



Dynamic Time Warping Based Static Hand Printed Signature Verification

Jayadevan R.

rjayadevan@rediffmail.com

*Department of Information Technology, Pune Institute of Computer Technology
Pune, Maharashtra, India.*

Satish R. Kolhe

srkolhe2000@gmail.com

*Department of Computer Science, North Maharashtra University
Jalgaon, Maharashtra, India.*

Pradeep M. Patil

patil_pm@rediffmail.com

*Department of Electronics Engineering, Vishwakarma Institute of Technology
Pune, Maharashtra, India.*

Abstract

Static signature verification has a significant use in establishing the authenticity of bank checks, insurance and legal documents based on the signatures they carry. As an individual signs only a few times on the forms for opening an account with any bank or for insurance related purposes, the number of genuine signature templates available in banking and insurance applications is limited, a new approach of static handwritten signature verification based on Dynamic Time Warping (DTW) by using only five genuine signatures for training is proposed in this paper. Initially the genuine and test signatures belonging to an individual are normalized after calculating the aspect ratios of the genuine signatures. The horizontal and vertical projection features of a signature are extracted using discrete Radon transform and the two vectors are combined to form a combined projection feature vector. The feature vectors of two signatures are matched using DTW algorithm. The closed area formed by the matching path around the diagonal of the DTW-grid is computed and is multiplied with the difference cost between the feature vectors. A threshold is calculated for each genuine sample during the training. The test signature is compared with each genuine sample and a matching score is calculated. A decision to accept or reject is made on the average of such scores. The entire experimentations were performed on a global signature database (GPDS-Signature Database) of 2106 signatures with 936 genuine signatures and 1170 skilled forgeries. To evaluate the performance, experiments were carried out with 4 to 5 genuine samples for training and with different 'scores'. The proposed as well as the existing DTW-method were implemented and compared. It is observed that the proposed method is superior in terms of Equal Error Rate (EER) and Total Error Rate (TER) when 4 or 5 genuine signatures were used for training. Also it is observed that the False Acceptance Rate (FAR) of the proposed system decreases as the number of genuine training samples increases.

Keywords: Static, Aspect ratio, Radon transform, DTW-grid, Closed area, Skilled forgery, Verification, Scores

1. Introduction

Thousands of checks are being processed in a day in most banks and insurance companies and there is a great need for automatic verification of the static hand printed signatures present on them. Handwritten signature verification is a process of verifying whether a given signature belongs to a particular individual whose signature characteristics are known in advance. Automatic verification of signatures present on financial and legal documents (static) is essential when it is difficult to distinguish genuine signatures from skilled forgeries

on the basis of visual assessment. The large volumes of documents in such applications also make automatic signature verification desirable. A skilled forgery as shown in Fig. 1 is produced when the forger tries to reproduce an individual's actual signature with close imitations by looking at a genuine signature sample [1]. Such forgeries are produced when the forger has unrestricted access to one or more samples of the writer's actual signature. These forgeries are very difficult to be identified by a human document examiner, as the human visualization system is not fast and powerful enough in distinguishing the genuine and skilled forgeries. Automating the signature verification process may solve this problem to some extent.



Fig. 1: (a) A genuine signature and (b) its skilled forgery from the GPDS-Signature Database

The genuine signatures of an individual are never identical as shown in Fig. 2. If a signature verification system is too coarse, then it will also accept forgeries due to the lack of discriminating power. If the system is too meticulous it may reject genuine signatures because of the weak similarities of genuine signatures. Therefore an ideal signature verification system has to minimize intrapersonal variation and maximize interpersonal variations [2]. The feature set of the signatures play a main role in such verification systems. As a signature can be considered as a distribution of ink over a two dimensional plane, the feature extraction refers to representing various qualities of this distribution in a form that can be easily compared with the corresponding qualities in other signatures.

An extensive overview of the work done in the context of static signature can be found in [3, 4]. An individual signs only a few times for almost all banking and law enforcement applications. As a result the number of genuine signatures available for training is limited. Some of the works on neural networks and Hidden Markov Models (HMM) require 40 genuine signature samples for training [5, 6]. In [7] a back propagation neural network is used where 22 genuine samples are required for training the network. Practically it is very difficult to collect and store 40 signature samples from an individual when he/she opens an account with any bank. The main endeavor in the method described here is to minimize the number of genuine signature samples required for training.

The proposed work here is different from that of [8] where DTW is used to segment the signature into a fixed number of components and computes a component-wise dissimilarity measure. Stability was included in the work suggested in [9] for the on-line signature verification problem. In [10] stability is suitably adopted for the static (off-line) method where weights were assigned to various components of a signature depending on their stability. Stability of a component was quantified by using the knowledge of the warping paths between signatures of the same person.

The paper is organized into three main sections. The preprocessing and feature extraction section describes the preprocessing involved as well as the extraction of features that can represent the signatures better. The preprocessing in the form of normalization has been done before extracting features from the signature. The horizontal and vertical projection features of a signature are extracted using discrete Radon Transform. A combined vector

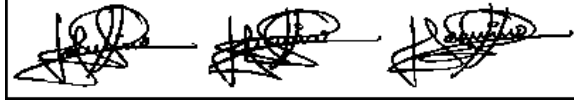


Fig. 2: Three genuine signatures of an individual from GPDS-Signature Database

of vertical and horizontal projections has been taken as the main feature vector. After the preprocessing and feature extraction section, the matching technique is described in detail. Results and comparisons of the proposed and existing method are shown in the experimentation section. All the experiments were performed on a global signature database (GPDS-Signature Database) of 2106 signatures with 936 genuine signatures and 1170 skilled forgeries [11, 12].

2. Preprocessing and Feature Extraction

To minimize the intrapersonal differences and to maximize the interpersonal differences, the main preprocessing step involved here is the normalization of the signature images belonging to an individual. All the images in the GPDS-Signature database are cropped binary images. Aspect ratio of a signature refers to the ratio of its width to height. The aspect ratios of the signatures of an individual are generally close to each other. After finding the average aspect ratio of the genuine signatures, the genuine as well as the test signatures are normalized to a specific size with width ‘ w ’ and height ‘ h ’ without changing their average aspect ratio. As a result of this normalization, the distortion in shape will be more for the forgeries than that of genuine signatures.

If ‘ N ’ genuine signatures are available for training and (w_i, h_i) are the width and the height of the i^{th} genuine signature sample, the average aspect ratio ‘ R ’ of an individual is,

$$R = \frac{1}{N} \times \sum_{i=1}^N \frac{w_i}{h_i} \quad (1)$$

The new width ‘ w ’ and height ‘ h ’ for the specific size are computed as follows.

$$w = \max[w_1, w_2, \dots, w_N] \quad (2)$$

$$h = \frac{w}{R} \quad (3)$$

A signature can be considered as a distribution of ink over a two-dimensional mesh, the horizontal and vertical projections of a signature are the two main features of it. These features can be extracted using the discrete Radon transform. The Radon transform of any two-dimensional function $f(x, y)$ is the line integral of f parallel to the y' -axis.

$$R_\theta(x') = \int_{-\infty}^{\infty} f(x' \cos\theta - y' \sin\theta, x' \sin\theta + y' \cos\theta) dy' \quad (4)$$

where,

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \times \begin{bmatrix} x \\ y \end{bmatrix} \quad (5)$$

The Radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. The beams are spaced 1 pixel unit apart. Actually it

computes the projections at angle θ . Fig. 3 illustrates the geometry of the Radon transform. The vertical (V) and horizontal (H) projection vectors can be extracted by giving the values 0 and 90 degrees to θ .

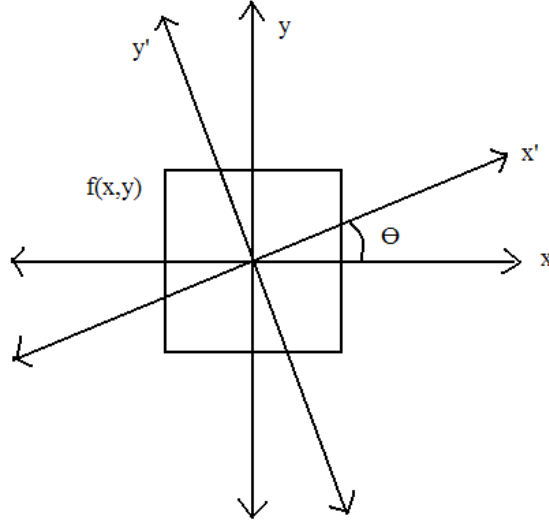


Fig. 3: Geometry of the Radon Transform

A new feature vector ‘ P ’ is formed by combining the vertical and the horizontal projection vectors.

$$P[k] = V[j], \text{ for } k = j = 1, 2, 3, \dots, w \quad (6)$$

$$P[k + i] = H[i], \text{ for } k = w \text{ and } i = 1, 2, 3, \dots, h \quad (7)$$

The vertical-projection (V), horizontal-projection (H) and the combined-projection-vector (P) of a signature in GPDS-Signature database are shown in Fig. 4, Fig. 5 and Fig. 6 respectively. All these three vectors have been used extensively for experimentation.

In [10] only vertical projection is taken as the main one-dimensional feature of the signature. In this paper it is established through experimentation that the combined-projection-vector is superior to vertical projection in minimizing intrapersonal differences and maximizing interpersonal differences. In other words, it can be stated that the combined-projection-vector has more resolving power than the vertical projection alone as a feature.

3. The Proposed Matching Technique

The proposed matching technique of two feature vectors is based on the difference cost associated with the matching path computed through Dynamic Time Warping (DTW) algorithm and the closed area formed by the path around the diagonal of the rectangular DTW-grid. The total dissimilarity between the vectors is proposed as a product of the area and the difference cost.

3.1 Calculating the Difference Cost

The features of the reference and the test signatures are matched using Dynamic Time Warping (DTW) algorithm, which is based on dynamic programming. The purpose is to compute the difference cost between two one-dimensional feature vectors. Earlier DTW

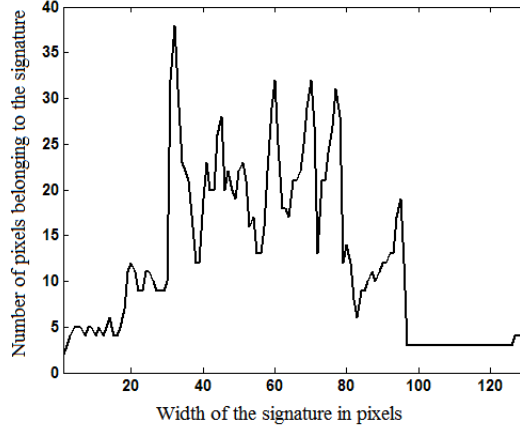


Fig. 4: The vertical projection of a signature in GPDS-Signature database

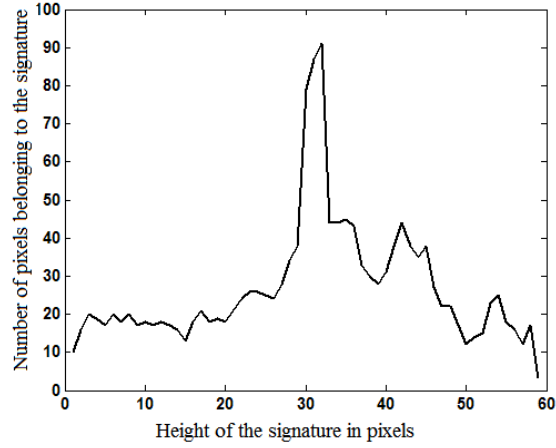


Fig. 5: The horizontal projection of the same signature

algorithm was used for speech processing as it allows stretching and compression of sections of feature vectors [13]. The matching between the two vectors is done and a path is found using a rectangular grid as shown in the Fig. 7. The reference (stored) vector \vec{r} of length L is aligned along the X-axis and the test vector \vec{t} of length L is aligned along the Y-axis respectively. As a result of the normalization step performed before extracting the features, the vectors are of same length.

Each node (i, j) on the grid represents a match of the i^{th} component of \vec{t} with the j^{th} component of \vec{r} . The cost matrix associated with the grid stores the value of the cost function associated with matching the i^{th} component of \vec{t} with the j^{th} component of \vec{r} . Let $c(i, j)$ represents the cost associated with the node (i, j) . The cost at the starting node $(1, 1)$ is defined as 'zero', that is $c(1, 1) = 0$. A warping path is a concatenation of nodes starting from the node $(1, 1)$ to the node (L, L) . To be more precise all the warping paths start from the node $(1, 1)$ and end at the node (L, L) . The main aim here is to find the path for which the least cost is associated. That specific path provides the difference cost between the two feature vectors.

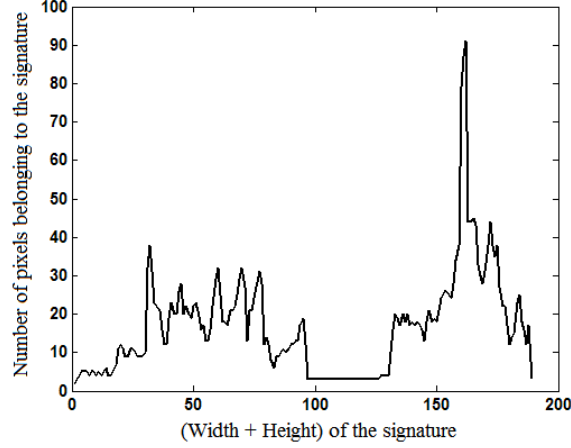


Fig. 6: The combined vector of the vertical and the horizontal projections

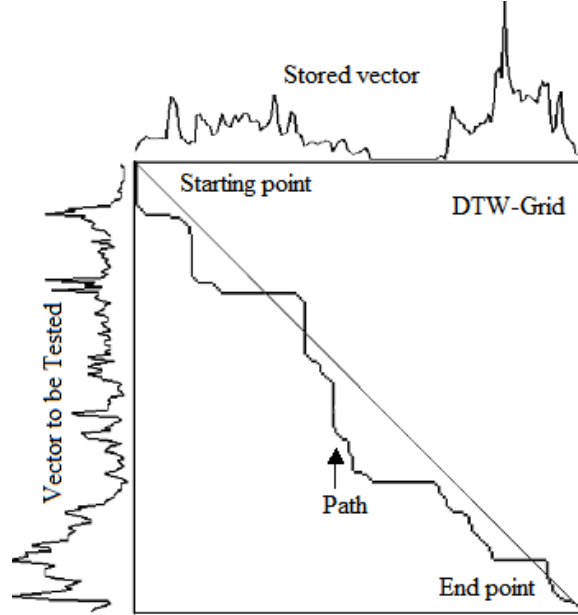


Fig. 7: Matching two vectors using DTW-Grid. The path with least difference cost is also plotted

Let (x_k, y_k) represents a point (node) on a warping path at the instance ' k ' of matching. A path starting from $(1, 1)$ and ending at (x_k, y_k) has a cost $D(x_k, y_k)$ associated with it.

$$D(x_k, y_k) = D(x_{k-1}, y_{k-1}) + c(x_k, y_k) \quad (8)$$

where (x_{k-1}, y_{k-1}) is the previous node on the same path.

Since $(1, 1)$ is the starting node for all paths, $D(1, 1) = 0$.

$$D(x_k, y_k) = \sum_{m=1}^k c(x_m, y_m) \quad (9)$$

The problem of finding the optimal path can be reduced to finding a sequence of nodes (x_k, y_k) , which minimizes the accumulated cost for a complete path ending at node (L, L) .

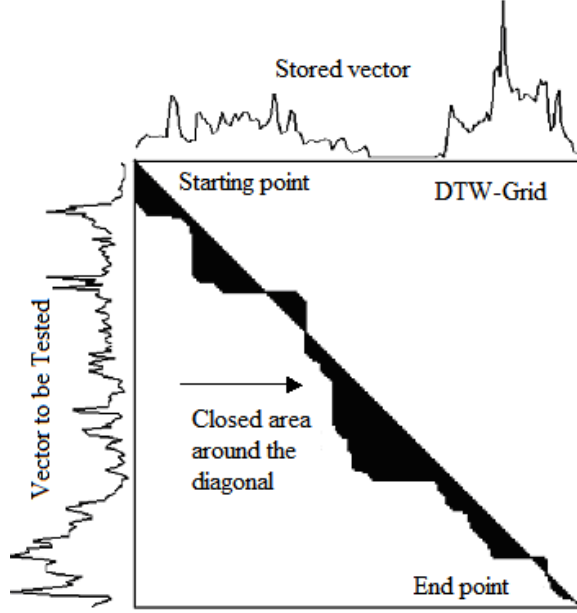


Fig. 8: The closed area (in dark) created by a path around the diagonal of the grid

$$D^{min}(x_k, y_k) = \min[D(x_{k-1}, y_{k-1})] + c(x_k, y_k) \quad (10)$$

The difference cost associated with the path is $D^{min}(L, L)$. The major optimizations to the DTW algorithm arise from observations on the nature of good paths through the grid. Some of the optimizations, which were outlined in [12] and applied in the method proposed here are,

3.1.1 Monotonic Condition

The path will not turn back on itself, both the $(x_k \text{ and } y_k)$ indexes either stay the same or increase, they never decrease.

3.1.2 Continuity Condition

The path advances one step at a time. Both $(x_k \text{ and } y_k)$ can only increase by 1 on each step along the path.

3.1.3 Boundary Condition

The path starts at the top left $(1, 1)$ and ends at the bottom right (L, L) .

3.2 Calculating the Closed Area Created by the Path

It is clearly mentioned by Sakoe and Chiba in [13] that a good path is unlikely to wander very far from the diagonal. So a new approach is used here based on that assumption by giving importance to the closed area created by the path (with minimum difference cost) around the diagonal. The closed area created by a path around the diagonal of the grid is shown in Fig. 8. For an ideal match in which both the matching vectors are same, the path will be through the diagonal only and the closed area associated with the path around the diagonal will be 'zero'. As the dissimilarity increases between the matching vectors, the path is likely to wander far from the diagonal and as a result the closed area formed around the diagonal of the grid also increases. The closed area around the diagonal can be computed as follows.

If $N(p_i, q_j)$ is a node of the DTW-grid lying on the matching path, it may be on the left side of the diagonal or on the right side of the diagonal or on the diagonal of the grid itself. The position of the node can be determined by checking the values of ‘ i ’ and ‘ j ’ of $N(p_i, q_j)$. The position of $N(p_i, q_j)$ is represented by $P(p_i, q_j)$. It is mainly used to plot the closed area created by the matching path around the diagonal.

$$P(p_i, q_j) = \begin{cases} \textit{left}, & \textit{if}(i > j) \textit{ of } N(p_i, q_j) \\ \textit{right}, & \textit{if}(i < j) \textit{ of } N(p_i, q_j) \\ \textit{diagonal}, & \textit{if}(i = j) \textit{ of } N(p_i, q_j) \end{cases} \quad (11)$$

In order to calculate the closed area created by the matching path around the diagonal the nodes between the path and the diagonal have to be counted at every row. This can be achieved by assigning a value $V(p_i, q_j) = 1$ to the nodes located between the matching path and the diagonal as shown below. Other nodes lying outside the closed area will have a value $V(p_i, q_j) = 0$.

$$\begin{cases} \textit{If } P(p_i, q_j) = \textit{left}, & \textit{then } V(p_i, q_j) = 1 \\ & \textit{for } j = j, j + 1, \dots, j + d, \textit{ where } (d = i - j) \\ \textit{If } P(p_i, q_j) = \textit{right}, & \textit{then } V(p_i, q_j) = 1 \\ & \textit{for } j = i, i + 1, \dots, i + d, \textit{ where } (d = j - i) \\ \textit{If } P(p_i, q_j) = \textit{diagonal}, & \textit{then } V(p_i, q_j) = 1 \end{cases} \quad (12)$$

The total area A_c created by the path can be computed by counting the number nodes with value $V(p_i, q_j) = 1$.

$$A_c = \sum_{i=1}^L \sum_{j=1}^L V(p_i, q_j) \quad (13)$$

The area A_c thus computed is used in the following steps to compute the total dissimilarity.

3.3 Computing Total Dissimilarity

It is hereby proposed that the total dissimilarity measure $D_M(t, r)$ between the one-dimensional combined-projection-feature vectors of ‘ \vec{t} ’ and ‘ \vec{r} ’ is,

$$D_M = A_c \times D^{\min}(L, L) \quad (14)$$

Where A_c is the total area created by the path around the diagonal and $D^{\min}(L, L)$ is the difference cost associated with the path.

3.4 Training

In the training phase a threshold value ‘ τ_i ’ is calculated for each and every genuine signature ‘ G^i ’ sample by computing its dissimilarity with other genuine signature samples ‘ G^j ’ available for training.

$$\tau_i = \textit{mean}[D_M(G^i, G^j)] \forall i, j \leq N \quad (15)$$

where ‘ N ’ is the number of genuine signature samples available for training.

3.5 Verification

The signature to be tested is called here the test sample ‘ S^t ’. It has to be compared with each and every genuine sample present and a score ‘ v_t ’ is computed. The decision to *accept* or *reject* is based on the value of the computed score.

$$v_t = \text{mean}\left[\frac{1}{\tau_j} \times D_M(S^t, G^j)\right] \forall j \leq N \quad (16)$$

4. Experimentation

All the experiments have been performed on the “Grupode Procesado Digital de Senales” (GPDS) signature database [11, 12] containing 2106 signatures with 936 genuine signatures and 1170 skilled forgeries. It contains signatures from 39 individuals: 24 genuine signatures for each individual, plus 30 forgeries of his/her signature. The 24 genuine specimens of each signer were collected in a single day writing sessions. The forgeries were produced from the static image of the genuine signature. Each forger was allowed to practice the signature for as long as s/he wished. Each forger imitated 3 signatures of 5 signers in a single day writing session. The genuine signatures shown to each forger are chosen randomly from the 24 genuine ones. Therefore for each genuine signature there are 30 skilled forgeries made by 10 forgers from 10 different genuine specimens.

4.1 Comparison with the Existing Method

The proposed as well as the existing method were implemented and tested on the same database mentioned above. Experiments were carried out with 4 to 5 genuine samples for training and with different ‘scores’ for verification. The performance of the proposed method was compared with the existing DTW method of [10] by using only vertical projection as the feature. The results were compared in terms of Equal Error Rates (EER) and Total Error Rates (TER) in the tables and graphs below, where the False Rejection Rate (FRR) indicates the possibility(%) of rejecting genuine signatures. False Acceptance Rate (FAR) indicates the possibility (%) of accepting skilled forgeries. The Total Error Rate (TER) is the sum of FRR and FAR. The Equal Error Rate (EER) is the point at which FAR = FRR. Lower values of EER and TER indicate superior performance. Table 1 shows the results when four genuine signature samples are used for training.

It is clear from the table that the lowest TER of 52.692 is associated with the proposed method. Also the average TER (for different scores) of the proposed method is lesser than that of the existing method. The EERs of the two methods are shown in the graphs of Fig. 9 and Fig. 10.

It is clear from Fig. 9 and Fig. 10 that the EER of the proposed method is less than that of the existing method. As a result the proposed method is better than the existing method when four genuine signature samples were used for the training phase. Table 2 shows the results when five genuine signatures are used for training.

It is also clear from the table that the lowest TER of 44.017 is associated with the proposed method. The average TER of the proposed method is also lesser than that of the existing method [10]. The EER s of the two methods are shown in the graphs of Fig. 11 and Fig. 12.

It is clear from Fig. 11 and Fig. 12 that the EER of the proposed method is less than that of the existing method. As a result the proposed method is better than the existing method when five genuine signature samples are used for the training phase.

Table 1: The results after using 4 (four) genuine signature samples for training

<i>Method</i>	<i>Score</i>	<i>FRR</i>	<i>FAR</i>	<i>TER</i>
<i>ExistingMethod</i>	0.7	96.368	1.2821	97.650
	0.8	82.692	4.5299	87.221
	0.9	59.615	12.65	72.265
	1	35.043	24.274	59.317
	1.1	17.094	38.974	56.068
	1.2	8.7607	50.684	59.444
	1.3	3.8462	64.017	67.863
<i>ProposedMethod</i>	1.1	47.65	13.59	61.24
	1.2	38.248	17.094	55.342
	1.3	32.692	20.769	53.461
	1.4	27.564	25.128	52.692
	1.5	23.077	29.829	52.906
	1.6	19.231	34.957	54.188
	1.7	15.598	39.231	54.829

Table 2: The results after using 5 (five) genuine signature samples for training

<i>Method</i>	<i>Score</i>	<i>FRR</i>	<i>FAR</i>	<i>TER</i>
<i>ExistingMethod</i>	0.7	94.872	0.2564	95.128
	0.8	76.923	4.5299	81.452
	0.9	52.991	12.735	65.726
	1	27.564	25.641	53.205
	1.1	11.966	41.026	52.992
	1.2	3.6325	59.658	63.29
	1.3	2.1368	71.88	74.016
<i>ProposedMethod</i>	1.1	45.726	9.8291	55.555
	1.2	36.752	14.786	51.538
	1.3	27.564	18.291	45.855
	1.4	22.009	22.051	44.06
	1.5	17.949	26.068	44.017
	1.6	14.744	30.94	45.684
	1.7	11.538	36.068	47.606

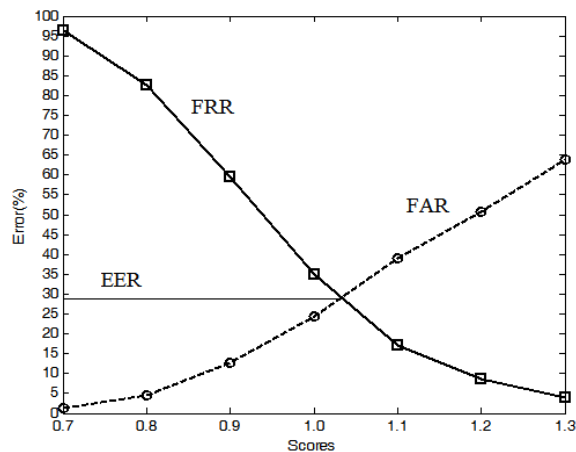


Fig. 9: EER of the existing method when four genuine samples were used for training (EER = 29)

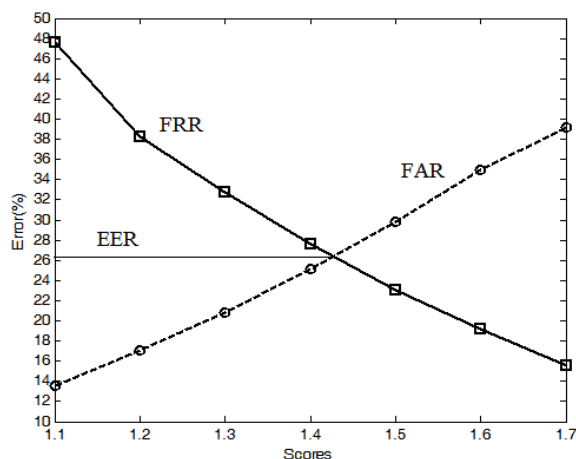


Fig. 10: EER of the proposed method when four genuine samples were used for training (EER = 26.5)

4.2 Selecting the Best Feature Vector

The feature used in the previous section is the vertical projection for comparison with the existing method. It is hereby proposed to use a combined projection vector (Fig. 6) of vertical and horizontal projections to increase the performance of the system. Experiments were carried out with vertical, horizontal and combined projections as the feature vectors and the following results were observed. The EER as well as the TER of the proposed method with various feature vectors were also compared. Table 3 shows the results of experimentations. It is clear from the table that the lowest TER of 38.334 is associated with the combined projection vector. Also the average TER of the combined projection vector is lesser than that of vertical and horizontal projections.

4.3 Change in FAR Against the Number of Training Samples

It is also observed that for any score the false acceptance rate (FAR) of the proposed method decreases as the number of genuine samples used for training increases. In the existing methods FAR increases as the number of genuine samples increases for all scores. This clearly indicates that the discriminative power to classify the forgery and original of

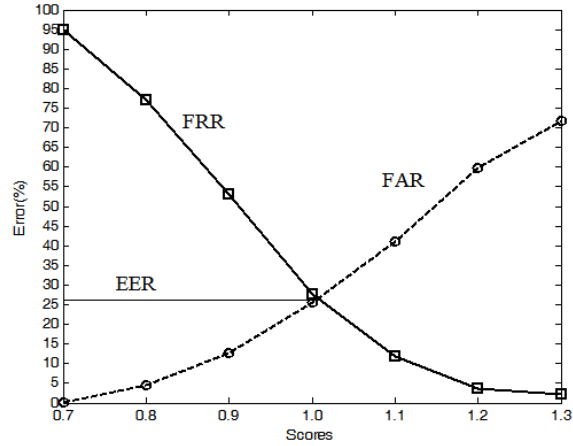


Fig. 11: EER of the existing method when 5 genuine samples were used for training (EER = 26)

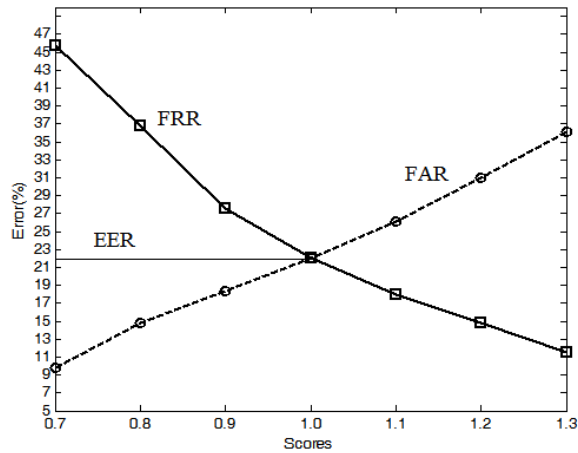


Fig. 12: EER of the proposed method when 5 genuine samples were used for training (EER = 22)

the proposed system increases as the number of training sample increases. The results for randomly selected scores are as shown in Fig. 13.

5. Conclusions

It is evident from the experimental results that the proposed matching technique using the closed area created by the matching path around the diagonal of the DTW mesh is handy in improving the performance of the existing method in terms of EER and TER. The selection of the combined vector of horizontal and vertical projections also improves the performance of the system, as the resolving power of the combined projection feature vector is more than that of horizontal and vertical projections. As the performance in terms of EER and TER of the proposed method is superior when lesser number of genuine samples is used in the training, it will be suitable for applications like banking and law enforcement where lesser number of training samples is available. The accuracy of the proposed system (in terms of FAR) is more than the existing system for greater number of genuine signature samples available for training.

Table 3: Results with various feature vectors when five genuine signatures were used for training

<i>Feature</i>	<i>Score</i>	<i>FRR</i>	<i>FAR</i>	<i>TER</i>
<i>Vertical Projection</i>	1.2	36.752	14.786	51.538
	1.3	27.564	18.291	45.855
	1.4	22.009	22.051	44.06
	1.5	17.949	26.068	44.017
	1.6	14.744	30.94	45.684
	1.7	11.538	36.068	47.606
<i>Horizontal Projection</i>	1.2	35.043	15.726	50.769
	1.3	29.701	20.342	50.043
	1.4	23.291	26.752	50.043
	1.5	19.444	31.88	51.324
	1.6	16.667	37.009	53.676
	1.7	11.752	41.282	53.034
<i>Combined Projection Vector</i>	1.2	36.325	8.2906	44.615
	1.3	27.137	12.564	39.701
	1.4	22.436	16.752	39.188
	1.5	17.308	21.026	38.334
	1.6	13.675	26.581	40.256
	1.7	10.043	31.111	41.154

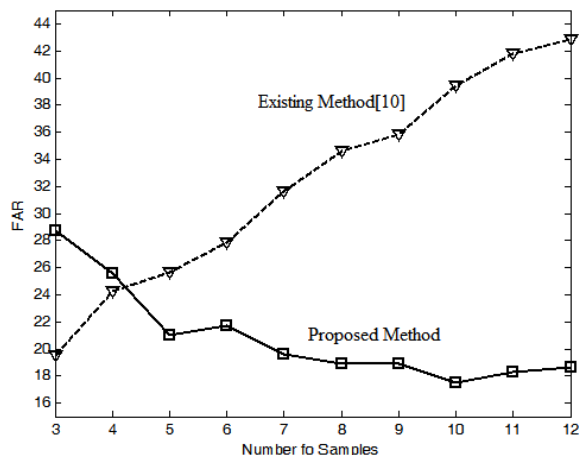


Fig. 13: Variation in FAR of the proposed as well as the existing method as the number of samples used for the training increases for randomly selected scores

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