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# Static Handwritten Signature Recognition using Discrete Random Transform and Combined Projection based Technique

Hifzan Ahmed  
Department of Electrical  
Engineering  
Jabalpur Engineering College,  
Jabalpur, India  
[hifzan.ahmed@rediffmail.com](mailto:hifzan.ahmed@rediffmail.com)

Hari Mohan Rai  
Assistant Professor  
Department of ECE  
Dronacharya College of Engineering,  
Gurgaon, India  
[harimohanrai@ieee.org](mailto:harimohanrai@ieee.org)

Shailja Shukla  
Prof and Head  
Department of CSE  
Jabalpur Engineering College,  
Jabalpur, India  
[shailja270@gmail.com](mailto:shailja270@gmail.com)

**Abstract--** In this paper, we proposed Discrete Radon Transform (DRT) technique for feature extraction of static signature recognition to identify forgeries. Median filter has been introduced for noise cancellation of handwritten signature. This paper describes static signature verification techniques where signature samples of each person was collected and cropped by automatic cropping system. Projection based global features are extracted like Horizontal, Vertical and combination of both the projections, these all are one dimensional feature vectors to recognize the handwritten static signature. The distance between two corresponding vectors can be measured with Dynamic Time Warping algorithm (DTW) and using only six genuine signatures samples of each person has been employed here in order to train our system. In the proposed system process time required for training our system for each person is between 1.5 to 4.2 seconds and requires less memory for storage. The optimal performance of the system was found using proposed technique for Combined projection features and it gives FAR of 5.60%, FRR of 8.49% and EER 7.60%, which illustrates such new approach to be quite effective and reliable.

**Index Terms--** Median Filter, Projection based Global Features, DRT, DTW.

## I. INTRODUCTION

Signature verification or recognition is the process of verifying one input of a person against one input in the database. There are two types of signatures [1] [2] [3]. The first type is called offline signature or static signature where the images of signatures are scanned and digitized into computer as a 2 dimensional image. The second type is called online signature or dynamic signature, which is captured by digital pen or tablet device. The handwritten (static) signature has many purposes and meanings. It can be used to witness intentions (e.g. signing of a contract), to indicate physical presence (e.g. signing in for work), as a seal of approval or authorization and as a stamp of authenticity. Thus, numerous applications for the off-line signature verification are available. Described as follows are a few examples of applications for the system. Despite its user friendliness and lack of invasiveness, signature recognition has not yet dominated the market, like other biometric technologies (especially fingerprint and hand geometry recognition). It is being extensively used in document verification and authorization. It is also being used now-a-days in several banking applications, credit-card transactions and e-commerce applications. Though signature recognition has not yet invaded the market, it certainly has the potential of becoming one of

the leading biometrics in commercial applications. Offline signature verification task is more difficult than online signature verification because offline systems signature images can be easily imitated and dynamic information in signature images is considerably degraded or lost during acquisition processes. The Genuine signature from the data base is shown in Figure 1 (first row) and forgery for the same signature is shown in Figure 1(2<sup>nd</sup> row).



Fig. 1. Genuine Signatures (1<sup>st</sup> row), Forgery Signatures (2<sup>nd</sup> row)

An ideal signature verification system has to minimize intrapersonal variation and maximize interpersonal variations [4]. The main steps involved for design of a signature verification and recognition system are Pre-processing, feature extraction, training and classification [5]. Feature extraction is a gathering of characteristic data which provides an output result as a set of the unique information about the signature. The feature set includes global features and local features [6]. Global features used to simplify a whole object with a single vector. Accordingly, their use in standard categorization techniques is simple. On other hand, Local feature are worked out at multiple points in the image and therefore more robust to occlusion and litter. However, they may necessitate specific classification algorithms to handle cases in which there are varieties of feature vectors per image. Global features and local texture features give unlike information regarding the image because the support varies over which texture is computed. It is a fact that any forgery must contain some deviations if compared to the original model and that a genuine sample is rarely identical to the model although there must be similarities between them. Such similarities make it possible to determine the features needed for the verification process.

The rest of the paper is organized as follows. In section II the Preprocessing is introduced which contains subsequent portions like thresholding of signature image,

cropping and noise reduction. Section III includes Feature Extraction by Discrete Radon Transform (DRT). In section IV, discusses system training implementation details. In section V, verification part of the system is described. Finally, the Experimental results and conclusion are drawn in sections VI and VII respectively.

## II. PREPROCESSING

In image representation, pixels are the term used most widely to denote elements of a digital image [7]. The signatures to be processed by the system should be in the digital image format for that purpose we need to scan the signatures from our database for the verification purpose. In first step, data was acquired from the person and after that signature was scanned to train our system for further processing which is shown in figure 2(a). The next step in the method deals with signature preprocessing. In this step signature was taken and using Otsu's method, which chooses the threshold to minimize the intraclass variance of the black and white pixels. The gray threshold function uses Otsu's method. The gray threshold function ignores any nonzero imaginary part of signature.

After thresholding, signature was converted in binary format i.e signature in black on white background which is shown in figure 2(b). As soon the image was obtained inversion was performed which changes the signature.

In figure 2(c) pixels containing 1's is the signature boundary which is our area of interest. The outer rectangular boundary which contains all 0's in rows and column should be eliminated by the automatic cropping system as shown in Figure 2(d). We remove the noise and sharpen the edges of the cropped signature image by using median filter; it is an effective method that can suppress isolated noise without blurring sharp edges. There are also nonlinear neighbourhood operations that can be performed for the purpose of noise reduction to do a better job of preserving edges than simple smoothing filters. In median filtering, the neighbouring pixels are ranked according to brightness (intensity) and the median value becomes the new value for the central pixel [7][8]. Neighbourhood averaging can suppress isolated out-of-range noise, but the side effect is that it also blurs sudden changes such as sharp edges.

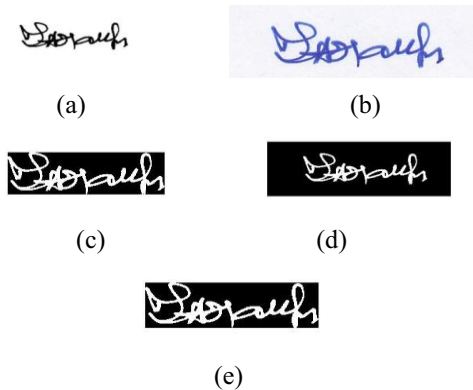


Fig. 2 . (a) Scanned Signature image, (b) Binary image, (c) Inverse binary image, (d) Cropped image, (e) Filtered signature image

The filtered signature image is shown in figure 2(e). Specially, the median filter substitutes a pixel by the median of all the neighborhood pixels.

$$Y[m,n] = \text{median}\{x[i,j], (i,j) \in w\} \quad (1)$$

Where 'w' represents a neighbourhood centered around location (m, n) in the image.

## III. FEATURE EXTRACTION

Features of signature's image are classified into Global and Local features. Global features are extracted from a whole signature, based on all sample points in the input signature. Global features of the signature image can be extracted by the Hough transform, Discrete Cosine Transform (DCT), Discrete Radon Transform (DRT) etc. But in this paper we are using Discrete Radon Transform (DRT) for extracting the projection based features (Horizontal and Vertical projection).

The Radon transform is the projection of the image intensity along a radial line oriented at a specific angle [8]. The Radon Transform of a function  $f(x,y)$  denotes  $g(s, \theta)$  is defined as its line integral along a line inclined at an angle  $\theta$  from the  $y$  - axis and at a distance  $s$  from

$$g(s, \theta) = \int_{-\infty}^{+\infty} f(s \cos \theta - u \sin \theta, s \sin \theta + u \cos \theta) du \quad (2)$$

where,

$$s = (x \cos \theta + y \sin \theta)$$

$$u = (-x \sin \theta + y \cos \theta)$$

The radon function computes projections of an image matrix along specified directions [9][10]. The Horizontal projection feature vector which is one dimensional can be extracted by giving the 90 degree value to  $\theta$  . The Horizontal projection is shown in figure 3.

A new feature vector 'S' is formed by combining HP & VP. The Combined projection is shown in figure 5.

$$S(k) = HP[j] \text{ for } k=j=1,2,3,4,\dots,h \quad (3)$$

$$S(k+i) = VP[i] \text{ for } k=h \text{ and } i=1,2,3,4,\dots,w \quad (4)$$

Where, h is the height and w is the width of the filtered signature image.

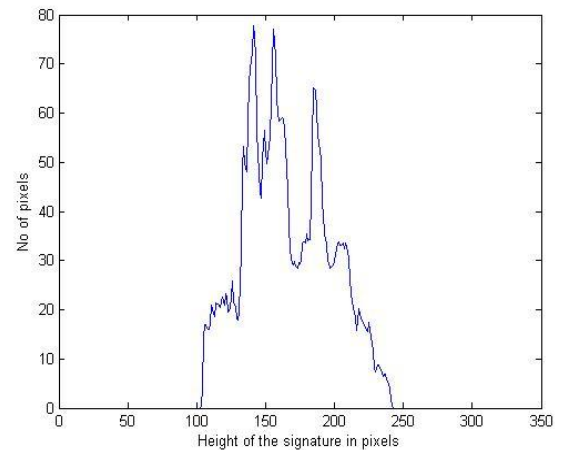


Fig. 3. Horizontal Projection

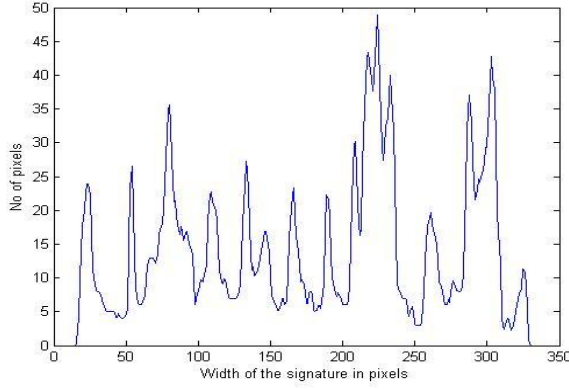


Fig. 4. Vertical Projection

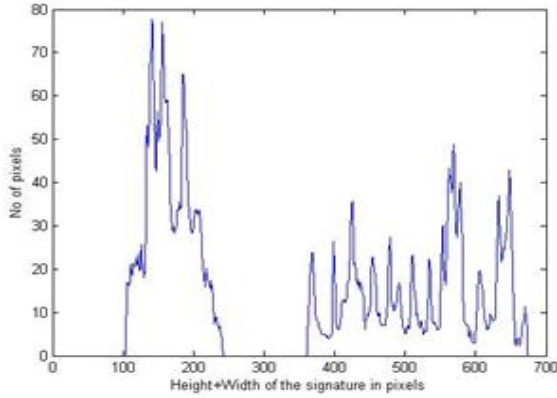


Fig. 5. Combined Projection

#### IV. TRAINING

Dynamic time warping algorithm using Euclidean distances between the features of the two points is used for alignment of the two signature's one dimensional feature vectors [11]. The Dynamic Time Warping gives the Total dissimilarity between the feature vectors which is proposed as the difference cost. This was first proposed by Sakoe and Chiba [12]. In order to understand DTW, two concepts need to be dealt with, features and distances. Distances have been classified as Local and Global. Local distance is a computational difference between a feature of one feature vector and a feature of another vector. Global distance is the overall computational difference between an entire feature vector and another feature vector of possibly different length. Suppose there are two feature vectors of signatures which are reference 'x' and test 'y' where M and N are the length (or no of values) of these feature vectors respectively and matching between these two vectors are performed by DTW algorithm. The reference and test vectors for Combined projection feature are shown in figure 6. The Euclidean distance function is defined by  $d(x,y)$  is given by equation (5).

$$d(x,y) = \|x - y\|^2 \quad (5)$$

Let  $d(m,n)$  represents the cost associated with node  $(m,n)$ . The cost (local distance) of the starting node is

represented by  $d(1,1)$  which is assigned to zero and last node is represented by  $(M,N)$ . The initial condition defines as  $D(1,1) = d(1,1)$  and  $D(m,n)$  is the global distance up to  $(m,n)$  and local distance at  $(m,n)$  is given by  $d(m,n)$  and it is given by equation (6)

$$D(m,n) = d(m,n) + D(m-1, n-1) \quad (6)$$

We can find least global distance by iterative process, given by equation (7) and DTW algorithm restricted by three conditions boundary, continuity and monotonic. The total dissimilarity between starting and last node is represented by  $D(M,N)$  and matching between reference and test vectors for Combined projection are shown in figure 7.

$$\begin{aligned} D(m,n) &= d(m,n) \\ &+ \min [D(m-1,n), D(m-1,n-1), D(m,n-1)] \quad (7) \\ DTWdist &= D(M,N) \end{aligned}$$

The training of the system for a particular person is performed in K number of genuine signature samples for that particular person [11][13][14]. The training of system is performed by equation (8) where S1 is the training score [15].

$$S1 = \frac{2}{(K(K-1))} \sum_{i=1}^{k-1} \sum_{j=i+1}^k DTWdist(S_i, S_j), i,j \leq K \quad (8)$$

#### V. VERIFICATION

Verification of the signature is performed on test signature image  $S_t$  then it is decided whether signature is genuine or forgery. The test image is compared with all the genuine signature samples which are used for training the signature data. The purpose is to compute the difference cost between two one-dimensional feature vectors. Here we calculate the K difference cost between test signature image to each of the K genuine signature images  $S_i$  and also calculate the mean of K difference cost [11][13]. In our signature verification system we used K=6 number of genuine signatures. The verification of the system is performed by equation (9) where S2 is verification score [15].

$$S2 = \frac{1}{K} \sum_{i=1}^k DTWdist(S_t, S_i) \quad i \leq K \quad (9)$$

Now we calculate the score in equation (10). The decision to accept or reject is based on the value of the score.

$$Score = \frac{S1}{S2} \quad (10)$$

#### VI. EXPERIMENTAL RESULT

The experimentation is performed on our database which includes 550 genuine and 250 forgery signatures. For training purpose we use 126 genuine signatures with 6 genuine signatures of each person. All the individual signatures are scanned with 300 dpi resolution by a Canon Scan Lide 100 scanner and stored in JPEG format.



The quality performance of the system is measured by False Rejection Rate (FRR), False Acceptance Rate (FAR), Total Error Rate (TER) and Equal Error Rate (EER). From the results shown in the Table 1 we can see that for the Horizontal projection based feature, the threshold value of 0.75 gives minimum TER of 47.61, FRR of 17.21 and FAR 30.40. The figure 8 shows that EER is 25.6 for score value 0.817.

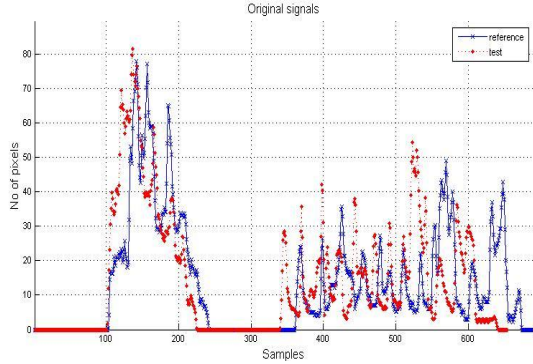


Fig. 6. The reference and test vectors

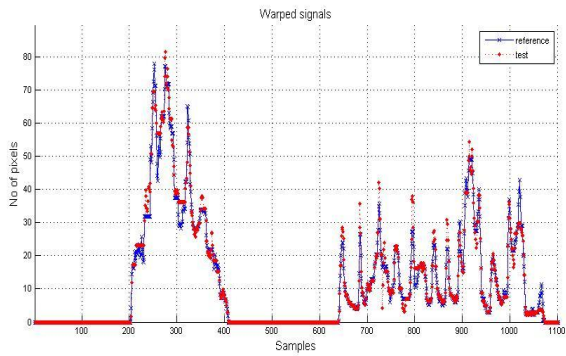


Fig. 7. Matching warped signals between reference and test vectors

TABLE 1 HORIZONTAL PROJECTION BASED FEATURE

SCORE(THRESHOLD)	FRR	FAR	TER
<b>0.3</b>	0.23	80.80	81.03
<b>0.4</b>	0.94	71.20	72.14
<b>0.5</b>	3.06	58.80	61.86
<b>0.6</b>	6.36	48.40	54.76
<b>0.7</b>	12.50	36.00	48.50
<b>0.75</b>	<b>17.21</b>	<b>30.40</b>	<b>47.61</b>
<b>0.8</b>	24.29	26.40	50.69
<b>0.9</b>	36.08	20.80	56.88
<b>1.0</b>	46.93	15.60	62.53
<b>1.1</b>	57.31	10.40	67.71
<b>1.2</b>	68.16	5.20	73.36
<b>1.3</b>	79.01	2.40	81.41

From the Table 2 we can see that for the Vertical projection based feature, the threshold value of 0.71 gives minimum TER of 22.50, FRR of 12.50 and FAR 10.00. The figure 9 shows that EER is 11.79 for score value 0.704.

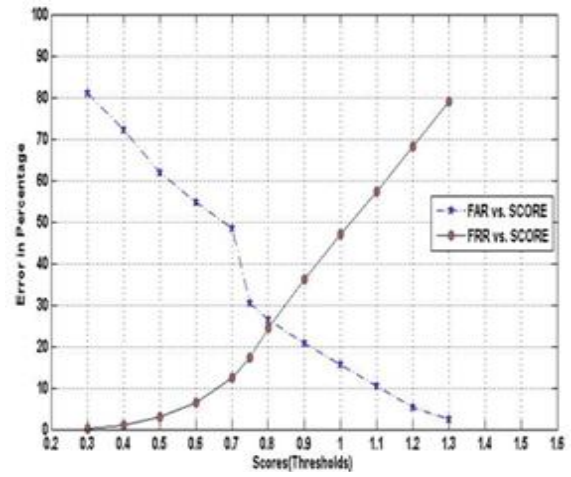


Fig. 8. Equal Error Rate for Horizontal projection

It is also clear from table 2 that the Vertical projection features based signature verification system gives better and improved results over Horizontal projection features based signature verification system, because generally the width of signature contains more information than the height of the signature.

TABLE 2 VERTICAL PROJECTION BASED FEATURE

SCORE(THRESHOLD)	FRR	FAR	TER
<b>0.3</b>	0.00	73.60	73.60
<b>0.4</b>	0.23	48.80	49.03
<b>0.5</b>	0.94	30.80	31.74
<b>0.6</b>	3.53	19.20	22.73
<b>0.7</b>	11.55	12.00	23.55
<b>0.71</b>	<b>12.50</b>	<b>10.00</b>	<b>22.50</b>
<b>0.8</b>	23.58	3.60	27.18
<b>0.9</b>	38.67	0.80	39.47
<b>1.0</b>	54.48	0.40	54.88
<b>1.1</b>	73.82	0.00	73.82
<b>1.2</b>	83.96	0.00	83.96
<b>1.3</b>	92.92	0.00	92.92

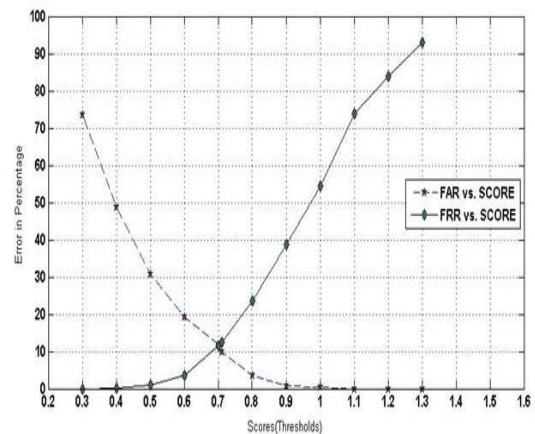


Fig. 9. Equal Error Rate for Vertical projection

From the Table 3 we can see that for the combined projection based feature, the threshold value of 0.74 gives minimum TER of 14.09, FRR of 8.49 and FAR 5.60, that means it accept 14 forgery signature out of 250 and reject 36 genuine signature out of 424. The figure 10 shows that EER is 7.60 for score value 0.72. Hence Combined projection features based signature verification system gives better and much improved results over Horizontal and Vertical projection features based signature verification system. The reason is that Combined projection based feature contain sum of Horizontal and Vertical (height and width) projection based features of signature images. The lower the EER is, the better is the system performance [16][17].

TABLE 3 COMBINED PROJECTION BASED FEATURE

SCORE(THRESHOLD)	FRR	FAR	TER
0.3	0.00	86.40	86.40
0.4	0.47	59.60	60.07
0.5	1.18	37.20	38.38
0.6	1.89	22.00	23.89
0.7	5.19	10.40	15.59
0.74	8.49	5.60	14.09
0.8	18.17	4.00	22.17
0.9	37.50	1.20	38.70
1.0	57.55	0.00	57.55
1.1	72.41	0.00	72.41
1.2	85.62	0.00	85.62
1.3	91.51	0.00	91.51

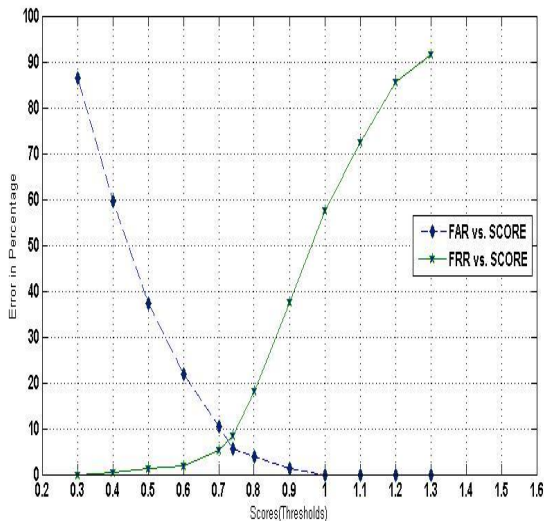


Fig. 10. Equal Error Rate for Combined projection

## VII. CONCLUSION

A method of feature extraction was proposed for off-line signature verification and recognition system. The experiments were carried out with Horizontal projection, Vertical projection and Combined projection as the feature vectors and following results with different

verification score where observed. From the Experimental and testing results we found that by using the combination of Horizontal and Vertical projection based features obtains FRR, FAR and TER which is less than Horizontal and Vertical projection based features separately. The time required for training the system is about 1.5 to 4.2 seconds and also the memory requirements are less because we are using one dimensional feature vector.

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