To better describe the adopted methodology, we depict the used data stream generation. We have 60 samples per user. Thus, to assess the performances of our method, we define an evaluation protocol. For that purpose, we divide the process into sessions. At each session, we present eight new queries to the system. They are composed of five genuine samples and three impostor ones. According to the literature, the number of genuine samples per session is generally up to ten. Differently, we opt in our work for only five genuine samples, which allows precisely controlling the approach performances. The genuine queries are presented according to the chronological order of the database capture; whereas, the impostor queries are randomly introduced.

As a result, we obtain 12 adaptation sessions (60 genuine samples / 5). Since we store the first sample as reference in the enrollment phase, during the last session we present only 4 genuine samples. Three impostor attacks are randomly generated in each session by the samples of other users of the database. The biometric data stream is then divided into 37.5% (3/8) of impostor samples and 62.5% (5/8) geniune samples. The attack rate is higher than that generally used in keystroke dynamics studies [7], [28] (70% genuine and 30% impostor).

The initial thresholds are set for an EER equal to 3%. Then, after each query acceptance, the reference is updated according to the double serial mechanism, and the decision thresholds are adapted based on Equation (5).

### C. Results

Although the reference initially contains only a single sample, the obtained results are promising. Fig. 2 depicts the Receiver operating characteristic (ROC) curves with the associated EER and AUC performances for the twelve adaptation sessions of the different experimentations applied to the GREYC 2009 database. Fig. 3 illustrates the ROC curves and the performances (EER, AUC) of the first and the last adaptation sessions obtained using both databases.

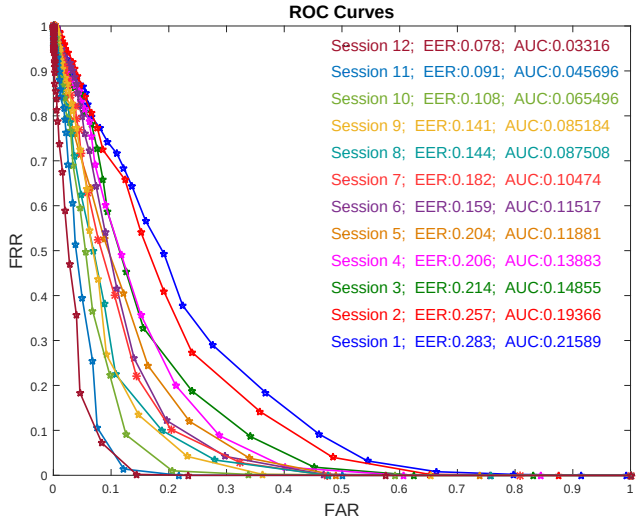
We choose four distance metrics to associate to the KNN classifier because we test a very large number of distances, but those that demonstrate competitive performances are hamming, statistical, euclidean and Manhattan. Comparing the metrics with each other, we note that the hamming distance and the statistical one perform better than others for the two considered databases.

We compare our approach with that of Giot *et al* [5], in which the authors applied the average mechanism based on 3 different classifiers: SVM, neural network and statistical distance. Thereby, an examination of the classifiers' performance is essential. Table II summarizes the compared results.

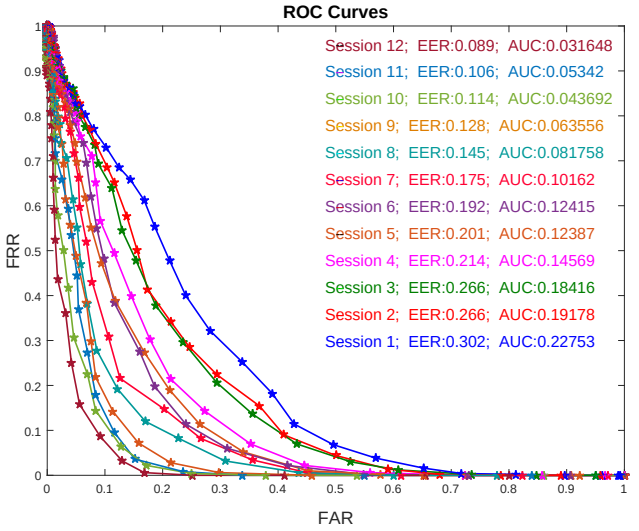
TABLE II. Comparison of the chosen classifier with those of previous work for GREYC 2009 database.

| Adaptive mechanism | Reference size Minimum | Reference size Maximum | Classifier | EER | AUC |
|---|---|---|---|---|---|
| Double | 1 | 10 | KNN (Hamming) | 6.1% | 0.013 |
| serial | 1 | 10 | KNN (Statistical) | 6.3% | 0.017 |
| mechanism | 1 | 10 | KNN (Euclidean) | 7.8% | 0.033 |
| | 1 | 10 | KNN (Manhattan) | 8.9% | 0.031 |
| Average | 5 | 15 | SVM | 6.96% | - |
| mechanism | 5 | 15 | Neural network | 8.75% | - |
| [5] | 5 | 15 | Statistical | 10.75% | - |

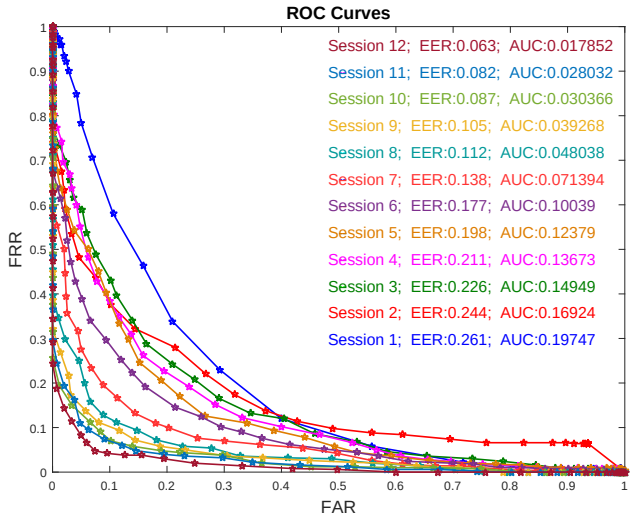
The best performance achieved in [5] is an EER equal to 6.96%, while using an SVM classifier and the reference was composed of 5 samples as minimum size and 15 samples maximum. In the present study, we use the same database as in the work of [5], thus obtaining two better performances: an EER equal to 6.3% using the KNN based on the statistical



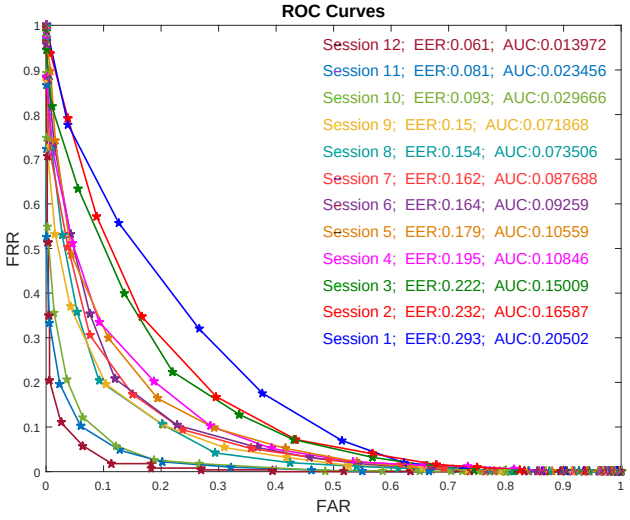

(a) Euclidean distance




(b) Manhattan distance

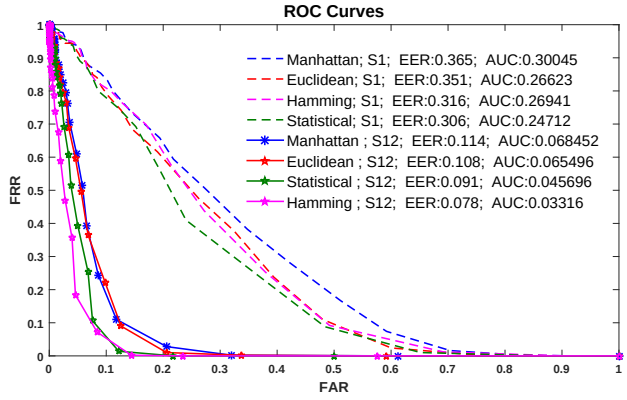



(c) Statistical distance

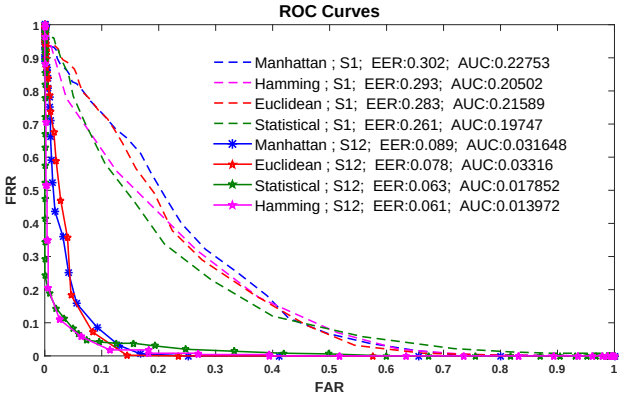



(d) Hamming distance

Figure 2. Roc curves evolving overs all adaptation sessions (GREYC 2009 database) and the associated performances (EER, AUC)




(a) WEB GREYC




(b) GREYC 2009

Figure 3. Roc curves of the first and the last adaptation session (S1,S12) and the associated performances (EER, AUC)

distance, and 6.1% using the KNN based on the hamming distance. We will benefit from the minimisation of the size of the reference while keeping better performances to facilitate the industrialisation of the keystroke dynamics modality. In addition, the KNN classifier compared to other classifiers, has the advantage of a low computing time which facilitates its deployment on the web server.

To highlight the benefit of the chosen adaptation criterion, we also test different types of thresholds:

- Global thresholds: A single threshold is set for all users and during the use of the password.
- Individual thresholds: The thresholds are user dependent but remain set during the system utilization.
- Variable thresholds: The thresholds vary according to users and over time.

As demonstrated in previous work, [34], the variable thresholds are performing better, as provided in Table III.

TABLE III. COMPARISON OF OBTAINED RESULTS (EER) WITH DIFFERENT THRESHOLDS.

| Distance metrics | Thresholds | GREYC 2009 | WEB GREYC |
|---|---|---|---|
| Hamming | Variable | 6.1% | 7.8% |
| | Individual | 7.3% | 9.5% |
| | Global | 8.1% | 10.7% |
| Statistical | Variable | 6.3% | 9.1% |
| | Individual | 6.9% | 10.4 % |
| | Global | 7.6% | 11.7% |
| Euclidean | Variable | 7.8% | 10.8 % |
| | Individual | 8.4% | 12.8% |
| | Global | 9.7% | 14.2% |
| Manhattan | Variable | 8.9% | 11.4 % |
| | Individual | 9.3% | 13.6 % |
| | Global | 10.1% | 15.3 % |

For our experimentation, the evolution of the size of the reference over time is significant. Since the number of accepted queries is not the same for all users, the size of the reference differs from one user to another at the end of the session. Table IV shows the minimum size and the maximum size of users' references in each session. As the maximum number of samples in the reference (10 samples) is rapidly reached, we therefore deduce that the growing window phase is quickly interrupted. Hence, the sliding window phase is more sustainable. Moreover, we notice that the slower the growing window phase is, the lower the performances are. In fact it is due to the weak recognition of the geniune user at the beginning. This is the case of the KNN based on Manhattan distance, unlike the other distance metrics especially the statistical one. Besides, user's having the minimum reference size are those whos keystroke dynamics is suffering from intra class variations more than the others.

To enforce the advantages of the proposed adaptation approach we tested other algorithms of the literature. We firstly tested the growing window mechanism with a reference containing a single sample initially. The size of the reference increases infinitely thanks to the adaptation mechanism. Secondly we applied the sliding window mechanism based on a reference sized 10. Thirdly the double parallel mechanism is conducted using two sub-references. One of them contains a single sample initially and it is adapted with the growing window mechanism. The other comprises 10 samples initially and it is adapted with the sliding window mechanism. Finally we also tested the proposed double serial mechanism while the reference is initialized to 5 samples and its maximum size is fixed to 10. All of these mechanisms are implemented by the KNN classifier with 4 distance metrics. The obtained results are summarized in Figure 5.

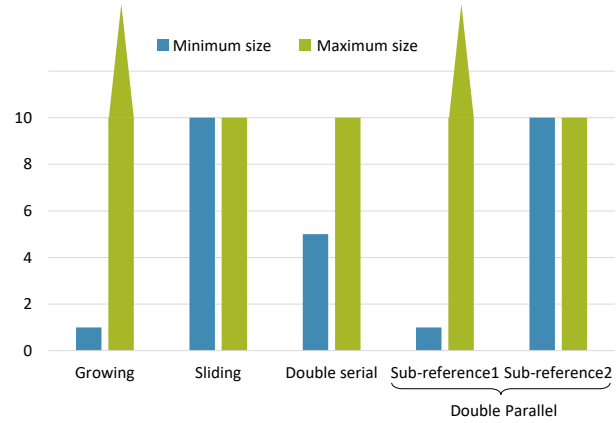



Figure 4. The minimum and the maximum size of the reference for the compared mechanisms.

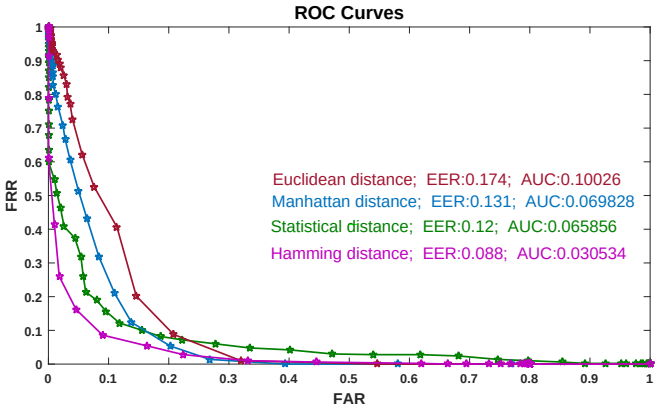
By applying the sliding window mechanism and growing window mechanism separately, the obtained results are less efficient. The performance achieved with the double parallel mechanism is good. But the double serial mechanism remains the best performing. While increasing the initial size of the reference by 5 samples we obtained better performances. This is due to the larger description of the keystroke dynamics of the users. But the performance difference at the final session is not very large. This is why we chose an approach based on a single sample in the learning phase in order to familiarize it with the industrial applications environment.

## V. CONCLUSION AND FUTURE WORK

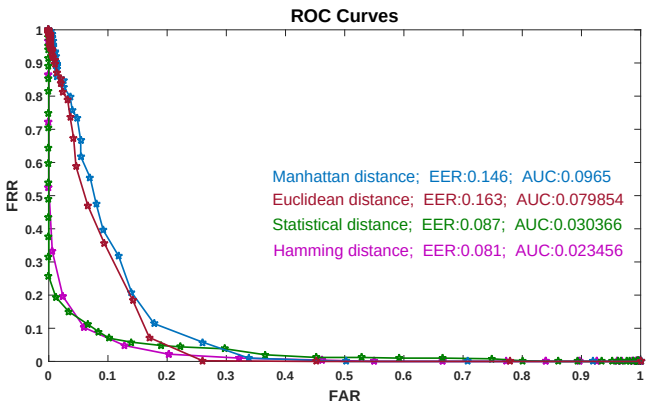
This paper investigates a novel method, which considers the conditions necessary for the application in real life of the keystroke dynamics modality especially for web services. In fact, in spite of its great advantage to reinforce the security of the password-based applications facing hacking attacks, this modality has not been industrialized yet. The main interest of the proposed method is that it minimizes as much as possible the number of samples used in the learning phase. Indeed, a unique sample is required initially. Besides, we adopt the double serial adaptation mechanism to remedy to the intra-class variations of the users' characteristics: It consists in combining the growing window and the sliding window mechanisms. The growing window serves to enlarge the users' galleries so as to capture more intra-class variability. After reaching the maximum size of the reference, which is fixed to 10, the sliding window mechanism takes place. It permits describing and following the temporal variation of the users' keystroke dynamics. Also, the adaptive threshold criterion has a great impact on the improvement of the obtained results. It is adapted to the gallery variation of each user. Thanks to all these choices, we have obtained a competitive performance with a minimal size of the reference template (one sample for the enrollment and ten for the maximum size of the reference gallery). The accomplished results have improved the state

TABLE IV. EVOLUTION OF THE USERS' REFERENCE SIZE FOR EACH DISTANCE METRIC OVER ALL ADAPTIVE SESSIONS: ILLUSTRATION OF THE MINIMUM AND THE MAXIMUM SAMPLES NUMBER.

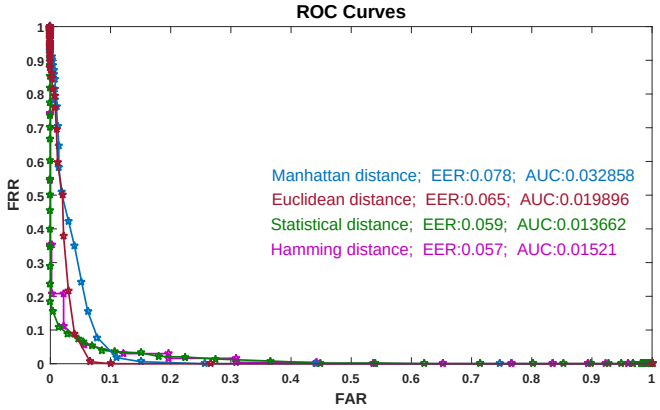
| Number of adaptive sessions | Min-Max number of samples in the reference | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | GREYC 2009 database | | | | WEB GREYC database | | | |
| | Hamming | Statistical | Euclidean | Manhattan | Hamming | Statistical | Euclidean | Manhattan |
| 1 | 2-4 | 2-5 | 2-4 | 2-4 | 2-5 | 2-5 | 2-4 | 2-4 |
| 2 | 6-10 | 5-10 | 4-8 | 3-7 | 5-9 | 6-9 | 4-8 | 4-8 |
| 3 | **10-10** | 7-10 | 7-10 | 6-10 | 8-10 | 7-10 | 7-10 | 6-10 |
| 4 | 10-10 | **10-10** | **10-10** | 9-10 | **10-10** | **10-10** | **10-10** | 9-10 |
| 5 | 10-10 | 10-10 | 10-10 | **10-10** | 10-10 | 10-10 | 10-10 | **10-10** |
| 6 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |
| 7 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |
| 8 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |
| 9 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |
| 10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |
| 11 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |
| 12 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 | 10-10 |



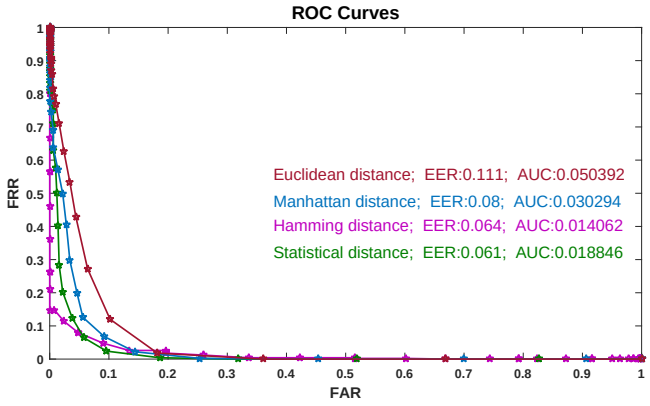

(a) Growing (1 features)




(b) Sliding (10 features)




(c) Double serial mechanism (5 features)




(d) Double parallel mechanism (10 features)

Figure 5. Roc curves of the last adaptation sessions and the associated performances (EER, AUC) of different adaptation mechanisms applied to the GREYC 2009 database

of the art results by more than 0.8% going up to 4%. The achieved comparison of the different metrics combined with the KNN classifier have been also interesting. In fact, it reveals which metric provide the best results. Eventually, the hamming and statistical distances are the most efficient compared to others. We also implemented the double serial mechanism with different reference sizes and compared it to the double parallel, the growing window and the sliding window mechanisms. The double serial mechanism demonstrated the best performances.

We are interested in investigating an improved method that achieves better performance from the first sessions. Thus, preliminary experiments of a user specific adaptive mechanism are being conducted. In addition, further works will concern long term validation on real web services.

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