Online Signature Verification for Forgery Detection

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***Abstract*—The increasing trend of using e-versions of document transmission and storage requires the electronic verification of sender/author. This research presents an efficient and robust online handwritten signature verification system targeting verification rates better than the available state-of-the-art systems in the presence of skilled forgeries. Fourier analysis is employed on the signatures to represent feature vectors in higher dimensional space followed by Local Fisher Discriminant Analysis to obtain compress representation while enhancing inter-class scatter between signature patterns. Signature modeling is performed using m-mediod-based modeling approach where m-mediods are put on to represent data distribution in each class. Connected component labeling is applied to binarized images of Urdu text to extract ligatures which are separated into primary ligatures and diacritics. Fast Euclidean Distance is used as dis(similarity). A total of 2414 signature samples including skilled forgeries are considered in our study. The evaluation of the proposed system on Japanese signature dataset provided by SigWiComp2013 realized promising results than the competitors.**

***Keywords*—Fast Euclidean distance; m-mediod; local fisher discriminant analysis**

I. Introduction

A person's authentication is much more demanding in the current era and requires more secure methods to serve the purpose. From the last few decades, there has been an increase in research interest aiming at the development of robust online handwritten signature verification systems. Biometrics can be defined as a process to identify an individual through some characteristics unique to him. Literature categorizes biometric traits into physiological traits and behavioral traits. Physiological methods include facial patterns, fingerprints, iris, hand geometry and retina. While behavioral verification employs traits like handwritten samples (signature, handwriting etc.) and the voice of a person.

Normally, the process of signing is unique to every individual. Two persons with the same name may present different signatures and signing process (inter-personal variation). On the other hand, depending upon the environment or conditions (physical health, fatigue, signing instrument/surface) during the signing process, the same individual's sign may differ in some aspects (intra-personal variations).

Two approaches are widely researched in literature, which are offline/static signature verification systems and online/dynamic signature verification systems [1]. Offline verification systems [2] bank upon extracting features such as size, shape, signing time and rotation angle etc. from scanned signatures. The actual signing process is performed at paper using a pen and then transformed into digital form by scanning it into computer. Online handwritten signature verification (OHSV) systems [3], on the other hand, record dynamic signature properties such as pen pressure, angle, pen up/down time etc. along the entire signature length.

Online Signature Verification [4, 5] catches the attention of researchers from the past few decades and still is an enduring research area. An online signature is made up of a series of sample points. The features of an online signature can be represented as time series data. Time series is a series of values which are measured as a function of time [6]. Researchers have researched and proposed a variety of procedures and methodologies for the evolution of highly robust online signature verification systems to date including Template Matching Approaches, Structural Approaches and Statistical Approaches. Time series of two signatures compared with Euclidean Distance (ED) -based dynamic time warping (DTW) is shown in Fig. 1. Usually, time series data exhibits higher dimensionality which is sometime difficult to incorporate in its original form. There exists in variety of approaches that transform higher dimensional data to lower dimension and speed up the upcoming processes. These include Fourier Transform [7, 8], Discrete Wavelet Transform (DWT) [9, 10, 11], and Discrete Cosine Transform (DCT) [12, 13]. Using DWT in feature extraction from handwritten digital signatures yielding superior verification rate in comparison to time domain verification system is found in [14].

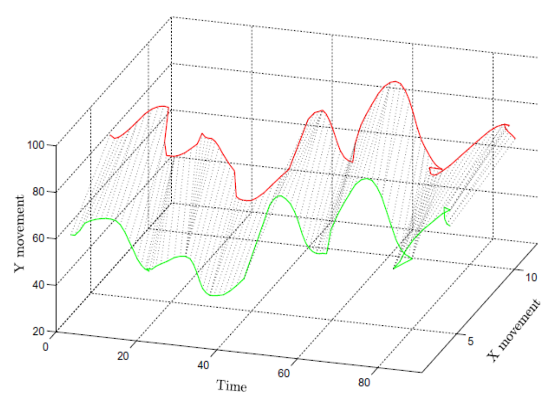

Fig. 1. Two signatures compared with ED-based DTW (Image Source: [15]).

Manjunatha et al. in [9] proposed a three step method (signal modeling, feature extraction and feature matching) for verifying the signature uses both genuine and forged signatures. The *x* position and the *y* position of all the signature points are extracted and represented, for each point, as one dimensional (1D) time domain signal along with pen moving angles as a third time domain signal. Due to length variability of these time domain signals, DWT is employed to reduce the dimensionality and extract features from these signals in a compact representation. However, system performance can further be improved by exploiting a different transformation. In [10], DWT is used to enhance the feature vectors in order to maximally separate genuine and forged signatures. More recently, Cpalka et al. in [13] used the combination of DWT and DCT for signatures' local information extraction. Wavelet packet with a fixed number of features and coefficients is employed to get better results than wavelet transform in [11].

Diaz et al. in [12] presented DCT based online signature verification approach in which a feature vector is created by applying DCT on 44 signatures features and extract the DCT coefficients to represent the feature vector in the reduced feature space. In [13], Cpalka et al. applied DCT on the coefficient vectors obtained from wavelet transform for dimensionality reduction.

Fourier Transform can also be seen as a promising approach for dimensionality reduction. As a proper transform can become an efficient tool for analyzing dynamic characteristics in time series patterns, Fast Fourier Transform also revealed many useful characteristics, in terms of signal frequency which was not the case in the actual signal [8].

II. Proposed Online Signature Verification Methodology

Our study is aimed at developing an OHSV system. Firstly, our emphasis was on selecting a suitable feature vector representation method for dimensionality reduction. Next, a feasible distance-oriented approach among the available state-of-the-art approaches for similarity measurement is identified for modeling and classification of signatures. The main contribution of our research work is the introduction of a new feature vector representation scheme to get more desirable results than the current results witnessed in different signature competitions held worldwide as well as handling forgeries at various levels.

A. System Overview

Mostly every static/dynamic signature verification system is trained by enrolling samples (reference signatures) which are then preprocessed. From the preprocessed signature samples, features are extracted which are useful in distinguishing these samples at the classification stage. Signature Modeling is then carried out for the registered individual's signature samples and a threshold is computed. Classification phase requires a query signature (test signature) of user claiming to be a particular individual which is preprocessed, and same features are extracted as done in the training phase. If the user is already enrolled in the system, then the query signature is compared against the learnt model and accepted or rejected based on the threshold value [16]. For a new user, first its model of normality is learned from the provided set of reference signatures and a confidence or threshold value is computed and then compared with the corresponding model of normality to verify an individual. Dissimilarity score crossing a certain threshold rejects that user, otherwise authenticates him.

The process of OHSV can be sub-categorized into following steps namely data acquisition, preprocessing, feature extraction, and classification (training and verification) [17].

B. Data Acquisition

An OHSV system starts with some input to the system. For an OHSV system, input is captured at runtime (i.e., dynamic) which is usually taken by means of a digital tablet or alike devices. This captured information is then processed after digitization. In general, performance assessment of OHSV systems or algorithms is reported by the authors by exploiting their self-established databases, which are not accessible to other researchers. On the other hand, a variety of standard signature databases established by different institutes and research groups have been witnessed in prior research work in the domain of OHSV. In our research work, input comes from Japanese Online dataset taken from SigWiComp2013[17].

C. Preprocessing

Both the training and testing sets of signatures are inherent to noise and may also vary in length which makes preprocessing an important step. The degree of signature's preprocessing should be carefully done [10], [18]. Preprocessing should be performed with the objective to minimize loss to the signature temporal information, endpoints of strokes and points where the signature trajectory changes [19]. The most important function of preprocessing is to remove noise and additional jerks in the signatures [3], [20], [21]. We haven't applied any preprocessing on the signature samples in our research work.

D. Feature Extraction and Enhancement

Feature extraction is the most pivotal step of verification process as the accuracy of system is highly relied upon over features used. Feature is any unique property or attribute that can be measured to represent signature effectively. Features for an online signature verification system are termed as (i) global features, which represent the whole signature; (ii) local features, which are extracted for each recorded point of signature sample; (iii) and segmental features, where features are extracted for each segment of signature sample unlike local or global features [22, 23]. A variety of features have been proposed and used in that falls within one of the stated categories. Total writing time, number of pen ups/downs and the number of strokes etc., are the examples of global features [18], [21], [24]. Some of the local features are speed, local curvature, pressure, tangential and centripetal acceleration [18], [21], [23]. Areas of high/low pen's pressure and high/low speed are the two common segmental features [3], [9], [25], [26].

E. Dynamic Feature Vector

The dynamic feature set refers to how the signature is signed than how it appears/looks. Signature dynamics are challenging for imposters to imitate (paper citation) because these not only captures the information of the signature's overall shape, but also information of the individual sampling points (signature strokes) and other dynamics (speed) of the various signature strokes. Features are extracted from each point in OHSV as OHSV data requires to be represented in sequence of points. Dynamic features such as speed Spi and mean distance MDi for each sample i, are identified to have good discriminative potential. Selection of features plays an important role in the later processing and classification.

For this system, the dynamic information (raw data vector) obtained from the dataset comprises the following three-dimensional (3D) time-series data represented as in (1). Where *xts* and *yts* show position information of the signature and pts comprises pen down/up information at each sampling point at time *ts*. In this research, we are using pen down/up, speed and mean distance as our feature vector.

$$\mathrm{T(S)} = \{(\mathrm{xts, yts, pts})\} \quad (ts = 0,1,2,\ldots,\mathrm{n}) \quad (1)$$

Firstly, we compute the derivatives of the original *x* and *y* signature time series. We exploit these derivatives to computed speed *sp* for each signature sample *i* as given in (2).

$$\mathrm{Sp}_i = \sum_{s=1,t=1}^{n} \sqrt{(\mathrm{xs}+1-\mathrm{xs})2 + (\mathrm{yt}+1-\mathrm{yt})2}\ (i = 1,2,\ldots,\mathrm{n}) \quad (2)$$

Next, we have extracted the mean distance feature (*MDf*) by averaging the two dimensional (2D) raw data feature vector *V(S)* as represented in (3).

$$\mathrm{V(S)} = \{(\mathrm{xts, yts})\} \quad (ts = 0,1,2,\ldots,\mathrm{n}) \quad (3)$$

Now our feature vector for signature sample *S* takes the form given in (4).

$$\mathrm{T(S)} = \{(\mathrm{MDf, Spf, Pf})\} \quad (S = 1,2,\ldots,\mathrm{n}) \quad (4)$$

After performing these basic operations on the acquired features, dimensionality of the signature samples is taken into account prior to signature model learning and classification.

F. Dimensionality Reduction for Feature Vector Representation

Dimensionality reduction is an important technique at this stage to deal with higher dimensionality problems in time series data. The goal of dimensionality reduction technique is to reduce the dimension of the samples while preserving most intrinsic and essential information even if multimodal scenarios exist within a dataset class.

It is possible to work in the raw point original coordinate space where signature sampling points are comparatively shorter. Conversely, direct manipulation of sampling point sequences for instance, greater than thousand or even more, seems to be impractical and unfeasible for feature extraction. The intention of applying dimensionality reduction is to come out with a feature extraction function *F* that decreases data dimensionality from *y* to *x* with $x \ll y$. Similarity signature modeling and classification is then carried out in the reduced output feature space.

Time series data modeling and representation has also been carried out in prior research using a renowned transformation namely Discrete Fourier Transform. Time series is modeled compactly using a fixed number of coefficients [8], which results in quick signature modeling and classification. For each normalized signature, Fourier descriptors are computed and the selection of descriptors exhibiting highest magnitudes is made. Fisher discriminant analysis (FDA) is then employed with the imaginary as well as real part of the harmonics selected using empirical evaluation to identify the most suitable and appropriate features along with their associated weights. Traditionally, FDA [4] has been employed to serve the purpose but FDA fails to handle multimodality problem within classes. To cope with the multimodality issue, locality preserving projection is proposed [27] but it fails to handle labeled data due to its unsupervised nature. Local fisher discriminant analysis (LFDA) [28] is proposed and widely used to deal multimodality in time series data at localized level by taking into account the local structures of data.

In this research work, we employed Discrete Fourier Transform (DFT) to represent the data distribution in the higher dimensional space data given in (5) followed by LFDA to obtain reduced and compressed representation. The n-point fourier transform of $\{MD_i\}$, stated as a series $\{\overline{MD_f}\}$ of n complex numbers $f = 1,\ldots.,n$ at discrete points. Where j is the imaginary unit $j = \sqrt{-1}$ and MD_f are complex numbers with the exception of CD_0 which is real. As the centroid distance-based time series is z-normalized, CD_0 which represents the mean of time series will always have a value of 0 and is ignored. Normally, DFT sequences are truncated after *n* terms. In our case, the feature vector is made up of $2(n-1)$ entries (from real and imaginary parts). More formally, let x_i and $\widehat{x_i}$ be the real and imaginary part of $\overline{MD}$.

$$\overline{MD_f} = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} MD_i \exp\left(-\frac{j2\pi fi}{n}\right) \quad f = 1,2,\ldots\ldots,n \quad (5)$$

Signatures can be denoted in the reduced coefficient feature space by a $2(n-1)$ dimensional vector of DFT coefficients $F_{\boldsymbol{DFT}}$ as shown in (6). The given F_{DFT} can be efficiently employed for feature vector representation of signature samples.

$$F_{DFT} = [x_1, \widehat{x_1}, \ldots\ldots x_{n-1}, \widehat{a_{n-1}}] \quad (6)$$

Parodi et al. [29] proposed a template protection scheme which needs a fixed-length and compact feature vector representation of the signature time series. Liu et al. [8] exploited Fourier analysis to have fixed-length compact feature vector representation for their proposed individuality model for OHSV. Lagendijk et al. [30] acquired a fixed-length representation of fingerprint minutiae by exploiting fourier transform. Discrete cosine transformation has been used by Rashidi et al. [31] to get reduced feature vector representation.

G. Signature Modeling

It has been seen in the work of Liu et al. [8], and Lagendijk et al. [30] that DFT based dimensionality reduction is a suitable selection for compressed representation of signature time series data in the reduced space with data samples exhibiting length variation. DFT gives a uniform and unwavering features space representation of signature samples to cope with the issue of varying lengths in signature datasets. We bring DFT based coefficient feature space representation into play to accomplish the learning of signature patterns in online signature datasets. The resulting learnt output patterns from the learning process can then lead to the correct identification of a previously unseen signature pattern and assigning it to the class it belongs to. It needs much skill to realize a learning system to serve the purpose. The complexity of the realization of a learning system is directly dependent on the number of different signature patterns (inter-class and intra-class variability) exhibited by the enrolled users. In this study, signature modeling doesn't take larger dataset for training session. The learning process is capable of proficiently learning signature patterns in the presence of small training set where the membership count for previously unseen pattern is sufficient for not considering it as an abnormal pattern.

Multimodal m-mediods based modeling and classification approach [32] best suit the sample's estimated multi-modal distribution contained by a given signature pattern. Our model learning method works with coefficient feature space representation of training data (data) yielded from DFT as an input. Labeled information (labels) is also taken by the system as an input. The number of outputs mediods to be perceived (#output) along with the maximum iterations in training (train_iter) as the input parameters are taken by the system. The outcome of this method is the number of outputs mediods (#output) along with their associated weights. Given training samples *TS(i)* having enhanced and improved feature vector representation of signature samples be associated with signature class *i*, its normality model is generated as:

1) Initialize the Learning Vector Quantization (LVQ) network with the number of outputs mediods. LVQ is initialized with the number of outputs mediods (Moutput) empirically and taking the number of samples presented in a class as upper limit yield in (7). Where $Ꞇ$ is the number of samples in a given class and *m* is used to denote the number of values randomly thrown to get the desired number of outputs mediods in the dataset.

$$\text{Moutput} = \begin{cases} Ꞇ \; if \; Ꞇ < 3*m \\ 3*m \; if \; Ꞇ > 3*m \end{cases} \quad (7)$$

2) Initialize the weights *Wc* as per output mediod. A variety of methods exist for weights initialization. A very general and common approach is to assign random weight values, but it may slow down the training process of LVQ. Also, it may output some of the clusters with no representation associated with it. To cope with this problem, we approximate a multivariate Gaussian distribution function (PDF) by exploiting the training data. This PDF approximation generates samples in greater number maximizing the possibility of closeness of at least one sample from the generated samples with groups concealed in the training dataset. The weight vectors in our approach are estimated from the training data using a single multivariate Gaussian probability distribution function PDF $N(\mu, \sum)$ in (8). Where $M \in TS(\mathrm{i})$, μ and $\sum$ are the mean and covariance estimations to $TS(i)$. $PDF\ N(\mu, \sum)$ is then employed to get the number of outputs mediods Moutput along with the initialization of corresponding weights *Wi* with $1 \le i \le Moutput$.

$$\text{PDF N}(\mu, \textstyle\sum) = \frac{1}{\sqrt{2\pi\sum}} exp\left[-\frac{(M-\mu)^2}{2\sum}\right] \quad (8)$$

3) Pass the feature vector (input) from $TS(i)$in succession and selection of the output mediod that is the nearest representative of provided input data during network training. That nearest output mediod is termed as the winning output mediod. Suppose DFT be the input feature vector and *Wc* denotes the associated weight of output mediod *i*, selection of the winning output mediod *i* is made in a way that the distance (Euclidean) between DFT and *Wc* is the smallest among all the output mediods, specified in (9) where *k* is the index of output mediod *i*.

$$\mathrm{k} = \mathrm{argmin}_i \|\mathrm{Wc}, \mathrm{F_{DFT}}\| \forall\, i \quad (9)$$

4) Adjust *Wc* to train LVQ so that it starts revealing the trend of the TS(i). In this process, the neighboring mediods are also important. *Wc* of *i* and its neighboring mediods are adjusted to reveal topology preserving estimation of $TS(i)$. As a result, we have output mediods exhibiting similar trend which are very nearer in the LVQ network structural space. A subgroup of the weights comprising the wining neuron *i* with the center surrounded by its neighborhood is updated in (10) where $\alpha(t)$ is the learning rate of LVQ.

$$\mathrm{W_k(t+1)} = \mathrm{W_k(t)} + \alpha(\mathrm{t})\|\mathrm{Wc}, \mathrm{F_{DFT}}\| \quad (10)$$

5) Converge the network training gradually from rough to refining of *Wc* by dropping down the learning rate. At the start, higher values are taken in the learning process to accomplish representation of input space by a quick adjustment of *Wc*. Convergence slows down after successive iterations resulting in lesser effect of new arriving data on LVQ. The LVQ network continues to learn and adjust itself to correctly describe the trends in signature data. Exponential decrease in $\alpha(t)$ over time *t* is given as in (11) where $train_{iter}$ are the maximum training iterations.

$$\alpha(\mathrm{t}) = 1 - e^{\frac{2(t-train_{iter})}{train_{iter}}} \quad (11)$$

6) Iterate through step 3-5 for all the training iterations and discard the output mediods holding no sample.

7) Determine the index *(x, y)* of the closest pair of *Wc* as in (12). Where Wi and Wj denotes the weight vector representations for output mediods *i* and *j* respectively.

$$(x, y) = \mathrm{argmin_{(i,j)}} \|\mathrm{Wi,Wj}\| \times \sqrt{|\mathrm{Wi}| + |\mathrm{Wj}|} \forall\, i, j \wedge i \neq j \quad (12)$$

8) Pairs which are closet are merged by using the weighted average. For instance, *Wx* and Wy are the weight vectors linked with output mediods indicating the most similar groups and *x* and *y* are the # of sample signatures mapped to these mediods respectively. *Wxy* (new weight vector) for the resultant merged group can be computed using (13).

$$\mathrm{W}_{xy} = \frac{|\mathrm{Wx}| \times \mathrm{Wx} + |\mathrm{Wy}| \times \mathrm{Wy}}{|\mathrm{Wx}| + |\mathrm{Wy}|} \quad (13)$$

9) Repeat Step 6-8 as late as weight vector *Wc* count add up to *m* and adjoin *W* to *M(i)* demonstrating the sample *i*.

Once we have done with mediods identification *M(k)*, the next step is to figure out set of normality ranges (NR) for each class. Normality ranges are identified to keep a set of samples to be a part of class that falls within the defined ranges and to maximally distinguish between normal and abnormal samples in the best possible way. However, defining an NR doesn't seem so simple as the work normality suggests because these ranges are defined in generalizations in terms of common patterns a signer exhibits. Since, a given class k may encompass different normality ranges *NR(k)* and each mediods within that class may comprises different *NR(k)*; a set of *NR(k)* for each class is identified after finding out the mediods as follows:

1) Start with NR(k) = {}.

2) From the list of identified mediods M(k), determine the index of the closest pair *(i, j)* at index *(x, y)* and update *NR(k)*. Suppose *Mi* and *Mj* are the two mediods indexed at *(x, y)*, closeness of mediod pair *(i, j)* is determined in a way that the Euclidean distance between *Mi* and *Mj* is the smallest among all the other identified mediods exist in the list, specified by (14) and (15).

$$(x, y) = \text{argmin}_{(\mathrm{i,j})} \|\mathrm{Mi}, \mathrm{Mj}\| \forall\, i, j \wedge i \neq j \quad (14)$$

$$NR^{(k)} = NR^{(k)} \cup \left[\left|M_x, M_y\right|\right] \quad (15)$$

3) Mediod Pairs which exhibit closeness are merged by using the weighted average. For instance, x and y are the weights linked with mediods *Mx* and *My* indicating the most similar pair. *Mx* and *My* are merged together to get a new vector *Mxy* which is computed using (16).

$$\mathrm{M}_{xy} = \frac{|\mathrm{Mx}|\times\mathrm{Mx} + |\mathrm{My}|\times\mathrm{My}}{|\mathrm{Mx}| + |\mathrm{My}|} \quad (16)$$

4) Repeat step 2 & 3 until M(k) converges to 1.

From the normality ranges *NR(k)* of a given class, normality ranges for each mediods *NR(m)* are identified. For each signature sample, traverse each class we have in the *TS(i)* in a continuous fashion and find out the closest match of mediods with that sample. We use *NR(k)* (attainable normality ranges) to get *NR(m)*. Given the *NR(m)* is the closest mediod for a given class; it results in the utmost samples of a given class to be kept in the NR of that mediod whereas allowing least possible samples from other classes to be contained within *NR(m)*. This process results in minimizing the false acceptance and false rejection of signature samples.

H. Signature Classification

After the identification of mediods *M(k)* and their equivalent normality ranges *NR(k)*, classification of signature samples *TS(i)* in a multimodal fashion is carried out. Classification involves grouping objects exhibiting similar behavior in their corresponding classes. The classification process for new signatures samples is carried out based on closeness of that previously seen/unseen sample to the learnt models of the available identified classes in the dataset. DFT based representation of feature vector for an unseen sample is computed and passed to the list of identified mediods of the entire set of dataset classes to serve the purpose as follows:

1) Calculate the query sample distance *QS(i)* with all the *M(k)* of different classes and ascending sort the outcomes.

2) Initialize index i of the mediod nearest to *QS(i)* to 1.

3) Label the i^{th} nearest mediod index with *Mi* and the equivalent class index to *Mc*. If the query sample *QS(i)* falls within the NR of i^{th} mediod, classify it in the equivalent class and finish the classification phase.

4) Increment the index from *i* to *i+1*.

5) Repeat step 3 and 4 until the value of index *i* exceeds the normality range of that mediod.

III. Experimental Studies of Proposed OHSV System

In this section, we present the experimental evaluation results to prove the effectiveness of our proposed methodology. Starting with an introduction about the dataset used in our experimental evaluations, we present the verification rates reported by the system at different levels of forgeries followed by comparisons with the competitors at hand.

A. Experimental Dataset

Japanese signature data collection is carried out using HP Elite Book 2730p tablet PC and a Microsoft INK SDK based developed data collection software with a sampling and resolution rate of 200Hz and 50 pixels/cm respectively. The online Japanese dataset contains ASCII files with the representation as: X, Y, and Z where X and Y denote position information and Z represent pen position information (Pen up (0), Pen down (100)). In the overall dataset collection process, 30 signers took part after a practice session to get acquainted with the signature capturing device. Forgers are allowed to see the genuine signatures of the authors whereas the original authors (signers) signed their signatures without having access to their previous signatures. The division of dataset into training and testing phases is as follows:

1) Training set: A total of 462 signatures (genuine) from 11 signers with 42 samples of each author and a total of 396 forgeries (skilled) with 36 samples per author are provided for the training session.

2) Testing set: The testing set contains 20 authors with 42 genuine signatures per author along with 36 forgeries each for both tasks. A detailed description is given in Table I.

The dataset reported is used in ICDAR2013[17] Competitions on Signature Verification and Writer Identification for Online and Offline Skilled Forgeries. Systems submitted by the online signature verification community that revealed best results under their experimental conditions are shown in Table I.

TABLE I. RESULTS FOR JAPANESE ONLINE SIGNATURE VERIFICATION (SOURCE: [17])

Mode	Detection Accuracy	FAR	FRR
Online	70.55	30.22	29.56
Online	**72.55**	**27.36**	**27.56**
Online	72.47	27.50	27.56

B. Evaluation Criteria

Evaluation of Signature verification systems is based upon the error rate they yield. The lower the error rate, the higher the performance of the system. There might be two types of errors. When a system accepts the signature exhibited by a forger, it is termed as False Acceptance Rate (FAR). Conversely, if the system rejects the signature exhibited by a genuine signer, it is referred to as False Rejection Rate (FRR). Most authors report the performance in terms of FAR and FRR. FAR and FRR are inversely proportional which means that if we try to keep FAR down, FRR goes up and vice versa. Some authors have used the term Equal Error Rate (EER) which is the point at which both FAR and FRR are equal. Lower EER means higher accuracy. When it comes to comparison of the different biometric verification systems, EER is a widely used metric.

C. Experiment: Evaluation of Proposed OHSV System

The objective of training is 1) to detect the genuine signature class from the available n reference signatures; 2) to detect the forged signature imitated by some other author for each class.

D. Training

In the training phase, we have sub-divided the training set into training and cross-validation for model learning and parameter tuning. In the first step, we identify the system parameter and then perform model learning based on those parameters. Model learning and verification is performed by exploiting858 reference signatures including genuine signatures and skilled forgeries. By varying the parameters i.e., threshold, # of mediods, # of iterations etc. An ideal value of threshold (i.e., 1.055) is identified. The detailed methodology is discussed in section 3.6. After threshold identification for each class, cross-validation involves the tuning of parameters i.e., threshold and normality ranges with the intention of minimizing false positive and false negative by exploiting the model and labeled information.

E. Evaluation

This phase sub-divides the evaluation set into training set and test set. From the training set, model is learnt, which in conjunction with the tuned parameters from the first phase is used to classify the test signatures into genuine and forged ones. Model learning and verification is performed by exploiting 1560 test signatures including genuine signatures and skilled forgeries. The detection and the forgery accuracy obtained in the training and the evaluation along with the competitor results are given in Table II and III respectively.

TABLE II. DETECTION & FORGERY ACCURACY IN TRAINING

Mode	# of authors	# of signatures (Total)	Detection Accuracy %	FAR %	FRR %
ICDAR2013	11	858	72.55	27.36	27.56
Our proposed approach	11	858	84.23	15.77	17.54

TABLE III. DETECTION & FORGERY ACCURACY (EVALUATION)

Mode	# of authors	# of signatures (Total)	Detection Accuracy %	FAR %	FRR %
ICDAR2013	20	1560	72.55	27.36	27.56
Our proposed approach	20	1560	82.84	17.16	19.46

IV. CONCLUSION AND FUTURE PERSPECTIVES

A. Conclusion

In handwritten signatures, there is a great interest toward the development of effective and robust signature methods for online signatures. The last few decades have witnessed extensive research in the development of OHSV systems and a wide range of verification techniques and framework proposed with promising results. However, there exist a number of challenges which make OHSV a hot research area. Due to the inter-class and intra-class variability, detection of signatures with respect to their corresponding classes with maximum precision is still a challenging task. Similarly, the robustness of the verification system against the imposter's imitation of generating the genuine signature patterns by minimizing false positive and false negative ratio is another challenge at hand.

To meet the challenges of OHSV systems, this research work is aimed at developing an OHSV system for the identification of signatures and the detection of skilled forgeries with accuracy greater than the available state-of-the-art approaches. To cope with the challenges of OHSV systems, we have presented a compact feature vector representation by incorporating speed, pen positions and mean distance as features for our system as given in Section III. From this compact representation, we have learnt the signature model and classify the signatures according to the identified system parameters. During the training phase, we have obtained 84.23% detection accuracy with 15.77% false acceptance rate and 17.54% false rejection rate. In the evaluation phase, we obtained 82.84% detection accuracy with 17.16% false acceptance rate and 19.46% false rejection rate.

B. Future Perspectives

Development of an OHSV system for targeting skilled forgeries is a very challenging task. We have attempted to address some of these issues with our proposed OHSV approach. The proposed system realizes very promising signature verification rates. However, the verification rates are slightly lower as the size of dataset in the evaluation phase increases. The most obvious extension of the proposed system is to speed up the processing by varying features as well as exploiting some other feature vector representation technique to achieve more compact and compressed representation. Another possible extension is to integrate our proposed approach with offline signature verification and then evaluate system performance in the hybrid environment in the near future.

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