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State-of-the-Art in Handwritten Signature Verification System

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***Abstract*—Recently, handwritten signature verification (HSV) has become atremendously active area of research. Considerable results have been achieved in terms of accuracy and computation so far. Generally, biometrics can be divided into two types:Behavioral (signature verification, keystroke dynamics, etc.) and Physiological (iris characteristics, fingerprint, etc.). Signature verification is widely studied and discussed by using two approaches, on-line and offline approaches. Offline systems are more applicable and easy to use in comparison with on-line systems in many parts of the world. However, it is considered more difficult than on-line verification due to the lack of dynamic information. This paper presents State-of-Art about both types of HSV Systems. In this paper, we present recent methods used to capture data as well as different methods and techniques used in pre-processing steps. Additionally, current methods used for features extraction and approaches used for verification in signature systems are presented. Finally, we discuss approaches as well as techniques thathave been used. In conclusion, we recommend encouraging ideas to be incorporated in the future.**

Keywords: Offline (static) signature, online (dynamic) signature verification system, featuresextraction.

I. INTRODUCTION

In the past few decades, due to the significant development and the usage of communication in the industry, such as banking agreement, medical records, official publications and bills [27][42], the interest of having powerful techniques to authenticate legitimate persons to access the resources and certain systems has increased dramatically [42]. One simple authentication technique is done by something you knowsuch as personal identification numbers (PINs) or passwords. But PINs and passwords can be forgotten. Furthermore, another conventional authentication is done by something you havesuch as smart cards, which are also not truly reliable since cards can be stolen. However, with the advancement of technology, another method of authentication and identification called biometric authentication has been introduced. Biometric authentication is based on something you are or you do. The term biometric is derived from the Greek words bio (life) and metric (to measure) [15]. By definition, biometrics is a technique in which users will be identified or authenticated based on their physiological or behavioral traits [15].

The biometric system can be classified into two types; physiological and behavioral. In the physiological type, users do not need to perform any actions since the system will derive data from direct measurement of some parts of human’s body such as fingerprint, palm-print, iris, retina-based. On the other hand, in the behavioral type, users should perform certain actions in order to acquire data, for example, speech, keystroke dynamics and handwritten signatures[15][22].Signature verification is a process of authenticating or identifying people based on the differences of their handwritten signatures [42].

HSV systems can be divided into two main types:

A. Online, which is also known as dynamic [11][18]. The dynamic systems can be employed by using a digitizer to extract signature’s information such as x, y coordinates, time and pressure.
B. Offline handwritten verification is a process of verifying signaturesusing static images [42].

Currently,most researchers focus on the on-line signature verification due to its popularity in today’s marketplace [5].

HSVsystem enjoys some advantages over other biometric systems due to its market popularity. Firstly, it is socially and legally acceptable by the society [15][42]. Secondly it is user-friendly, non-invasive as well as acquired in many applications [42]. Thirdly, acquisition hardware for both online and offline has become ubiquitous which is inexpensive and already integrated in some devices such as tablets, PC and Smartphone[15][42]. Lastly, a signature can be easily changed whenever compromised similarly to passwords while it is not possible in other biometric systems [15][42].

On the other hand, HSV system suffers from several disadvantages.There are some inconsistencies to a person's signature.It is vulnerable to direct attacks using skilled forgery [11]. Moreover, it has a higher error rate compared to other biometric systems [42]. Finally, Handwritten Signatures are affected by the emotional and physical state of the signer[42].

The rest of this research paper is organized as follows. Section II presents the importance of this study.Section III addresses state of the art, theback-ground information about HSV system, which shows the current process in this area including online and offline handwritten systems. Finally, conclusion and future research will be discussed in section IV and V.

II. THE IMPORTANCE OF THIS STUDY

As we have mentioned earlier that HSV system has become an active area research due to its variation in

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algorithms, methods and techniques have been used to implement such systems. Studies showed that Equal Error Rate (EER) is ranging from 2% to 5% in online verification systems .Similarly,the ERR for offline verification systems is still high with 10% to 30%. However, despite the fact that use of online handwritten signature has increased remarkably in credit, debt, visa and bank cheques [29]. According to recent studies, there is a big lost of money in the USA banks which is about $53 Million [4] due to detecting thief which considered as signature forgery. The problem arises when the signature is required immediately to complete a process like credit or other online payments. Therefore, we think it is important to have State-of-Art in these areas to be aware with the current advancement and developments. Additionally, investigate why the EER still has not reached reasonable performance level to be used in all environments. Finally, pave the way to build and develop better handwritten signature verification in term of computation and accuracy.

III. STATE OF THE ART

Handwritten Signature Systems areeasy to use, non-invasive, can be changed easily whenever a signature is compromised and well accepted by the society. Therefore, the use of a HSVsystemas a technique for identification and authentication has significantly increased in the last decades[3]. In general, HSV systems can be classified into online and offline[11][18]. Offline handwritten systems deal with static images whereas; online handwritten systems deal with the obtained data from the acquisition hardware. With the advancement of technology, the interest of online handwritten signature is preferred since a signature can be acquired easily by using digitizing tablets, smartphone and PDAs. Furthermore, online HSVsystems usually yield a better result. In general, HSV systems can be divided into five main stages: data acquisition or registration, preprocessing, feature extraction and selection, comparison or verification and finally performance evaluation[5][13][15][18]. The order of these stages is shown in Figure 1.

A. Data Acquisition

The first step in HSV systems is data acquisition. Based on the data acquisition methods, the HSV systems can be divided into two types: offline and online.In the offline HSV systems data can be obtained by using offline acquisition devices such as a scanner or camera. Users sign their signature on a paper then the paper will be scanned. Obviously, the process of data acquisition will be done after the writing process [21]. The online category can be implemented by using various digitizing tools such as digitizing tablets and special pens, PDAs[15][21][37][42]. However, researchers in [11][42] used online public databases such as SVC2004, BIOMET and MYCT to evaluate system performance. The detail of each database can be found inthis paper[42].

B. Pre-processing

When the raw dataobtained from the tablet or any other devices, some pre-processing steps need to be applied in order to increase the system performance. Pre-processing is considered as a crucial step since users usually sign with different size and use different locations in the tablet regionfor their signatures. In addition,users usually cannot orientate themselves during the signing. However, in [18] a baseline was drawn in the signing area in order to help users to orientate themselves during the signing. Moreover, in the offline handwritten signature systems,noise is commonly considered as a major issue that may be introduced during the scanning process[2][3][27][20].

On the other hand, researchers in [12]do not applyany preprocessing steps in order to preserve the timing characteristics. They believed that applying pre-processing may result in losing some unique properties of the signer. Additionally, the tablet ,which they used, had a good resolution rate. The pre-processing step includes normalization, re-sampling, smoothing [15][18][42]as well as image enhancement to remove the noise using median filter [2][3][27][20], cropping signature images and image

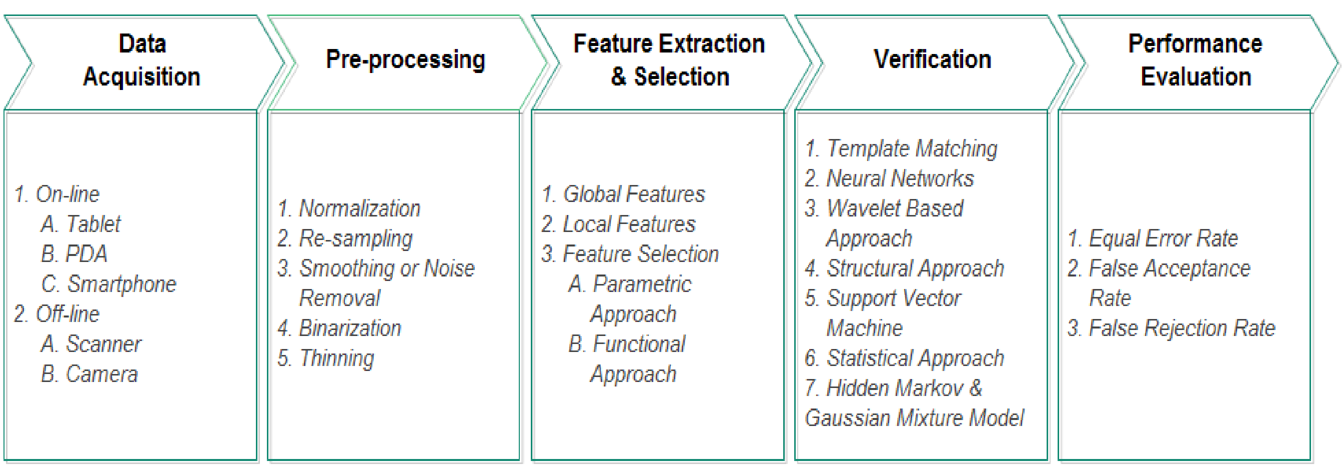

Figure 1: Stages in HSVSystem

binarization using Otsu binarization algorithm [3][27].
Usually, pre-processing steps can be composed of the following:

1) Normalization

The raw data, which is obtained from the tablet or any other sorts of methods, needs to be normalized because the different size of the signatures is considered as one of the major problems in the signature verification systems. Therefore, it is essential to apply normalization techniques to increase the system performance [15]. Signature size can be normalized by using one of the dimensions (width or height), which does not remove the writer's unique characteristics such as signature size [42]. Furthermore, translate normalization is also used, in which the signature centroid can be achieved by re-assigning the coordinate origin [26]. Size can be normalized in offline HVS by applying skeletonization algorithm [2].

In addition, orientation normalization is considered as the most difficult normalization because it is often hard to find the dependable reference angle [18]. However, as mentioned earlier in the previous sections, orientation problem can be avoided by drawing a baseline in the signing area. Finally, some investigators applied the duration normalization [16], in which the duration of all genuine writing signatures becomes the same for all the samples. Conversely, duration normalization is not adopted by some researchers since the difference of the signing duration is measured as an extremely vital feature [18].

2) Re-sampling

Some researchers performed re-sampling techniques to re-sample the input signature. The main aim of re-sampling is to remove the redundant data [11][15][42]. Basically, two types of re-sampling can be done which are temporal and spatial re-samplings. The former includes uniformly re-sampling signals at equi-distance point by applying interpolation [18]. The latter involves re-sampling signature curve at equi-distance points [50]. However, researchers in [18] avoided re-sampling techniques. They indicated that using re-sampling may result in losing crucial information such as speed characteristics of a genuine singer.

3) Smoothing or Noise Removal.

Some researchers applied smoothing techniques in order to remove the noisy points, which may be produced by the digitizing tablet, camera, scanning devices and pen [42][50]. Smoothing can be done by finding moving average or other weighted moving average [42].Moreover, [30] used median filter to remove noise their proposed combined online and offline approach.

4) Binarization

Some researchers have done binarization in which the image is binarized i.e. signature is represented in black pixels and other areas are in white pixels. It is worth mentioning that this method is usually implemented in offline HSV system[30].

5) Thinning

Radhika and Gopika proposed using thinning to represent signature strokes with minimum cross- sectional width by eliminating few foreground pixels [30].

C. Feature Extraction and Selection

Feature extraction has been considered as one of the most crucial steps in the HSV systems [15][18][42]. Up to now, so many approaches have been introduced by researchers for online and offline HSV systems. Technically, by using a typical commercial tablet, x and y coordinates, pressure and Azimuth and Altitude can be captured [18]. Mostly, there are two main types of features, which are global features and local features [5][13][20][42].

1) Global Features

A feature is called global when it is extracted from the whole signature. This basically means that the x and y values need to be shrunk into one value [2][5][13][20]. Examples of global features are density and wavelet transforms[2], means of x and y[5], average pressure, Pen tilt and average velocity[42] and correlation coordinates, signature duration, standard deviation of x and y[13]. A list of extracted global features can be found in these papers [9, 13].

2) Local Features

Local features correspond to specific sample points along the trajectory of the signature [2][5][20][42] such as x and y velocity, x and y acceleration. List of local features can be found in [20].Local features in offline HSV systems can be divided into two groups: statistical and geometrical features [2]. The statistical features are usually taken from the pixels of the signature image. Arya and Madasu et al.[23] obtained 8 partition features by using the horizontal method. Geometrical features describe the geometrical characteristic of image signature. Geometrical features have a tolerable property against distortion, style variation, rotation variation and degree of translation [38].

Apart from the above approaches and methods for feature extraction, Vargas et al.[42] proposed two different approaches for offline HSV systems, which are static and pseudo-dynamic approaches. In the first approach, measuring the geometrical features will be involved whereas, in the dynamic approach, the estimation of dynamic information of the image will be tried. Finally, segmentation has also been considered as a potential technique by many researchers since it usually results in improving the performance [5][39][47]. According to Richardi et al. [34], segmentation divides the signature into different segments. Moreover, Wirtz[46] considered the natural stroke as a segment. Furthermore, Schmidt [39] selected extreme points such as x and y then used them for segmentation. Finally, Rhee [33] proposed a robust technique called model-guided segmentation. He invented segment-to-segment comparison by dividing the signatures into the same number of segments.

3) Feature Selection

With regard to feature selection, based on the different types of features, mostly two different types of approaches have been proposed: parametric and functional approaches. The combination of these two approaches has also been proposed [20][21].

a) Parametric Approach

In the parametric approach, the comparison will be done from a set of global features [14].

b) Functional approach

Conversely, in the functional approach, the complete signals (x(t), y(t), p(t)) will be added to the feature set then the comparison will be point-to-point between reference and test signatures [17][20].

Many researchers have preferred the functional approach since it usually yields better result. Nevertheless, the parametric approach enjoys the simplicity and computation speed [12]. It is worth mentioning that, during designing HSV systems some external factors have to be taken into account. For instance, when a handwritten signature will be developed for the bank and teller application, the computation time is extremely important as well[15].

Gupta [14] and Gurrala[15] mentioned some limitations and issues for both approaches. With regard to parametric one, the number of global features that necessary to be calculated is considered as a major issue. Moreover, the number of samples that will be used in creating the reference signature is regarded as a problem, too. Finally, measuring the distance is also classified as a major issue. Similarly, the function based approach also suffers from some drawbacks. First, how many local features should be used. When segmentation is considered, how the segmentation should be done. Lastly, distance computation is also considered as a big challenge.

D. Verification

Verification is a process of making a decision whether a signature is genuine or a forgery. Many approaches have been introduced by researchers so far. Garcia-Salicetti et al. [13] structured the verification algorithms into two main approaches: distance based and model based approaches. The most well-known distance approach is a dynamic time warping (DTW), which is useful when signatures have different length. While, hidden Markov model (HMM) has long been used in model based approaches [13].Similarly, Al-Omeri et al. [2] classified the signature verification systems in terms of approaches used into seven types.

1) Template Matching

Inglis et al. [19] stated that template matching is a process of pattern comparison, in which a test signature will be matched with stored genuine signatures in the database. DTW is the most common algorithm used for template matching. DTW originated from speech recognition systems, and then has been widely used in the HSV systems. DTW uses a dynamic programming algorithm to find the best matching path.

In the recent years, some researchers have used different versions of DTW after some modifications. Firstly, Keogh et al. [8] proposed a Derivative DTW (DDTW), and they found that DDTW usually yields better result than standard DTW. Likewise, Yaniv and Burshtien[48] introduced enhanced DTW, which was found, to overcome the problems introduced by [35] in standard DTW as well as it yields better results in term of accuracy and speed. More recently, Salvador and Chan [35]have introduced fastDTW which is an approximation of DTW. They proved that the fastDTW is more accurate and twice faster than original DTW when a large amount of data is applied. On the other hand, Feng and Wah[17] proposed a new warping technique which is called extreme point warping (EPW). Unlike standard DTW, which is warping all points; EPW only warps important points such as peaks and valleys. They proved that EPW found to be more adaptable than standard DTW.

2) Neural Networks (NN)

Neural Networks (NN) are another approach which has been introduced. Power, ease of use, capabilities in learning and generalizing properties make the NN be widely used in signature verification systems [2]. Velez et al. [45] designed an offline signature verification system based on NN in which, signature class tested with comparison NN. Likewise, Alan et al. [1] proposed a method for verifying handwritten signatures based on NN. Static and dynamic features were extracted for NN training then Network topologies applied.

3) Wavelet Based Approach

In this approach, Multi resolution wavelet transform is applied to decompose the high pass and low pass signals. The high pass information is used in order to represent the sharper variation in the time domain. Furthermore, in order to achieve more accurate matching signature, curves have to be composed into multi resolution signals [2]. Samaneh and Moghaddam[36] applied discrete wavelet transform algorithm in their offline HSV systems.

4) Structural Approach

In the structural approaches, symbolic data structure such as trees, graphs and strings are used to represent patterns of the signature. In this type of system, the forgery's symbolic representation will be compared to prototypes stored in the database [2]. The concepts of structural comparison have been used by researchers. Likewise, Ramachandra et al. [31] proposed a signature verification system based on graph matching cross validation. Good results achieved for skilled forgeries when structural approach has been used, but the limitation is that large training setis required which leads to extensive computational time.Also, Support Vector Machineapproach is still not suitable for skilled forgeries andsuitable for simple and random forgeries.

5) Support Vector Machine (SVM)

SVM is used by some researchers: SVM is considered as kernel based techniques and represents the machine learning algorithm developments. SVM is widely used in classification and regression problems [10]. Fauziyah et al. [10] developed an online HSV system based on SVM. The system characterized the signature as pen-stroke containing x-y coordinates, and then applies the SVM algorithm to find similarity between two signatures. Similarly, Raza and Pourreza[44] proposed an offline system using SVM. In the best case, they achieved the same 96%identification rate and false acceptance rate (FAR) of 17%when applied on Persian signature set. In the best case, theyachieved the false rejection rate (FRR) of 19% and FAR of 2%when only casual forgeries are considered and FAR of 22% inthe case of only skilled forgeries when applied on Stellenboschdataset

6) Statistical Approach

Some researchers have used statistical concepts to perform some statistical operation such as the relation, the deviation between signatures to find similarities and dissimilarities [2]. Normally, statistical approaches follow the concept of the correlation coefficient, which refers to the measure of the strength and direction of the linear relationship between two sequences. Correspondingly, Mahalanobis technique is also used [9]. Debnath et al. [7] proposed a statistical approach for offline HSV systems. They applied the statistical methods to the array values. They converted the signatures into a set of 2D arrays of binary data in order to compute the mean and average. Later, the correlation coefficient was applied to decide whether a signature is authentic or forgery. Furthermore, another system based on statistical approach has been developed, but this time they used the standard deviation instead of using the correlation coefficient algorithm.

7) Hidden Markov Model (HMM) and Gaussian Mixture Model (GMM)

HMM and GMMhave been widely used.HMM and GMM are considered as well-known statistical approaches for developing HSV systems. In the HMM, the system will be modeled as set of Markov processes with unknown parameters [5]. GMM is a technique, which uses multidimensional Gaussian probability in order to cluster low dimensional data [5].

Zou et al. [24], proposed an online HSV system by using HMM for segmenting the input signal into to several segments. Then, the two adjacent segments were joined and obtained its spectral and tremor information using fast Fourier transformation. They showed that the results obtained were highly favorable. Moreover, Yang et al. [47] developed a system by using HMM, and they achieved 1.75% for false rejection rate and 4.4% for the false acceptance rate. Another example of using HMM can be found in [12]. Richardi and Drygajlo[22] used GMM to develop an online HSV system. They found that using GMM is devilishly favorable since the system performance was reasonably high, in which the EER was 1.7%. Meanwhile, some researchers used these two approaches together which is called fusion approaches. Ly-Van et al. [13] proposed a system using HMM with multivariate Gaussian Mixture for each stage.

E. Performance Evaluation

The performance of HSV systems can be evaluated based on two terms, the FRR and FAR [15][18][37].FRR measures the numbers of genuine signatures regarded as forgeries whereas FAR evaluates the number of forgeries classified as genuine[37]. These two types of error are correlated, which means by reducing the FRR the FAR will be increased, and vice versa [15]. It is worth mentioning that the FAR must be avoided in practical applications while the FRR should be tolerated [21]. To handle the FAR issue, the system has to be tested against different classes of forgeries[21]. Usually, there are three types of forgeries:

1- Random forgery in which, the users use their signature instead of the original signature to enter the system.
2- Simple forgery, in which forgers make no attempt to mimic the genuine signature.
3- Skilled forgery, which is considered as the most dangerous because forgers will be given time to mimic as closely as possible the genuine signature in terms of static and dynamic information [32], an example of forgeries has been shown in figure 2.

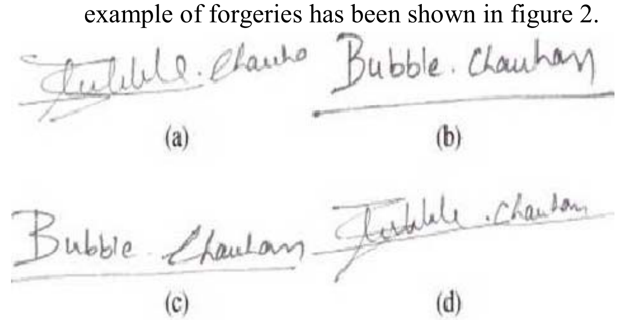

Figure 2**:**(a) original signature (b) Random forgery (c) Simple forgery (d) Skilled forgery [2]

Finally, EER is commonly used to gauge the performance of the HSV systems. EER is a point where FRR curve intersects with the FAR curve [18]. Figure 3 shows the detail of EER, FRR and FAR.

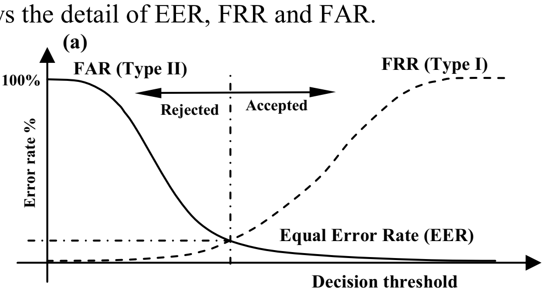

Figure 3:EER by using the FRR and FAR curves[37]

IV. CONCLUSION

In this paper, we presented the state art of HSV. The detailed documentation about both online and offline verification system is also presented. We have explained different methods as well techniques in all stages of developing HSV systems. It can be identified that both systems suffer from disadvantages such as low EER and Slow computation when group of features are considered. Meanwhile, some studies have achieved a good level of performance ranges from 1% to 3% of EER. However, it can be identified that there is still a big room for improvements in terms of performance and accuracy. To conclude, this study recommends that HSV needs more consideration before using it in real-time application and especially in banks as well as highly sensitive information systems. These kinds of systems are not highly reliable in term of EER compared to other biometric systems for example Iris Recognition, Finger-prints and etc.

V. FUTURE WORK

It can be identified that further researches need to be done in this area to improve the EER in term of computation time and accuracy. Therefore, we recommend the following future works:

- Adapt more approaches in verification step such as combining different approaches to achieve better results
- Develop international databases to test developed algorithm when they are published to be sure about the authenticity of algorithms
- Attempt to combine the online and offline approaches with the aim of obtaining reasonable results
- Attempt to ask two signatures instead one during verification. This may help to achieve a better error rate.
- Try to improve the quality of extracted features including local and global features as these kinds of system mostly relying on its features.

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