Spectral Analysis of Keystroke Streams: Towards Effective Real-Time Continuous User Authentication

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Abstract: Continuous authentication using keystroke dynamics is significant for applications where continuous monitoring of a user's identity is desirable, for example in the context of the online assessments and examinations frequently encountered in eLearning environments. In this paper, a novel approach to realtime keystroke continuous authentication is proposed that is founded on a sinusoidal signal based approach that takes into consideration the sequencing of keystrokes. Three alternative time series representations are considered and compared: Keystroke Time Series (KTS), Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT). The proposed process is fully described and analysed using three keystroke dynamics datasets. The evaluation also includes a comparison with the established Feature Vector Representation (FVR) approach. The reported evaluation demonstrates that the proposed method, coupled with the DWT representation, outperforms other approaches to keystroke continuous authentication with a best overall accuracy of 98.24%; a clear indicator that the proposed keystroke continuous authentication using time series analysis has significant potential.

1 INTRODUCTION

Keystroke dynamics are a form of behavioural biometrics which can be used to authenticate keyboard (keypad) users (Gaines et al., 1980; Alshehri et al., 2016b). Broadly, we can identify two forms of keystroke authentication: (i) static authentication and (ii) continuous authentication. The first is used in the context of one-time authentication, for example password or pin number access to a system; thus in the context of fixed texts. Some examples, from the literature, concerning this form of authentication can be found in (Bleha et al., 1990; Killourhy and Maxion, 2009; Syed, 2014). The second form of authentication is typically applied in the context of continuous free text where it is desirable to continuously monitor the identity of a user; examples regarding this form of authentication can be found in (Shepherd, 1995; Monrose and Rubin, 1997; Dowland and Furnell, 2004; Gunetti and Picardi, 2005; Ahmed and Traore, 2014). One application, where continuous authentication is applicable, is in the case of students completing online assessments as part of distance and online learning systems.

The focus of the work presented in this paper is continuous authentication. The reasons for this are as follows: (i) there is little reported work concerning continuous authentication using keystroke dynamics due to the challenges involved, and (ii) the increasing prevalence of internet facilitated distance learning (eLearning, Massive Open Online Courses and so on) where continuous authentication is desirable.

In this paper, we introduce a novel mechanism for keystroke continuous authentication, namely Keystroke Continuous Authentication based Spectral Analysis (KCASA) mechanism. The proposed model is motivated by conceptualising the process of keyboard usage as a continuous stream of keystroke events, thus as a time series which can be transformed into the spectral domain to extract typing patterns. More specifically, the idea is to convert a given keystroke stream from the temporal domain (raw data) to the sinusoidal (frequency) domain. The intuition is that such transformations for time series streams lead to faster, and more accurate, detection of patterns (Chan and Fu, 1999; Keogh et al., 2001). Therefore, keystroke streams can be effectively employed for real-time/continuous user authentication. In this study, two types of spectral transform are considered: (i) Discrete Fourier Transformation (DFT) and (ii) Discrete Wavelet Transform (DWT).

The remainder of this paper is structured as follows.

In Section 2 a problem statement is provided together with a discussion of current issues with respect to keystroke continuous authentication. This is followed. in Section 3, with some definitions and preliminaries concerning the proposed model. Section 4 then discusses the proposed process for finding the similarity between keystroke sinusoidal signals, while Section 5 presents the proposed KCASA model. The evaluation of the proposed approach is given in Section 6. Finally, the paper is concluded with a summary of the main findings, and some recommendations for further work, in Section 7.

2 PREVIOUS WORK

The fundamental approach of using keystroke dynamics for user authentication is founded on two keystroke timing features: (i) key hold time (KH^t), the elapsed time between a key press and a key release; and (ii) flight time (F^t), the time between n consecutive key presses (releases), also sometimes referred to as flight time latency or simply latency (Obaidat and Sadoun, 1997). Both can be indexed using either a temporal or a consecutive numeric reference. Whatever the case, both flight time and hold time can be used to construct a distinctive typing profile associated with individual users (Gaines et al., 1980). These profiles are typically encapsulated using a feature vector representation of some form. In other words, typing profiles are frequently constructed using vectors of statistical values, such as the average and standard deviation of hold times, or the digraph flight time latency of selected frequently occurring digraphs. Authentication is then conducted by comparing the similarity between stored feature vectors represented typing (reference) profiles, which are known to belong to a specific user, and a previously unseen profile that is claimed to belong to a particular user. Although there has been only limited reported work directed at keystroke continuous authentication, what reported work there has been has used a feature vector representation; this has met with some success.

However, there are some limitations regarding the utilisation of the feature vector representation in the context of keystroke continuous authentication. One of the main limitations is the size of the required feature vectors; a significant number of digraphs and/or trigraphs has to be considered which is infeasible in the context of real-time continuous authentication. In (Monrose and Rubin, 1997) the feature vectors were composed of the flight time means of all digraphs in the training dataset. The continuous authentication was then conducted by repeatedly generating "test" feature vectors for a given user, one every minute, and comparing with stored reference profiles. If a statistically similar match was found, then this was considered to be an indication of user authentication. Although the typing profile was composed of all digraph features, the overall reported accuracy was a dsappoiting 23%. Similarly, in (Dowland and Furnell, 2004) the mean and Standard Deviation (SD) of the flight times for all digraphs and trigraphs in the training dataset were used. Some 6,390 digraphs were needed to make up a sufficient typing profile.

Some researchers have attempted to use an abstraction of typing features to decrease the size of the feature vectors. In (Gunetti and Picardi, 2005) the flight time, for frequent n-graphs, was used, although the approach was applied in the context of user identification (as opposed to user authentication). Thus, given a previously unseen sample, the shared n-graphs in the sample and the stored n-graphs were identified and collected in separate arrays. The elements in the arrays were then ordered according to flight time and the difference between the arrays computed by considering the orderings of the elements; a measure referred to as the *degree of disorder* was used (an idea motivated by Spearman's rank correlation coefficient (Zar, 1972)). Identifying a new sample required comparison with all stored sample (reference) profiles, a computationally expensive process. In the reported evaluation, 600 reference profiles were considered (generated from 40 users, each with 15 samples); the time taken for a single match was 140 seconds (using a Pentium IV, 2.5 GHz). However, construction typing profile using the average flight time of only shared n-graphs contained in the training data might not be representative of the n-graphs in the samples to be authenticated. This can, in turn, affect the authentication accuracy, especially in the context of real-time continuous authentication where typing patterns are extracted from free text; a substantial number of n-graphs are required. Furthermore, it can be observed from the study presented in (Gunetti and Picardi, 2005) that the authentication of one sample relies on all other samples in the training data. This can also lead to an efficiency issue in the context of continuous authentication.

In (Ahmed and Traore, 2014) an Artificial Neural Network classifier was used to build a prediction model to overcome the limitation of the work presented in (Gunetti and Picardi, 2005). Key-down time was used together with average digraph and monograph flight times to predict missing digraphs based on the limited information in the training data; thus, there was no need to involve a great number of keystroke features while constructing the typing pro-

file. This mechanism worked reasonably well in the context of static authentication in a controlled setting; typing of the same text using the same keyboard layout in an allocated environment. Thus how this would work in the context of continuous authentication remains an open question. A more general criticism of the feature vector approach is that the feature vector values are either typing pattern abstractions (for example average hold times) or only represent a subset of the data (for example only frequently occurring digraphs).

It is proposed in this paper that the established feature vector representation may not be ideally suited to keystroke continuous authentication. It is argued that by representing keystroke dynamics as time series, and transforming these series to the frequency domain, can lead to a better intepretation of typing patterns with respect to real-time continuous authentication. To the best knowledge of the authors, no prior work in the literature has considered the concept of the sinusoidal representation of keystroke dynamics in the context of continuous keyboard authentication. However, it should be noted that in (Alshehri et al., 2016b) the authors first proposed the idea of keyboard based user authentication using time series, but with respect to static text. In (Alshehri et al., 2016a) it was suggested that this could also be applied in the context of continuous text, although only hold time was considered. This paper presents a much more sophisticated implementation of the approach, encompassing: (i) the concept of transforming keystroke time series into the sinusoidal (frequency) domain, (ii) utilsing additional keystroke timing features to enhance authentication effectiveness, (iii) usage of a transformed sinusoidal sliding windows to achieve authentication, (iv) a data cleaning process for keystroke dynamic to be applied prior to any authentication being carried out and (iv) a dynamic method for bespoke similarity thresholds applicable to individual users.

3 REPRESENTING KEYSTROKE DYNAMICS AS TIME SERIES

As already noted, the process of typing produces a Keystroke time series $K_{ts} = \{e_1, e_2, \ldots, e_n\}$ where e_n is an independent data event, and $n \in \mathbb{N}$ is the length of the time series. Each data event e_i represents a tuple of the form $\langle t_i, k_i \rangle$ where: (i) t_i is a temporal index of some form, and (ii) k_i denotes some associated attribute (feature) value. Thus, $K_{ts} = \{\langle t_1, k_1 \rangle, \langle t_2, k_2 \rangle, \ldots, \langle t_i, k_i \rangle\}$. Such a time series can be viewed as a 2D plot with t along the x-axis and attribute value k along the y-axis (Figure 1). With respect to the work presented in this paper, the value for t_i is set to be a sequential ID number (sequence of key presses), whilst k records either flight time (F^t) or hold time (KH^t). Note also that in this paper only the univariate time series representation is considered, that is, in the evaluation section, we consider F^t and KH^t as independently and compare their effectiveness in the context of the proposed model. Figure 1 shows four pairs of K_{ts} sequences, each featuring $n = 300$ keystrokes, using F^t as the keyboard dynamic. The figure shows four (random) subjects selected from the datasets used for evaluation purposes as reported on in Section 6. Inspection of the figure clearly indicates that individual subjects poses distinct keystroke patterns and that these patterns can consequently be used to generate distinct typing profiles.

The generated keystroke time series can be used directly as described in (Alshehri et al., 2016b). However, as already noted, the usage of such "raw" time series is expensive in terms of efficiency and storage capacity (Agrawal et al., 1993). Thus the idea presented in this paper is to use some forms of transformation of the time series; it is conjectured that this will yield accurate results more efficiently. Two transformations are considered: the Discrete Fourier Transform (DFT) and the Discrete Wavelet Transform (DWT). Each is discussed in further detail in the following two sub-sections.

3.1 The Discrete Fourier Transform

The Discrete Fourier Transform (DFT) has been widely adopted with respect to time series data of all kinds (see for example (Agrawal et al., 1993; Vlachos et al., 2004)). In this paper, DFT has been used to transform keystroke time series data from the temporal domain to the frequency domain. The idea is that this will then allow comparisons of keystroke times series in a more efficient manner (than if the transformation had not been conducted) without losing any salient information. The compression is conducted by representing the keystroke stream as a linear combination of sinusoidal coefficients. Similarity between the transformed coefficients for any pair of corresponding signals can then be computed for authentication purposes.

Given a keystroke time series $K_{ts} = \{e_1, e_2, \ldots, e_n\}$, where $k_i \in e_n$ is either a F^t or a KH^t value, and n is the length of the keystroke time series. The DFT transform compresses K_{ts} into a linear set of sinusoidal functions with amplitudes p, q and phase w:

$$K_{ts} = \sum_{i=1}^{N} (p_i Cos(2\pi w_k F_i^t) + q_i Sin(2\pi w_i F_i^t)) \quad (1)$$

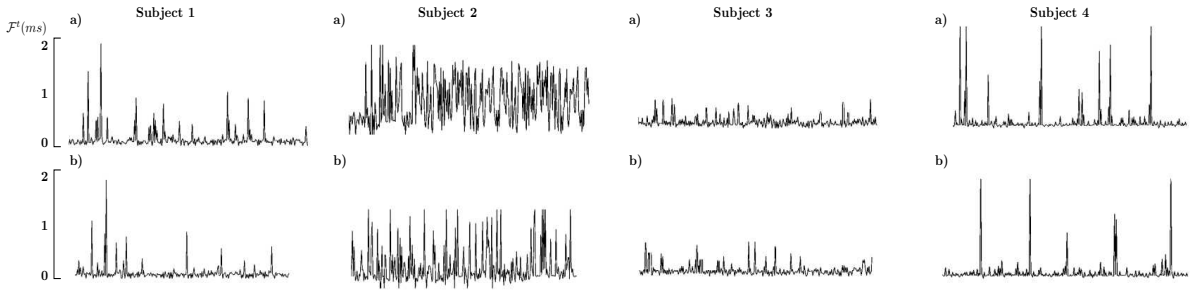


Figure 1: Keyboard time series examples ($n = 300$) for four subjects, two examples per subject, writing unspecified free text.

The time complexity for transforming (each) K_{ts} time series is $O(n \log n)$ using the radix 2 DFT algorithm (Janacek et al., 2005; Cooley and Tukey, 1965).
Using the DFT transform, the obtained K_{ts} is composed of a new magnitude (the amplitude of the discrete coefficients) and phase spectral shape in which the similarity can be computed between pairs of transformed K_{ts}. Similarity measurement will be discussed in further detail in Section 4. Further detail concerning the DFT can be found in(Harris, 1978).

3.2 The Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is an alternative form of time series representation that considers the time span over which different frequencies are present in a time series. DWT is sometimes claimed to provide a better transformation than DFT in that it retains more information (Chan and Fu, 1999). DWT can be applied to time series according to different scales, orthogonal (Haar, 1910) and nonorthogonal (Gabor, 1946). In this paper, an orthogonal scale is used for the DWT, more specifically the well known Haar transform was adopted (Haar, 1910) as described in (Chan and Fu, 1999). Fundamentally, a Haar wavelet is simply a sequence of functions which together form a wavelet comprised of a series of square shapes. The Haar transform is considered to be the simplest form of DWT; however, it has been shown to offer advantages with respect to time series analysis where the time series feature sudden changes. The transformation is usually described in terms of Equation 2 where, in the context of this paper, x is some keystroke dynamic.

$$\phi(x) = \begin{cases} 1 & \text{if} \quad 0 < t < \frac{1}{2} \\ -1 & \text{if} \quad \frac{1}{2} < t < 1 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The time complexity for transforming (each) K_{ts} time series, using the Haar transform is $O(n)$. Further detail concerning the Haar DWT transform can be found in (Edwards, 1991) and (Burrus et al., 1997).

4 SIMILARITY MEASUREMENT

Comparison of the transformed keystroke time series, for the purpose of continuous authentication, requires some kind of similarity measure. Given two keystroke time series, S_1 and S_2, of the same length, the simplest manner in which this can be achieved is to compare the sum or average of the Euclidean distances between all pairs of corresponding points in S_1 and S_2. The smaller the sum (average) the more similar the two time series are; If the sum (average) is 0 then S_1 and S_2 are identical. However, this simple approach does not take into account "offsets" (phase shifts and amplitude differences) that might exist in the time series. For the proposed KCASA model, detailed in the following section, Dynamic Time Warping (DTW) was therefore adopted. The advantage offered is that DTW takes into consideration phase shifts between pairs of signals whereas Euclidean distance does not (Ye and Keogh, 2009).
In more detail, the operation of DTW can best be described by considering two (transformed) keystroke time series $S_1 = \{a_1, a_2, \ldots, a_i, \ldots, a_x\}$ and $S_2 = \{b_1, b_2, \ldots, b_j, \ldots, b_y\}$, where x and y are the lengths of the two series respectively, and (a_i and b_j) are DFT or DWT coefficients. A matrix M of size $x-1 \times y-1$ is then constructed whereby the value held at each cell $m_{ij} \in M$ is the distance from point $a_i \in S_1$ to point $b_j \in S_2$:

$$m_{ij} = \sqrt{(a_i - b_j)^2} \tag{3}$$

The matrix M is used to determine a minimum *warping distance* (*wd*), which is then used as a similarity measure. A *wd* is the accumulated sum of the values associated with a *Warping Path* (WP) from cell $m_{0,0}$ to cell $m_{x-1,y-1}$. A warping path is a sequence of cell locations, $WP = \{w_1, w_2, \ldots, w_i\}$, such that given $w_k = m_{i,j}$ the follow on location is either $m_{i+1,j}$, $m_{i,j+1}$ or $m_{i+1,j+1}$. The *wd* associated with a particular WP is then the sum of the values held at the locations in WP:

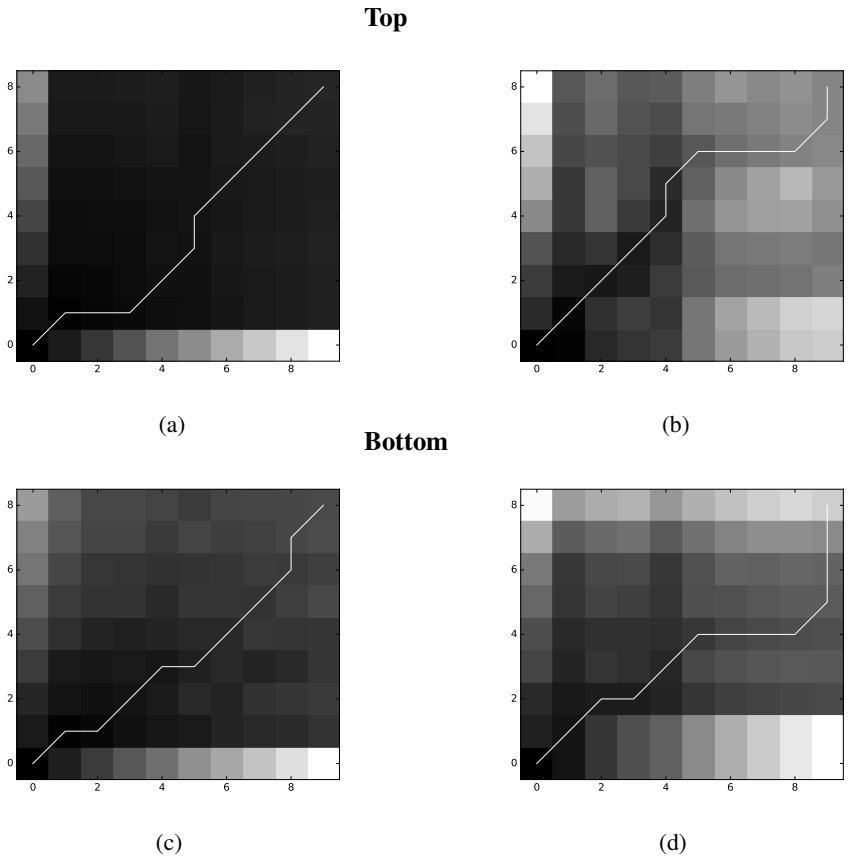


Figure 2: Warping Path (WP) examples. **Top:** WPs obtained from comparing two keystroke sinusoidal signals from the same subject typing different texts, (a) DFT and (b) DWT. **Bottom** WPs obtained from comparing two keystroke sinusoidal signals from two different subjects writing different texts, (c) DFT and (d) DWT.

$$wd = \sum_{i=1}^{|WP|} w_i \in WP \tag{4}$$

To arrive at a minimum wp, for each location the following location is chosen so as to minimise the accumulated wd. The"best" warping path is thus that which serves to minimise the distance from $m_{0,0}$ to $m_{x-1,y-1}$. The minimum wd for a pair of time series can therefore be interpreted as an indicator of the similarity between the two time series. Note that if $wd = 0$ the two keystroke time series in question will be identical.

To further illustrate the concept of DTW, Figure 2 presents four WPs, resulting from application of the DTW process. Figures 2(a) and 2(b) show WPs obtained when DTW was applied to keystroke sinusoidal signals for the same subject writing different unknown texts; Figure 2(a) using DFT and 2(b) using DWT. In contrast, Figures 2(c) and 2(d) show the WPs obtained when comparing keystroke sinusoidal signals associated with two different subjects, writing different texts; Figure 2(c) using DFT and 2(d) using DWT.

5 KEYSTROKE CONTINUOUS AUTHENTICATION BASED SPECTRAL ANALYSIS (KCASA) OPERATION

The proposed KCASA model operates using a windowing approach, continuously sampling keystroke stream subsequences $K_w \subset K_{ts}$. The window size w is predefined by the user. Thus $K_w = \{e_i, e_{i+1}, \ldots, e_w\}$ where i is a "start" time stamp. The keystroke stream subsequences can be made up of either flight time (F^t) or hold time (KH^t) values and can be processed simply as a straight forward time series, the Keystroke Time Series (KTS) representation. Alternatively, as proposed in this paper, the time series can be transformed, using the DFT or DWT representation as described above. In the evaluation presented later in this paper, the effectiveness of the DFT and DWT

representations is compared with the operation of the straight-forward KTS representation.

5.1 User Profile Calculation

A user profile $\mathcal{U}_p$ is a set of m non-overlapping keystroke streams (windows), or simply keystroke sinusoidal windows, $\mathcal{U}_p = \{W_1, W_2, \ldots, W_m\}$, where each window W has a length of ω. Note that $|\mathcal{U}_p|$ needs to be substantially greater than the window length ω, so that a number of subsequences (windows) can be extracted. Note also that the generated windows are prepared for the next transformation using DFT and DWT.

The value of ω is user defined. For the experiments reported on later in this paper, a range of ω values was considered from 25 to 150 key presses increasing in steps of 25, that is $\omega = \{25, 50, 75, 100, 125, 150\}$. By doing so, we can examine the effect of ω on performance in terms of accuracy. It was anticipated that a small window size would provide efficiency gains; desirable in the context of real-time continuous authentication.

The set $\mathcal{U}_p$ is also used to generate a bespoke σ threshold value. This is calculated by comparing all subsequences in $\mathcal{U}_p$ using DTW, and obtaining an average warping distance $\bar{wd}$ which is used as the value for σ:

$$\sigma = \bar{wd} = \frac{1}{|\mathcal{U}_p|} \sum_{i=2}^{|\mathcal{U}_p|} DTW(W_{i-1}, W_i) \qquad (5)$$

It has been shown that averaging the warping distances associated with a set of time series can lead to effective and more accurate classification of streaming data than if only one warping distance is considered (Niennattrakul and Ratanamahatana, 2009).

5.2 Subsequence Preprocessing and Noise Reduction

Prior to the commencement of the KCASA authentication process each newly collated keystroke time series must be "cleaned". The issue here is that F^t values can be substantial, for example when there is pause in the typing process. A limit is therefore placed on F^t values using a maximum flight time threshold value φ. Given a F^t value in excess of φ, the value will be reduced to φ. For the evaluation presented later in this paper, a range of values for φ were considered, from 0.750 to 2.00 seconds incrementing in steps of 0.25 seconds, thus: $\varphi = \{0.75, 1.00, 1.25, 1.50, 1.75, 2.00\}$.

With respect to key hold time KH^t, the time whereby a key is held down is normally no longer than 1 second. Inspection of the datasets used for evaluation purposes with respect to the study presented in this paper indicated that the highest recorded value of KH^t was 0.95 seconds. Consequently, it was felt that no maximum hold time threshold was required.

5.3 The KCASA Algorithm

The pseudo code for KCASA process is presented in Algorithm 1. As noted earlier in this paper, the principle idea is that, as typing proceeds, non-overlapping keystroke sub-series are collected, each of (window) length ω, and compared to previously obtained keystroke sub-series. On start up, an initial requirement is to confirm that the user is who they say they are by comparing the first collected sub-series with the user profile $\mathcal{U}_p$ as described in Sub-section 5.1. As the session proceeds, continuous authentication is undertaken by comparing the most recent sub-series W_i with the previously collected sub-series W_{i-1}. Algorithm 1 takes the following inputs: (i) window size ω, (ii) a similarity threshold σ (derived as described above in Sub-Section 5.1) and (iii) a φ threshold for F^t. The process operates continuously in a loop until the typing session is terminated (the user completes the assessment, times out or logs-out) (lines 4-6). Values for k are recorded as soon as the typing session starts (line 7). Note that in the case of flight time the value will be checked, and if necessary replaced, according to φ (lines 8 to 10). The k value is then appended to the keystroke stream $\mathcal{K}_s$. The *counter* is monitored, and sub-sequences are extracted whenever ω keystrokes have been obtained. The first collected sub-series ($W_1 \in \mathcal{K}_s$) is the startup time series; each subsequent sub-series W_i is then compared, using DTW, with the previous W_{i-1} sub-series.

6 EVALUATION

A series of experiments were conducted to evaluate the proposed KCASA mechanism so as to determine how well it performed in terms of the detection of impersonators. Comparisons were also undertaken with respect to a Feature Vector Representation (FVR), the established approach from the literature for keystroke continuous authentication. The metrics used for the evaluation were: (i) Authentication accuracy (Acc.), (ii) the False Acceptance Rate (FAR) and (iii) the False Rejection Rate (FRR). Note that FAR and FRR are the traditional metrics used to measure the perfor-

Table 1: Summary of datasets.

Dataset	# Sub.	Env.	Lang.	Features	Avg. size	SD
ACB	30	Free	English	F^t,KH^t	4625	1207
GP	31	Free	Italian	F^t	7157	1095
VHHS	39	Lab	English	F^t,KH^t	4853	1021

Algorithm 1 KCASA algorithm

Input: ω, σ, φ.
Output: Continuous authentication reporting

$counter = 0$
$\mathcal{K}_{ts} = \emptyset$
loop
  if termination signal received **then**
    break
  end if
  $k =$ keystroke feature (e.g. F^t or KH^t)
  if Flight time **&** $k > \varphi$ **then**
    $k = \varphi$ ▷ Noise reduction.
  end if
  $\mathcal{K}_{ts} = \mathcal{K}_{ts} \cup \langle counter, k \rangle$
  $counter++$
  if $REM(counter/\omega) == 0$ **then**
    $W_i =$ sub-series $\{\mathcal{K}_{ts_{counter-\omega}} \ldots \mathcal{K}_{ts_{counter}}\}$
    if $counter = \omega$ **then** ▷ Start up situation
      $Transform(W)$ ▷ Transform W to (DFT)/(DWT)
      Start up: authenticate W_i w.r.t $\mathcal{U}_p$ and σ, and report
    else
      Authenticate W_i w.r.t. W_{i-1} and σ, and report
    end if
  end if
end loop

mance of Biometric systems (Polemi, 1997). In more detail, the objectives of the evaluation were:

1. **Authentication Performance using the KCASA Model**: To compare the effectiveness of DFT and DWT in the context of the proposed KCASA approach, and the usage of the simple KTS representation (as proposed in (Alshehri et al., 2016b)), in terms of accuracy, FAR and FRR.
2. **Effect on Authentication Performance using Different Parameters**: To determine the effect of using different values for ω (the sampling window size) and φ (the maximum flight time threshold value).
3. **Efficiency**: to compare the run time efficiency of KCASA in the context of the three representations considered (DFT, DWT and KTS).
4. **Comparison with Feature Vector Approach**: To compare the operation of KCASA with the established feature vector based approach for keystroke continuous authentication.

Note that the evaluation was conducted using flight time and hold time so as to also analyse which feature yielded the better results.
The rest of this section is organised as follows. The datasets used for the evaluation are introduced in Sub-section 6.1. The results with respect to the first evaluation objective are considered in Sub-section 6.2, while those with respect to the second objective are considered in Sub-section 6.3. Efficiency is considered in Sub-section 6.4; and the comparison with the feature vector based approach in Sub-section 6.5.

6.1 Datasets

Three datasets were used with respect to the reported experiments taken from (Gunetti and Picardi, 2005), (Vural et al., 2014), and (Alshehri et al., 2016b). For ease of presentation the three data sets are identified using acronyms made up of the authors' surnames: GP (Gunetti and Picardi, 2005), VHHS (Vural et al., 2014) and ACB (Alshehri et al., 2016b).
The GP dataset was used with respect to the work reported on in (Gunetti and Picardi, 2005). The publicly available version of this dataset comprised 31 subjects typing free text in Italian (that used in (Gunetti and Picardi, 2005) comprised 40 subjects, however, the text associated with nine of the subjects was not included in the public version of the dataset). The VHHS dataset was collected in laboratory conditions. The subjects were asked to type both predefined text and free text in English; only the free text part was used with respect to the experiments reported on in this paper. The version of the authors' ACB dataset used with respect to the work presented in this paper comprised 30 subjects (an earlier version of the dataset consisted of only 17 subjects). Each subject was asked to provide free text samples (in English) in a simulated *online* assessment environment; the aim being to mimic the mode of typing when using an eLearning environment. Thus, the subjects used whatever keyboard they had at hand. Note that for the GP dataset only the F^t feature was available, whilst for the remaining two datasets both F^t and KH^t were

collected. Therefore the performance of KCASA using KH^t could not be evaluated using the GP dataset. Table 1 provides a summary of the three datasets used; the table also includes some statistical measurements concerning the average length of the time series in each dataset and associated Standard Deviations (SDs). For evaluation purpose, each record in each data set was divided into two; the first half was used to generate the typing profile $\mathcal{U}_p$ and the second for the continuous authentication evaluation.

6.2 Authentication Performance using the KCASA Model

The results obtained with respect to the evaluation directed at comparing the DFT, DWT and KTS KCASA representations, using either F^t or KH^t, are given in Tables 2 to 5; Tables 2 and 4 show the accuracy (Acc.), FAR and FRR results obtained using F^t, while Tables 3 and 5 present the results, using the same metrics, obtained using KH^t. For the reported experiments, $\omega = 75$ keystrokes and $\varphi = 1.25$ seconds were used as default settings. These parameters were used because experiments, reported on in the following sub-section, had indicated that these produced best results.

From Table 2, it can be observed that the DWT representation produced the best overall accuracy (average accuracy of 98.24% with an associated Standard Deviation (SD) of 1.07 when using F^t. With respect to FAR we can observe, from Table 4, that DWT also produced the best results, except in the case of the GP datasets where DFT was recorded as producing the best result. It can also be noted, from Table 4, that the DWT representation gave the best FRR results with an average of 1.50 and an associated SD of 0.14.

With respect to KH^t (Tables 3 and 5), a best average accuracy of 95.66% was obtained using DFT (with an associated SD of 2.40). Inspection of Table 5 shows that the best average FAR result was 0.04 when using the DFT representation, and the best average FRR result was 1.56 using DWT. Recall that evaluation using KH^t could not be conducted using the GP dataset because KH^t was not included in the GP dataset.

The results listed in Tables 2 to 5 are presented in summary form in Table 6. From this summary, it can be observed that the straightforward KTS representation did not perform well compared to the DFT and DWT representations. Also, from the results presented in the table, an argument can be made in favour of the DWT representation, coupled with F^t, which gave the best overall performance in terms of Acc, FAR and FRR.

6.3 Effect on Authentication Performance using Different Parameters

The results presented in the previous sub-section assumed a window size ω of 75 and a maximum F^t threshold value φ of 1.25. Recall that the latter is only applicable in the context of F^t. To evaluate the effect of these parameters, experiments were conducted using a range of values for ω and φ; $\{25, 50, 75, 100, 125, 150\}$ key presses for ω and $\{0.75, 1.00, 1.25, 1.50, 1.75, 2.00\}$ seconds for φ.

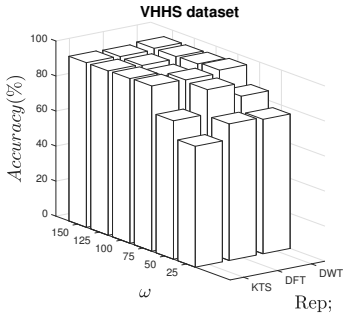


Figure 3: The effect of changes in the ω parameter on accuracy using KH^t feature for VHHS dataset.

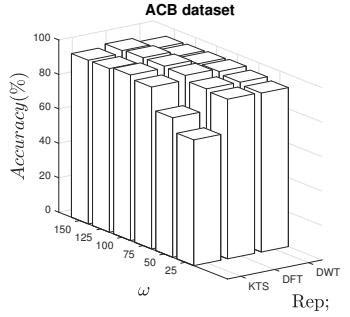


Figure 4: The effect of changes in the ω parameter on accuracy using KH^t feature for ACB dataset.

The accuracy results using KH^t, as the keystroke dynamic, are shown in the form of 3D bar charts in Figures 3 and 4 for the VHHS and ACB datasets respectively. From the figure, it can be seen that $\omega = 75$ produced better accuracy results for the two datasets in terms of all three KCASA representations, with the exception of the KTS representation in the ACB dataset where $\omega = 100$ produced a better accuracy.

The accuracy results obtained using F^t as the keystroke dynamics are presented, again in the form of 3D bar charts, in Figure 5. From this Figure, it can be seen that ω and φ values of 75 and 1.25, respectively, tended to produce best results, although the selection of φ does not seem to have had as much impact

Table 2: Accuracy results obtained using the three different KCASA representations when using F^t (best results in bold font).

Dataset	Flight time F^t		
	Accuracy		
	KTS	DFT	DWT
ACB	96.20	97.43	**99.22**
GP	95.47	96.94	**98.41**
VHHS	94.83	**97.43**	97.09
Average	95.50	97.27	**98.24**
SD	0.68	0.28	1.07

Table 3: Accuracy results obtained using the three different KCASA representations when using KH^t (best results in bold font).

Dataset	Key hold time KH^t		
	Accuracy		
	KTS	DFT	DWT
ACB	96.15	**97.36**	95.09
VHHS	94.33	93.69	**95.75**
Average	95.24	**95.66**	95.42
SD	1.29	2.40	0.47

Table 4: FAR and FRR results obtained using the three different KCASA representations when using F^t (best results in bold font).

Dataset	Flight time F^t					
	FAR			FRR		
	KTS	DFT	DWT	KTS	DFT	DWT
ACB	0.050	0.030	**0.026**	1.96	1.50	**1.37**
GP	0.039	**0.034**	0.035	1.98	1.72	**1.48**
VHHS	0.030	0.022	**0.016**	1.97	1.85	**1.65**
Avg.	0.040	0.029	**0.026**	1.97	1.69	**1.50**
SD	0.010	0.006	0.010	0.01	0.17	0.14

Table 5: FAR and FRR results obtained using the three different KCASA representations when using KH^t (best results in bold font).

Dataset	Key hold time KH^t					
	FAR			FRR		
	KTS	DFT	DWT	KTS	DFT	DWT
ACB	0.06	**0.04**	0.45	2.01	1.61	**1.38**
VHHS	0.03	**0.02**	0.04	1.97	1.91	**1.74**
Avg.	0.05	**0.04**	0.25	1.99	1.76	**1.56**
SD	0.02	0.01	0.29	0.02	0.22	0.25

Table 6: Summary of results presented in Tables 2 to 5.

Metric	F^t Feature			KH^t Feature		
	KTS	DFT	DWT	KTS	DFT	DWT
Acc	95.50	97.27	**98.24**	95.24	**95.66**	95.42
FAR	0.040	0.029	**0.026**	0.05	**0.04**	0.25
FRR	1.97	1.69	**1.50**	1.99	1.76	**1.56**

as the selection of ω. Note also that accuracy "levels off" as ω is increased.

6.4 Efficiency

To compare the efficiency of the considered KCASA representations, experiments were conducted in terms of the time to generate the user profiles in each case. For the experiments, ω was set to a range of values, as described earlier, whilst φ was kept constant at 1.25 because earlier experiments, reported on above, had demonstrated that the value of φ was less significant. The efficiency performance using F^t is presented in Figure 6 with respect to each of the three datasets considered. From the Figure, it can be seen that as ω increased the run time also increased. This was to be expected because the computation time required by the DTW process would increase as the size of the window ω increased. Interestingly, there are well-known solutions to mitigate against the complexity of DTW (see for example (Itakura, 1975; Sakoe and Chiba, 1978)); however, no such mitigation was applied with respect to the experiments reported on in this paper although this could clearly be done.

Overall the results indicated that when using the proposed transformations efficiency gains were made with respect to the simple KTS representation, with DFT producing better runtime results than DWT. It is interesting to note that the time given in (Gunetti and Picardi, 2005) to construct a user profile was 140 seconds, a significant difference compared to the proposed approach, although in (Gunetti and Picardi, 2005) the computing technology available in 2005 was used. It should also be noted that, in the context of KH^t, similar runtime results were produced to those presented in Figure 6, because both are using the same DTW similarity measure.

6.5 Comparison with Feature Vector Approach

From the literature, previous work on keystroke continuous authentication has frequently been founded on the Feature Vector Representation (FVR). It has already been noted that the proposed KCASA model has significant runtime advantages over the feature vector based approach (see Subsection 6.4). However, it was felt appropriate to conduct further experiments comparing the operation of KCASA with the feature vector based approach in terms of authentication ac-

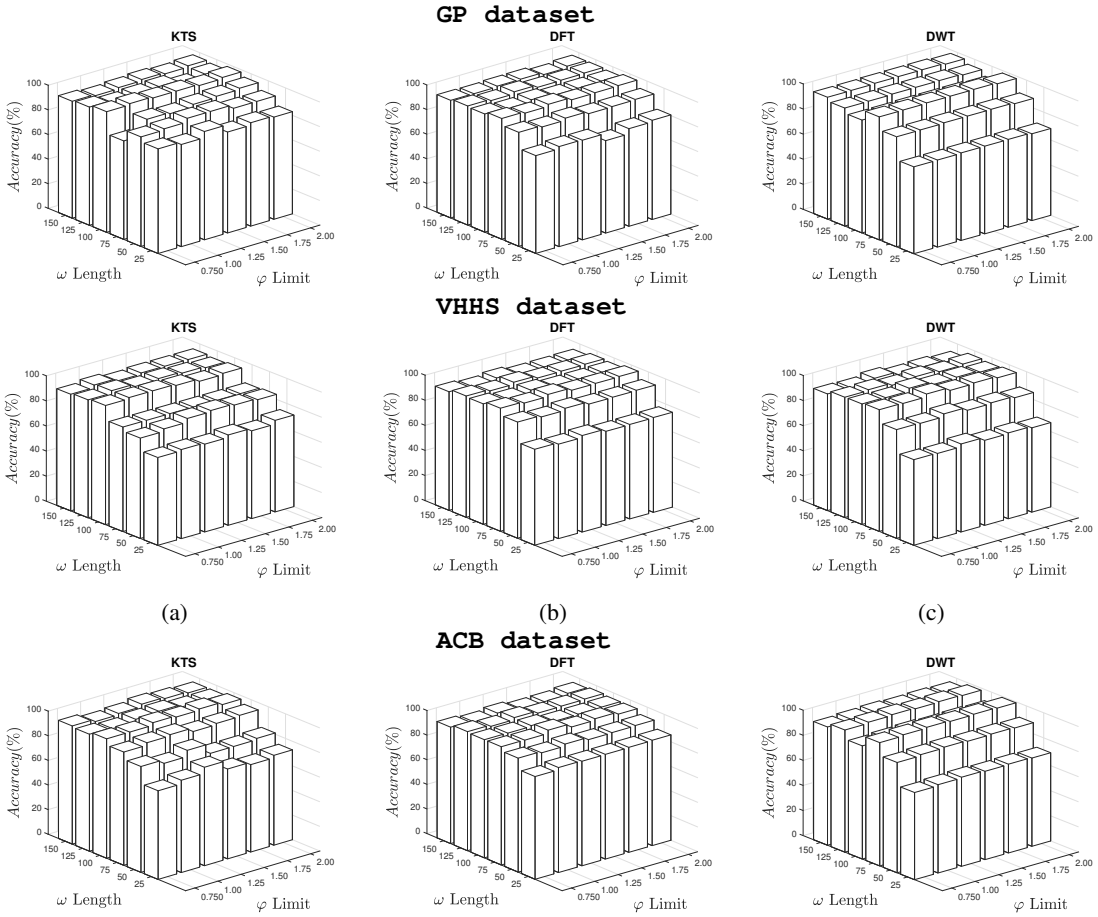
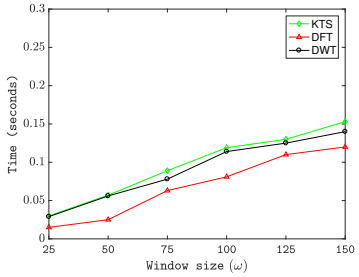


Figure 5: The accuracy results obtained for KTS, DFT and DWT using different values ω and φ.

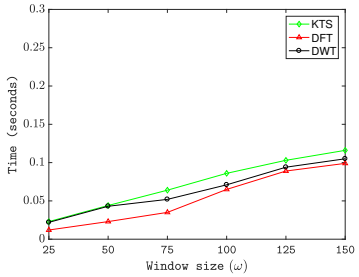
curacy. Using both F^t and KH^t appropriate feature vectors were generated. Consequently, further comparison could be made with the approach proposed in (Gunetti and Picardi, 2005) (see Section 2). The reason for selecting this approach was that, to the best knowledge of the authors, the approach had produced the best reported FAR and FRR results to date. However, the software for the approach was not publicly available; thus the authors encoded the mechanism themselves according to the description given in the original study. So as to conduct a fair comparison only F^t was considered, because the study in (Gunetti and Picardi, 2005) used F^t values. The average accuracy results obtained, when comparing the operation of FVR with the KTS, DFT and DWT representations, in terms of F^t, are given in Figure 7. The best accuracy result obtained for FVR was 90.15%, significantly worse than the accuracy results obtained using the KCASA representations which yielded a best accuracy result of 98.24% (when using the DWT representation).

7 CONCLUSION

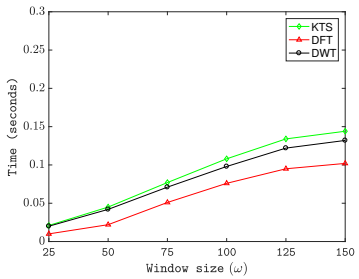
In this paper, a novel mechanism for realtime continuous keystroke authentication, called Keystroke Continuous Authentication using Spectral Analysis (KCASA) has been proposed, whereby authentication of user typing patterns is conducted by capturing keystroke dynamics in the form of spectral (frequency) streams. KCASA operates efficiently using either flight time F^t or hold time KH^t keystroke timing features. Two spectral transformations were considered to represent keystroke timing features: Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT). Keystroke spectral streams similarity was conducted using Dynamic Time Warping (DTW), although alternative time series comparison techniques could equally well have been applied. The KCASA model operates by continuously extracting non-overlapped keystroke sinusoidal signals captured using a sliding window of size ω. The most appropriate size for ω was found to be 75 keystrokes for both timing features (flight time F^t and key hold time



(a)



(b)



(c)

Figure 6: Runtime (seconds) comparison using flight time and the three KCASA representations with respect to each of the three datasets, (a) GP, (b) VHHS and (c) ACB.

KH^t). In the case of flight time, an issue was discovered with excessive flight times; flight times were thus capped with a maximum value defined by a parameter φ, the most appropriate value for φ was found to be 1.25 seconds. The reported experimentation and evaluation indicated that the most accurate representation was DWT using the F^t keystroke feature, while the most efficient was found to be DFT. Experiments were also reported on indicating that the proposed KCASA model outperformed the feature vector based approach used by comparator systems such as that reported in (Gunetti and Picardi, 2005). For future work, the authors intend to investigate the usage of multivariate keystroke time series (incorporating F^t and KH^t timing features together) within the context of the proposed KCASA model. Furthermore, the time complexity of DTW, in the context of the proposed representations, remains an open topic for future work.

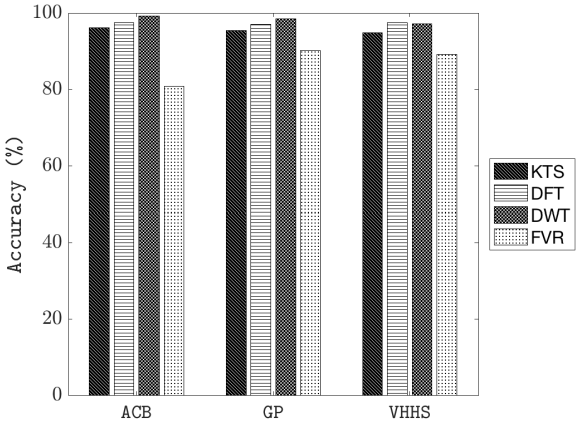


Figure 7: The obtained average accuracy using the three representations (KTS, DFT, DWT and FVR) with respect to the three datasets used. DWT shows a comparative performance with respect to KCASA model.

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