Journal of Applied Sciences

ISSN 1812-5654

science alert

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Journal of Applied Sciences 10 (15): 1632-1643, 2010
ISSN 1812-5654

Online Hand Signature Verification: A Review

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Abstract: In conjunction with the recent and amazing development of the Internet, online signature verification is being considered with inventive significance. Not only is online signature verification the least controversial of current biometric methods on the market, it is also one of the most acceptable, intuitive, fast and cost effective and operates with compact data. All these factors make it an ultimate solution for document authentication and enterprise workflow. Nowadays, a wide range of equipment is available for digitizing signatures such as palmtop or PDA-type devices, digitizer tablets, pointing devices and smart phones. This paper presents the state of the art in online signature verification. It addresses the most valuable results obtained so far and highlights the most beneficial directions of research to date.

Key words: Biometrics, personal authentication, online signature verification

INTRODUCTION

Classical user authentication systems have been based in something that you have (e.g., a key, an identification card, etc.) and/or something that you know (like a password, or a PIN). With biometrics, a new user authentication paradigm is added: something that you are (e.g., fingerprint, iris or face) or something that you do or produce (e.g., handwritten signature or voice). The convenience for paper and pen in the electronic era is the reason why people still use handwriting as a mean to convey, retain and facilitate communication. Together with this kind of information, handwriting is also a skill that individualizes people. Moreover, devices like PDAs, pocket PCS, tablet PCS, or 3G mobile phones might offer handwriting capabilities, because handwriting is considered as being more natural for humans and equally important to the possibility of size reduction by eliminating the keyboard. From this point of view, signature is a social and legal acceptable biometrics personal authentication method (Wu *et al*., 2005). A signature is a special case of handwriting, which includes special characters and flourishes. Many signatures can be unreadable. They are a kind of artistic handwriting (Cemil, 2005). Handwritten signature verification is the process of confirming the identity of a user based on the handwritten signature of the user as a form of behavioral biometrics (Nalwa, 1997; Jain *et al*., 1999, 2002).

Biometrics technology has a great potential for automatic personal verification and differently from other means for personal identification and verification (Pirlo, 1994). Of the various biometrics, signature-based verification has the advantage that signature analysis requires no invasive measurement and is widely accepted since signature has long been established as the most diffuse mean for personal verification in our daily life, including commerce applications, banking transactions, automatic fund transfers and so on (Ammar and Aqel, 2002; Plamondon and Srihari, 2000; Plamondon, 1994a).

There are two categories of verification systems are usually distinguished: static or off-line system for which the signature is captured once the writing processing is over and thus only a static image is available and dynamic or online system for which the signature signal is captured during the writing process, thus making the dynamic information available. This study deals with the online signature verification.

In online signature verification system, users write their signature in digitizing tablet, smart pens or hand gloves. The design of a online signature verification system initially involves the following four aspects: (1) data acquisition and preprocessing (input device), (2) feature extraction, (3) matching (classification), (4) decision making as shown in Fig. 1.

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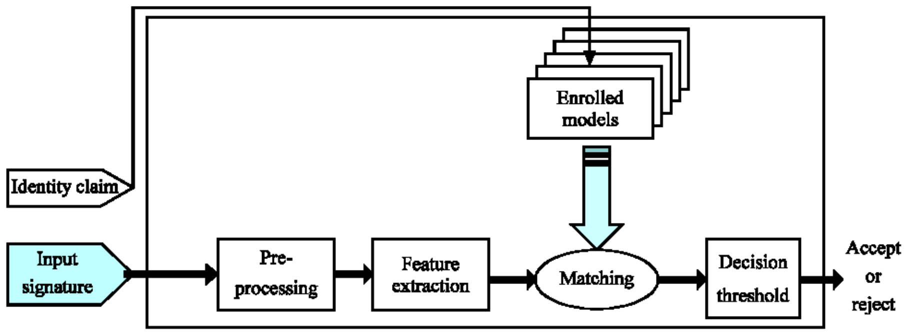

Fig. 1: Online signature verification system

Input device (input signature): The ordinary input device for on-line signature verification system is digitizing tablet, smart pen, or pen tablet.

Feature extraction: Some features will exhibit more discriminatory capability than others. Thus, once features are extracted, some features selection should be done. Two classes of features can be extracted in dynamic systems:

Static features: These features are extracted from the whole process of signing, such as maximum, minimum and average of writing speed, curvature measurements, etc. For this case, major complicatedness is related to the feature extraction step itself. The selection of stable, pertinent and efficient feature is not straight forward (Plamondon and Lorette, 1989).

Dynamic features: These features are the evolution of a given parameter as a function of time f(t), such as position x(t), y(t), velocity v(t), acceleration a(t), pressure p(t), etc. For dynamic feature methods, major difficulties are encountered in the matching step and the feature extraction step is almost non-existent (Plamondon and Lorette, 1989).

Matching: Matching consists of measuring the similarity between the claimed identity model and the input features. According to Jain *et al*. (2000) the four best-known approaches for pattern recognition are: (1) template matching, (2) statistical classification, (3) structural matching; and (4) neural networks.

Decision: Once a similarity measure is obtained, the decision implies the computation of a decision threshold. If the matching of similarity is greater than a threshold, the decision is ACCEPT, otherwise it is REJECT.

In an online signature verification system, the users are first enrolled by providing signature samples (reference signatures). Then, when a user present a signature (test signature) claiming to be a particular individual, this test signature is compared with the reference signatures for that individual. If the dissimilarity is above a certain threshold, the user is rejected.

During verification, the test signature is compared to all the signatures in the reference set, resulting in several distance values. One then has to choose a method to combine these distance values into a single value representing the dissimilarity of the test signature to the reference set and compare it to a threshold to make a decision.

There are two types of forgeries: a skilled forgery is signed by a person who has access to a genuine signature for practice and the random forgery is signed without having any information about the signature of the person whose signature is forged.

PERFORMANCE EVALUATION OF BIOMETRIC TECHNOLOGIES

Signature verification can be thought of as a two-class pattern recognition problem, one class consisting of genuine and the other consisting of forgeries. A great deal of variability can be observed in signatures from the same individual according to country, age, time, habits, psychological or mental state and physical and practical conditions. The only certainty in this domain is that when two signatures are identical, one of them is a forgery.

The performance of a biometric verification system is evaluated according to the error representation of a two-class pattern recognition problem, that is, with Type I and II error rates. The Type I error rate (False Rejection Rate (FRR)), measures the number of genuine signatures classified as forgeries as a function of the classification threshold. The Type II error rate (False Acceptance Rate (FAR)), evaluates the number of false signatures classified as genuine ones as a function of the

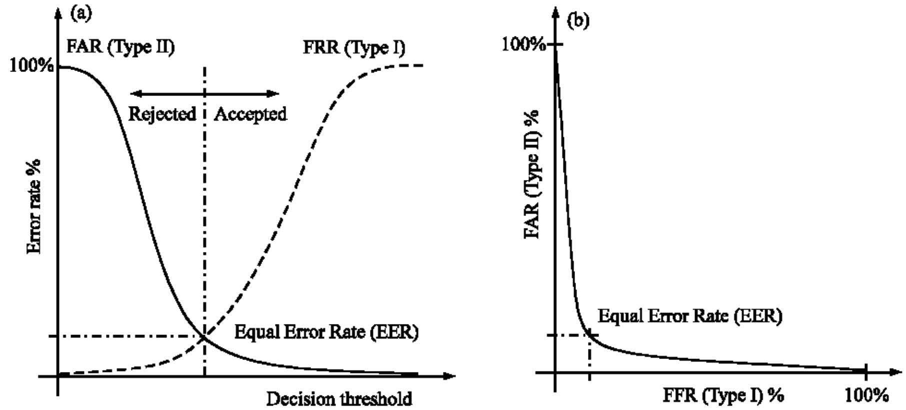

Fig. 2: Curves of FRR and FAR as a function of the classification threshold and the corresponding error trade-off curve

classification threshold. To evaluate the performance of our signature verification system, we adopt the Equal Error Rate (EER) at which the percentage of FAR equal the percentage of FRR. This EER provides an estimation of the statistical performance of the algorithm. It can be adopted as a unique measure for characterizing the security level of a biometric system.

Munich and Perona (1998) described that it is obvious that it can trade-off one type of error for the other type of error. If every signature accepted, there would have a 0% FRR and a 100% FAR and if every signature rejected, there would have a 100% FRR and a 0% FAR. The curve of FAR as a function of FRR, using the categorization threshold as a parameter, is called the error trade-off curve. It provides the behavior of the algorithm for any operating regime and it is the best descriptor of the performance of the system. From the practical point analysis, this curve is often simplified into a scalar, the Equal Error Rate (EER). The error rate at which the percent of false accepts equal the percentage of false rejects. This equal error rate provides an estimate of the statistical performance of the algorithm, it means that EER provides as estimation of its generalization error. Figure 2a and b show the curves of FRR and FAR as a function of the classification threshold and the corresponding trade-off curve.

Depending on the testing conditions and on the availability of data, a signature verification system can be validated with different types of forgeries.

THE STATE OF THE ART IN ONLINE SIGNATURE VERIFICATION

According to Gupta (2006), who cited Herbst and Liu (1977) and illustrated that the researchers used an experimental pen which was mounted with two orthogonal accelerometers and collected the sample signatures at the rate of 200 times per second. They observed that most signatures were taken time from 2 to 10 sec with an average time of about 5 seco.

In addition, the researchers further reported that each signature was partitioned by heuristically into segments and after the segments were aligned on the duration of the time interval matching segments were cross correlated and inconsistency between the reference and the test signature. It revealed that with the range of 1 to 2 sec of segments showed the best performance. Seventy users evaluated the method where the first 5 sample signatures were collected from each of the users. The number of reference signature(s) either one or two was selected such that the selected signatures and the remaining signatures were at least equal to a pre-specified value in terms of distance measurement. These were considered to be the best reference signatures. An additional 695 signatures as genuine test and 287 as forged signatures were used for testing purpose. From the experimental results, it revealed that more than 20% False Rejection Rate (FRR) and around 1% False Acceptance Rate (FAR) was obtained.

Gupta (2006) cited Liu *et al.* (1979) investigated and reported that the proposed two acceleration measurements used by Herbst and Liu (1977) along with the additional writing pressure during the signature process. They observed that the correlation involving waveforms of pressure demonstrated slight inequity since the correlation values dominated the gross form of the pressure waveform, but they found that it appeared more effective when low frequency paper contact components of the pressure waveform was removed. The researchers conducted some experiments using the acceleration and pressure correlations and separately where they used signatures from 24 subjects and obtained results less than 1% of FAR and near about 16% of FRR . It demonstrated the better results than earlier of Herbst and Liu (1977).

In the field of on-line signature verification, a number of studies have investigated. Gupta (2006) cited Crane and Ostrem (1983) presented a method in which testing consisted of a registration phase. In the registration phase, the mean and Standard Deviation (SD) of each feature was calculated from 10 or 12 sample signatures and a reference vector of feature. Furthermore, the reference signature vector was then compared to the test signature vector and calculated the Euclidean norm of the distance. Based on the distance, if small enough the signature accepted as genuine, otherwise rejected it as forgery. The system allowed up to 3 trials and a false rejection occurred only if all three signatures failed the verification test. The experimental result reported that the FAR (False Acceptance Rate) and FRR (False Rejection Rate) varying from 0.5% to about 3%.

In order to improve the efficiency of signature verification, De Bruyne (1985) proposed 18 global features sets which included six dynamic features and other static features. Dynamic features such as number of pen lifts, pen-up time and writing time, total time along with the maximum writing time and the velocity. On the other hand, the static features such as area, proportion, Standard Deviations (SD) of x and y values and total displacements ratio in the direction of x and y were considered. Ten sample signatures were used to compute the reference signature. The comparison has been done using test signature with the reference signature and with the forgeries as well. A maximum likelihood test was applied for the comparison tests. Eleven persons' signatures were used for testing purpose. The experimental results obtained 3% of FRR and 2% of FAR where 10 sample signatures were used.

Gupta (2006) cited Hastie *et al*. (1991) and reported that a model where a test signature was assumed to consist of a reference signature which was changed from time to time. The researchers described the following five-step signature verification method:

Step 1: Smoothing-a cubic spline approximation was used to average out the measurement errors
Step 2: Speed-speed was computed after smoothing
Step 3: Time warping-a time warp function was computed so that correspondence was found between the reference signature and the test signature
Step 4: Segmentation-the signature was segmented using low speed regions (e.g., low speed considered as 15% of mean speed) into a sequence of segments called letters
Step 5: Averaging-estimated the reference signature based on letters

The authors further reported that the results of using the method described above were presented in the study published by Nelson and Kishon (1991). The authors reported that the ten genuine signatures samples and four forgeries from each of 20 subjects were used for testing purpose. The experimental results obtained FRR of 0% and FAR of 18%. Nelson and Kishon (1991) also argued the point that a signature might play important roles in hand signature verification based on the shape and dynamics of a signature.

A hand signature verification system yielding good performance for point-of-sale applications designed by Lee (1992), who cited by Gupta (2006). The authors described that a database where 105 human subjects contributed total 5603 genuine signatures and 4762 forgeries in their research work. Three types of forgeries were used in their research work such as skilled, random and timing forgeries. To forge the each genuine signature, two forgers were used in which each forger contributed to all three types of forgeries. From each forger six samples of each type of forgery were collected. This process produced 3744 forgeries where $105\times2\times18 = 3780$ samples were used for experimental process. Furthermore, forgeries were collected randomly from the 105 individuals for 22 subjects. Eight dissimilar individuals contributed six skilled forgeries each of the 22 subjects. These provided total 792 forgeries where as $22\times8\times6 = 1056$ were used for verification purpose. It therefore appeared that a number of the forgeries were rejected. A subset of the database were used from total of 11 genuine signatures each for 22 individuals in which 6 were used for the reference signature and 5 for testing purposes. On the contrary, for the verification purpose, the researchers used 704 forgeries taken from 8 forgers for every one in which each contributed 4 forgeries for each individual. From their experimental result, it was reported that an EER of 3.8% was obtained.

A technique based on Bayesian neural networks for online hand signature verification of Chinese signatures presented by Chang *et al.* (1993) was reported in the paper published by Gupta (2006). The authors investigated and reported that a set of 16 features was used in their research which included the features such as total time, number of segments, average velocity, width/height ratio, average distance in the eight signature directions, upper-part/lower-part density ratio as well as left-part/right-part density ratio. The researchers used a database from 80 individuals who contributed total 800 genuine signatures and 200 simples. The experiment conducted for verification using 200 skilled forgeries by 10 forgers and obtained 2% of FRR and 2.5% of FAR.

A multilevel hand signature verification system that used global features as well as point-to-point comparison using personalised thresholds was presented by Plamondon (1994b). The author described that the system used a set of global features which included the percentage of pen-up time, total pen-down time and the percentage of time while the angular velocity is positive. Those features were used for the initial stage of verification. The author further added that the signature was normalised by rotation as well as scaling and local correlations were calculated between the part of test signature velocity values and the values of the corresponding reference signature through segments alignment based on the elastic matching. On the other hand, the second stage was carried out by a third stage implying computation of variations amongst the normalised values of the coordinate of the test and the reference signatures by local elastic pattern matching.

In the stage of the performance evaluation, 3 signatures from each of 8 human beings were used and 8 other persons contributed 3 forgeries for each of the 8 genuine signers in 64 sessions after having access to genuine signatures and with features on the dynamics of these signatures. Six other subjects were used to produce an additional set of genuine signatures, nine signatures were used for each one where three of which were used as reference signatures. Tests were carried out with the two databases for reconciling the differentiating function to minimised inaccuracies. For that reason, it appeared that test signatures as well as reference signatures were used in determining individual thresholds that minimised inaccuracies. Hence the results achieved FAR of 0.5% as well as FRR of 0.0%, which cannot be pondered as trustworthy. Besides, the testing was very restricted and the number of signatures evaluated was minimum.

Nelson *et al*. (1994) proposed a statistical method for hand signature verification which was found in the article published by Gupta (2006). The authors reported that the proposed method used a set of 25 features which was included two time-related features, 6 features related to velocities and accelerations, four shape-related features, eight features giving the distribution density of the path tangent angles and four giving angle-sector densities of the angular changes and a feature relating to the correlation between the two components of pen velocity. They also articulated the statistical basis of hand signature verification and then used three different methods for computing the distance between the reference signature and the test signature, such as the Euclidean distance method, Mahalanobis distance method and the quadratic discriminant method. A simple method of feature selection is described which essentially consists of computing the ratios of the Standard Deviation (SD) to the mean for each feature and rank-ordering the features according to this ratio. It was not reported that why a feature with least normalised standard deviation would contribute competent discrimination amongst the genuine signatures and forgeries. A combination of schemes were used such as individual best 8, 10, 12 or 14 of the 25 features, were evaluated. The achievement of all these sets was alike even though the individual best 8 and 10 found to perform the excellent result with FRR near 0%. The authors identified that using an Euclidean distance approach along with the best 10 features out of the 25 features and achieved as outcomes with 0.5% of FRR and 14% of FAR.

Lee *et al.* (1996) designed an on-line dynamic signature verification systems with a data base of more than 10,000 signatures in (x(t), y(t))-form was acquired using a graphics tablet. The authors further reported that they extracted a 42-parameter feature set at first and advanced to a set of 49 normalized features that tolerate inconsistencies in genuine signatures while retaining the power to discriminate against forgeries. They studied algorithms for selecting and perhaps orthogonalizing features in accordance with the availability of training data and the level of system complexity. For decision making the researches studied several classifiers types. A modified version of majority classifier yielded 2.5% EER and, more significantly, an asymptotic performance of 7% FAR at 0% FRR was reported using 15 parameter features.

Gupta and Joyce (1997) cited by Gupta (2006) proposed an algorithm with the aspire of using a small set of global features that are easy to compute and invariant under most two-dimensional transformations such as rotation, slant and size. They used 6 features in the initial experiments like total time, number of velocity sign changes in the x and y directions, number of acceleration sign changes in the x and y directions and total pen-up time. The authors further reported that the hand signature verification algorithm was used based on Euclidean distance. It showed that time by itself was the best single discriminator and pen-up time was also a good discriminator. Furthermore, the authors also added that the included path length in the set of attributes improves the performance of the technique and good results were obtained when path length was included and the reference signature built using 10 sample signatures. An FRR of about 0.5% was obtained with FAR of little more than 10%. The more comprehensive explanation can be found in the authors published article.

According to Gupta (2006) cited Nalwa (1997) investigated and reported that his proposed technique was based on applying jitter, parameterisation over normalised length, aspect normalisation, centre of mass, sliding computation window, moments of inertia, torque, weighted cross-correlation and warping, moving to coordinate frame and saturation. The author further enlightenment that to test the proposed algorithm three signature databases were used. The first comprised of 904 genuine signatures and 325 skilled forgeries from 59 different individuals. The second set comprised of 982 signatures from 102 individuals, collected in a solitary session. There were 401 skilled forgeries. A number of genuine signatures and forgeries were removed from the data set as well. The third data set comprised of 790 genuine signatures and 424 skilled forgeries from 43 signers. The outcomes from the three test databases as well as one that included all three, applying 4, 5 and 6 reference signatures were demonstrated. The experimental results obtained the EER within the range from 2 to 5%.

Kashi *et al*. (1998) described a method for the automatic verification of on-line handwritten signatures using both global and local features. The global and local features ware captured for various aspects of signature shape and dynamics of signature production. The researchers demonstrated that adding a local feature based on the signature likelihood obtained from Hidden Markov Models (HMM), to the global features of a signature, considerably improved the performance of verification. The authors further added that the performance of signature verification methods tested on the Murray Hill database. The test database 542 genuine signatures and 325 forgeries were used. Each reference set used the first 6 signatures of every one of the 59 subjects. There were 32 volunteers, who provided a total of 325 forgeries. The best result obtained from their research method with an EER of 2.5%.

Jain *et al*. (2002) cited by Kholmatov and Yanikoglu (2004) and Gupta (2006) reported that the researchers were used a method in which specific critical points like start and end points of a stroke as well as changes of trajectory points, were extracted for every signature. Moreover, the authors enlightened that the number of strokes was used as a global feature. Two types of local features, spatial and temporal, were extracted from the x and y coordinates. The proposed technique was tested using two datasets. The first dataset contained 520 signatures, ten signatures each from 52 writers, collected in one session. The second dataset was a superset of this dataset and contained a total of 1,232 signatures collected from 102 writers, seventeen of which contributed more than ten signatures in multiple sessions over a period of up to one year. Twenty writers provided three skilled forgeries each (a total of only 60) after viewing an original signature. The best error rates using a common threshold were 3.3% FRR and 2.7% FAR and the best error rates using writer-dependent thresholds were 2.8% FRR and 1.6% FAR. The FAR rates appeared to be based on random forgeries. No FAR for skilled forgeries was reported.

A new Dynamic Time Warping (DTW) technique for the signature verification was proposed by Feng and Wah (2003). The authors argued that the technique was originally used in speech recognition and has been applied in the field of signature verification with some success since few decades ago. The new warping technique proposed the authors named as Extreme Points Warping (EPW). The authors further reported that the techniques proved to be more adaptive in the field of signature verification than DTW, given the presence of the forgeries. EPW and DTW were compared on a database of 1000 signatures of 25 users. With the use of EPW, the equal error rate was improved by a factor of 1.3 and the computation time was reduced by a factor of 11. From the experimental observation the authors further pointed out that EPW was much faster than DTW and considerably better EER.

Ortega-Garcia ***et al.*** (2003) cited by Gupta and Joyce (2007) investigated and reported the signature verification results using the five time sequences, x and y coordinates, pressure, inclination and attitude as well as three derived sequences, path tangent angle, path velocity and log curvature radius. Furthermore, the authors described that if the first and second derivative of each of these sequences computed, the total time sequences were found 24. Hence, a signature sample that has say 1000 samples would generate 24,000 values. The functional values were then normalised to obtain zero mean and unit standard deviation. Signatures were modelled using Hidden Markov Models (HMM) based on the sequences. The performance was tested using a signature database of 15 genuine signatures and 15 forgeries each from 50 people. The tests were conducted using the same threshold for all, resulted in 4.83% EER which reduced to 0.98% by using user-specific thresholds.

A new stroke-based algorithm for dynamic signature verification was presented by Qu *et al*. (2004). The algorithm was developed to convert sample signatures to a template by considering their spatial and time domain characteristics and by extracting features in terms of individual strokes. Individual strokes were identified by finding the points where there found a (1) decrease in pen tip pressure, (2) decrease in pen velocity and (3) rapid change in pen angle. Experimental results were achieved for signatures from 10 volunteers over a 4 months period. All the collected genuine signatures were classified into training and verification classes. An experiment was performed to evaluate the performance of the verification system. A total of 110 signatures, split into 50 reference and 60 test signatures, from 10 volunteers were used in this experiment. Each volunteer performed 5 signatures to train their signature template and performed another 3 genuine signatures as test signatures. In addition, for each template, 3 skilled forgery signatures were performed by other volunteers. First, found the best 4 non-stroke features for the system (total time during the signing process, average writing speed, variance of pressure signal in 10 sliding windows and mean of the x displacement signal in 10 sliding windows). When the threshold was set to be 75%, the system achieved a FRR of 30% and FAR of 46.67%. In order to evaluate the performance of the stroke based features, the proposed system added one or two stroke based features to the 4 non-stroke feature system. Based on the previous non stroke based feature system, if adding time duration for velocity significant stroke as the 1st stroke based feature and correlation coefficient for the pressure significant stroke as the 2nd feature, both of them improved the system with 6.67% of FRR and 13.33% of FAR.

Yeung *et al*. (2004) SVC2004: First International Signature Verification Competition was organized on 2004. A signature database involving 100 sets of signature data was created, with 20 genuine signatures and 20 skilled forgeries for each set using small pen-based input devices such as Personal Digital Assistants (PDA). Of the 100 sets of signature data, only the 40 sets were released. When evaluated on data with skilled forgeries, the best team for competition gives an Equal Error Rate (EER) of 2.84%.

Quan and Ji (2005) cited by Gupta and Joyce (2007) presented a novel approach that applied the dynamic time warping (DTW) to match the crucial points of signatures. Firstly, the signatures were aligned through the DTW and the crucial points of signatures were matched according to the mapping between the signatures. Then the signatures were segmented at these matched crucial points and the comparisons were accomplished between these segments. The distance between the two was computed using a simplified Mahalanobis distance. The testing procedure was somewhat unclear but it appeared 6 samples for each signer were used to find a reference signature. It involved comparing each of the 6 samples with the other 5 and counting the number of matching points. The signature that has the largest total matching points was then selected as the reference for the individual. An EER of 3.8% was obtained using random forgeries.

The authors Fierrez-Aguilar *et al*. (2005b) presented an on-line signature verification system exploiting both local and global information through decision-level fusion. Global information was extracted with a feature-based representation and recognized by using Parzen Windows Classifiers. Local information was extracted as time functions of various dynamic properties and recognized by using Hidden Markov Models. Experimental results were given on the large MCYT signature database where 330 signers and total 16500 signatures were collected for random and skilled forgeries. Feature selection experiments based on feature ranking were carried out. The two proposed systems were also shown to give complementary recognition information which is successfully exploited using decision-level score fusion. The experimental results obtained from the system was promising where skilled forgeries EER of between 5 and 7% were obtained with 5 training signatures as well as 1-2% with 20 training signatures. On the other hand, the random forgeries EER were 1-1.5% for 5 training signatures and around 0.5% for 20 training signatures.

Fierrez-Aguilar *et al*. (2005a) used target dependent score normalization technique using SVC2004 database which is consists of 40 sets of signatures. Each set contains 20 genuine signatures from one contributor and 20 skilled forgeries from five other contributors. Obtained result with 7.14% of EER.

Shintaro *et al*. (2006) used user-generic Fusion model with Markov Chain Monte Carlo Method. The database consists of pen position, pen pressure, angle, altitude and azimuth based on the time sequence. From 330 individuals, 25 genuine signatures and 25 skilled forgeries were collected for each individual and obtained the best results with 4.06% of EER.

A multivariate autoregressive (MVAR) modeling in combination with a Dynamic Time Warping-based (DTW) segmentation technique was proposed by Osman *et al.* (2007). The authors described that the database consists of 16 genuine writers, each writer provided 150 signature samples over 15 sessions at a rate of 10 samples per session. Thus, a total of 2400 genuine. The skilled forgeries population consists of 8 forgers. The 8 forgers were used to forge 8 genuine writers; each forger provided 30 samples for each of the 8 writers Thus, a total of 1920 forgeries were collected. Obtained result 96.6% of accuracy in skilled forgery test.

A new stroke-based signature verification system was proposed by Chang and Shin (2007). According to the authors, it was crucial to find correct points of a testing signature to be spilt according to its template signature. In their study, they proposed a modified dynamic time warping algorithm (DTW) for the problem. Foremost, the stroke information of both template and testing signature was considered precious to prevent wrong splitting. Next, the number of stroke difference in genuine signature is not limited because the proposed method does not require much extra computational time. During the experiment, proposed method was verified with 1359 signatures written by 17 Japanese writers. 679 authentic signatures and 680 forged signatures were used. All the signatures were written by Japanese writers and composed Chinese characters such as Japanese Kanji. The signatures were written by pen tablet input device. All the forgery signatures were written by other writers watching the authentic signature. 40 authentic signatures were taken from every writer. Along with these data, 10 signatures per a writer were used for training data and rest authentic signatures were used for verification. Nevertheless, since the number of the signatures having the same number of stroke is smaller than 10 for one writer's signature, only 8 signatures were used for the training in the case. All the 40 forged signatures were used as a test data without selection. The test data were all the semi-skilled forgeries and the result obtained from the proposed was 3.85% of EER.

Signature verification has been an attractive field of research area because of the social and legal acceptance and widespread use of written signatures. An automatic signature verification technique was proposed by Hu and Wang (2007). The authors stated that it is still a challenging issue because of small sample size problem as well as large intra-class differences and, when considering forgeries, small inter-class variations. In order to solve these problems the researchers proposed a two-stage fusion method to get high accuracy. At first, an Enhanced Dynamic Time Warping (EDTW) algorithm and a normalized feature measure were used to build a classifier based on local features. The former enhanced the separability between genuine and forgery signatures, while the latter approaches the problem as a two-class pattern recognition problem, which make it possible to use training signatures as many as possible. However, local method is time and resource consuming, so they then designed another classifier based on global features using majority voting rule. The method fused the global and local method by two-sage serial strategy to build an on-line signature verification system. In their experiment, Task 2 of SVC2004 was used for skilled forgeries and achieved 3.02% of EER.

Rabasse *et al*. (2007) presented a method for the generation of synthetic handwritten signatures, in the form of a series of time-stamped pen data channels, for use in dynamic signature verification experimentation. The technique introduced a modelled variability within the generated data based on variation that is naturally found within genuine source data. In order to assess the quality of the synthesized images, a commercial dynamic signature engine was used within a verification scenario. A mode of operation of the selected verification engine is to provide a binary decision on whether a presented signature is genuine or forged when compared against a reference template formed from 3 signatures. The measure of confidence associated to this binary result is also returned a default confidence value over 80 out of 100 is taken to indicate a genuine signature. Signatures were obtained from the publicly available database used in the Signature Verification Competition (SVC2004). This database consists of 1600 text files containing separate signatures in the form of time stamped x, y and pen-on-tablet, pressure, azimuth and altitude sequences. Forty separate signers are represented in the data set. For each signer, 20 files represent genuine signatures and the remaining 20 represent skilled forgeries. The skilled forgeries were not used in this experiment. In order to examine this lower verification performance, the individual verification rates of the synthesized signatures with variability were assessed according to their position within the synthesis cycle. The researchers further investigated and reported that the synthesised signatures 1 and 100 were the closest to the seed signatures 1 and 2, respectively with the other 98 signatures being interpolations in between the seeds, because the synthesised signature 50 represented the mid-point interpolation. It was found that between positions 23 and 78 the average verification rate was above the value of 87.88% achieved by the genuine signatures.

An online signature verification system based on local information and on a one-class classifier, the Linear Programming Descriptor classifier (LPD) was presented by Nanni and Lumini (2008). The authors investigated and described that the information was extracted as time functions of various dynamic properties of the signatures, then the discrete 1-D wavelet transform (WT) was performed on these features. The Discrete Cosine Transform (DCT) was used to reduce the approximation coefficients vector obtained by WT to a feature vector of a given dimension. Moreover, the Linear Programming Descriptor classifier is trained using the DCT coefficients. The experimental results using all the 5000 signatures from the 100 subjects of the SUBCORPUS-100 MCYT Bimodal Biometric Database were presented, yielding performance improvement both with Random and Skilled Forgeries and obtained an EER of 5.2% in the Skilled Forgeries.

An approach to online signature verification using data glove has been presented by Kamel *et al*. (2008). To verify the efficiency of the proposed technique in handwritten signature verification, the 5DT Data Glove 14 Ultra was used. This glove uses 14 sensors to measure finger flexure (two sensors per finger) as well as the abduction between each finger. The system was interfaced with computer via cable to USB port. Data glove is a new dimension in the field of virtual reality environments, initially designed to satisfy the stringent requirements of modern motion capture and animation professionals. The researchers tried to shift the implementation of data glove from motion animation towards signature verification problem, making use of the offered multiple degrees of freedom for each finger and for the hand as well. Their proposed technique was based on the Singular Value Decomposition (SVD) in finding r singular vectors sensing the maximal energy of glove data matrix A, called principal subspace and thus account for most of the variation in the original data, so the effective dimensionality of the data can be reduced. Having modeled the data glove signature through its r-principal subspace, signature authentication was performed by finding the angles between the different subspaces. A demonstration of the data glove was presented as an effective high bandwidth data entry device for signature verification. The SVD-based signature verification technique was tested and its performance was shown to be able to produce Equal Error Rate (EER) of less than 2.37%.

Furthermore, in the area of online signature verification using data glove, a number of research have investigated and the experimental results have been reported by the researchers (Sayeed *et al*., 2007, 2008, 2009; Kamel and Sayeed, 2008).

Recently, Elahen and Mohsen (2009) was presented online signature verification system based on global information and an Adaptive Network Based Fuzzy Interface System (ANFIS). According to the authors, the proposed method for signature verification was divided into two phases. The first phase was based on the analysis performed by the method known as fractal dimension and the second phase used Adaptive Network Based Fuzzy Interface System for output. The system was tested with two different data sets: SUBCORPUS-100-MCYT database and Persian signature database. SUBCORPUS-100-MCYT was captured using a WACOM pen tablet model INUOS A6 USB with resolution 2540 lines per inch and sampling frequency of 100 Hz. The dataset consists of 100 signature contributors where 25 genuine signatures and 25 skilled forgeries were captured from each of the signature contributor. On the contrary, the Persian dataset was captured using digitizing tablet with sampling frequency of 50 Hz. A total number of 400 genuine signatures ware captured from 40 signature contributors. In addition, 200 random and 200 skilled forgeries were used to test the system performance. In case of producing the random forgeries, forgers tried to forge only the signature shape whereas skilled forgeries were captured when forgers were provided with the animation of each signing process and they could repeat the animation several times to learn the signing process.

Table 1: Experimental results in percentage (%)

	MCYT		Persian	
	Skilled	Random	Skilled	Random
FRR	5.3	1.9	2.91	1.25
FAR	9.02	4.6	5.0	3.3
ERR	7.16	3.3	3.95	2.29

Furthermore, the signature databases were divided into two parts: training and test sets for the purpose of the experimental setup. In case of skilled forgeries, training set consists of 10 genuine and 10 forgery signatures in MCYT database as well as 6 genuine and 6 forgery signatures in Persian database. On the contrary, test set consists of 3000 (30×100) in MCYT and 480 (12×40) in Persian databases. In case of random forgeries the same number of training set was used as well as signatures were used of every other user to evaluate the forgery detection. The experimental result obtained from their proposed system is shown in Table 1.

DISCUSSION

Online hand signature verification is a extremely potential field of research from both scientific and commercial points of view. In recent years, along with the continuous development of the Internet and the increasing security protection necessities for the growth of the e-society, the field of online signature verification is being considered with renewed significance given that it uses a customary individual confirmation technique that is accepted at both legal and societal levels. In addition, recent results achieved in international competitions using standard databases and test protocols have revealed that signature verification systems can have an accuracy level similar to those achieved by other biometric systems (Vielhauer, 2005). Finally, different from physiological biometrics, handwritten signature is an active method that requires the user to perform the unambiguous act of signing. Thus, online signature verification is principally useful in all applications in which the confirmation of both transaction and user is essential (Plamondon and Srihari, 2000; Vielhauer, 2005).

Therefore, the number of possible applications for online signature verification is constantly rising along with the development of various sophisticated and user-friendly input devices for online handwriting acquisition.

The ultimate result is that in the near future, along with a broad array of prospective applications, a noteworthy yearly growth is predicted in the global signature verification market (Ureche and Plamondon, 1999). Obviously, this tendency has been further exaggerated by research results in recent years, which have notably advanced the state of the art in the field. However, in order to reinforce the commercial and societal benefits associated with the online signature verification, extra efforts are essential.

In this article, the state of the art in online signature verification has been presented and the most important results have been addressed. Moreover, a number of most potential directions for research in this field have been highlighted. In the coming future, research need not be paying attention absolutely on accuracy excellence, since it has mostly been in the past. As an alternative, it should concentrate on a huge number of issues associated to miscellaneous circumstances of the application themselves.

Therefore, in the era of the e-society, online signature verification can no longer be pondered definitely limited to academics and research laboratories as the prospect of applying online signature verification in an array of applications is becoming a reality. Certainly, further research is essential to completely examine and interpret the potential of handwritten signatures, which remain extremely distinct signs, unambiguously representing the encouragement and convolution of human beings.

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