DISCRETE RADON TRANSFORM BASED STATIC HANDWRITTEN SIGNATURE VERIFICATION

Nazia Khan [#1], Neeraj Shukla [#2]

#1 MTech(Digital Communication),Gyan Ganga College Of Technology,Jabalpur,INDIA,07566467355.

#2 Department of Computer Science Engineering, Gyan Ganga College Of Technology,Jabalpur,INDIA,09826193481

ABSTRACT - Biometric security devices are now permeating all facets of modern society. Hand-written signature is widely used for authentication and identification of individual. The proposed algorithm uses automatic cropping system and Local Radon Transform. The method uses Radon Transform locally as feature extractor and Hidden Markov Model as classifier. To avoid interpersonal variation 3 signature images of the same person are taken and feature points are trained. These trained feature points are compared with the test signature images and based on a specific threshold, the signature is declared as original or forgery. When being trained using 3 genuine signatures of each person and 90 forgeries taken from our database, the proposed method obtained an equal error rate (EER) of 4.29%. The false acceptance rate (FAR) and false rejection rate (FRR) for proposed method was also kept as low as 5.00% and 4.44% respectively.

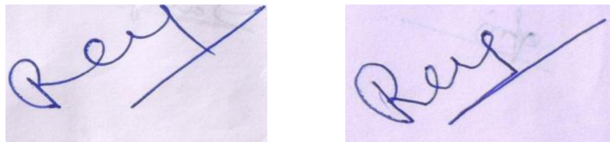
Categories and Subject Descriptors: Image Processing and Computer Vision
Keywords: Off-line Signature verification, on-line signature verification, biometrics, authentication systems Median filter, Local features, Discrete Radon transform.

I.INTRODUCTION

Biometrics is the set of technological means that enables the identification or verification of an individual from its physical or behavioral characteristics depending on their nature. It can be classified into two categories namely behavioral (signature verification, keystroke dynamics, etc.) and physiological (iris, face, voice characteristics, fingerprint, etc.). Off-line signature verification is considered as a behavioral characteristic based biometric trait in the field of security and prevention of fraud. A significant amount of work on offline signature recognition is available to detect forgeries and to reduce identification errors.

The main drawback of the handwritten signature is the easiest reproduction by the professional forgers. Usually, two acquisition modes are used for capturing the signature, which are off-line mode and on-line mode, respectively. The off-line mode allows generating a handwriting static image from a scanning document. In contrast, the on-line mode allows generating from pen tablets or digitizers dynamic information such as velocity and pressure.

In off-line systems the objective is to detect types of forgeries[11], which is related to intra and inter-personal variability.



(a) **(b)**

Fig 1: (a) Genuine Signature (b) Skilled Forged Signature

Simple forgery represented when the forger is familiar with the writer's name, but does not have access to a sample of the actual signature.
Random forgery or zero-effort forgery can be any random scribble or a signature of another writer.
Professional forgery is produced by an individual who has professional expertise in handwriting analysis.
Home-improved forgeries are produced when the forger has a paper copy of a genuine signature and opportunity to practice the signature at home.
Over-the-shoulder forgeries are produced immediately after the forger has witnessed a genuine signature being produced.

Generally, an off-line HSVS is composed of three stages: acquisition and preprocessing, feature generation, classification and verification. In the past decade, many methods have been developed for the classification stage, such as Template Matching, Neural Networks, Fuzzy Logic, Modified Direction Features and the Structural Model More recently, models based on the Support Vector Machines have been found to be well suited for signature modeling, as Offline Signature Verification Using Virtual Support Vector Machines.

II.SIGNATURE VERIFICATION CONCEPT

A signature is any written specimen in a person's own handwriting meant to be used for identification. A signature verification (SV) system authenticates the identity of any person, based on an analysis of his/her Signature through a set of processes which differentiates a genuine signature from a forgery signature. The precision of signature verification systems can be expressed by two types of error: the percentage of genuine signatures rejected as forgery which is called False Rejection Rate (FRR); and the percentage of forgery signatures accepted as genuine which is called False Acceptance Rate (FAR).While dealing with any signature verification system, we consider FRR and FAR as its performance evaluation parameters.

With the help of some reference papers it is seen that previously the work done in this field is to improve the accuracy of the system and also decrease the error rate.. By factorizing FAR and decreasing FRR, the problem can be solved..There are many conventional techniques for this, to compare two signatures based on their spatial domain and transform domain information. Among such techniques, Vertical Projection Profile (VPP), Horizontal Projection Profile (HPP), slant angle of signature, position centroid, etc tap into the information present in the spatial domain. On the other hand Discrete Cosine Transform (DCT) uses the information present in the transform domain to distinguish between the two signatures.

III. OVERVIEW OF PREVIOUS WORK

The inference taken form [1] proposes Simple filter which is also known as mean filter is computationally very simple and is useful when the scanned signature is very clear (less noisy).This is more useful in salt pepper noise cases. LBP (Local Binary Pattern) is efficient when there are a group of signatures to be tested which are signed using the same pen and has less presence of noise. If the signature to be tested is signed with different pens then LDP (Local Directional Pattern) is useful. So LDPs give more accurate result than LBPs when there is no pen dependence. LDPs and LBPS are more efficient in detecting skilled forgeries as well as simple and random forgeries.Two-dimensional images; therefore they often try to compare global features like size of the signature or similarities of the contour [2] [3] [4]. When measuring the efficiency of these systems, there is always a tradeoff between the rate of accepted forgeries and the rate of Rejected originals (type I and type II errors). By adjusting the parameters of a system a point can be reached where these two rates are equal. This rate is called the equal error rate (EER) and is typically used to characterize a signature verification system.

The inference taken form [2] take another approach in they try to guess the pen movements during the signing by starting at the left and bottom most line-end and then following it. There are also other approaches trying to reconstruct the signing process. In stroke, and sub-stroke properties are extracted and used as a basis for the comparison. Based on own experience, these latter approaches seem to be the most promising, because their results can be explained (and therefore improved) in a semantically meaningful way.

The inference taken form [3], four different types of global features have been used for the classification of signatures. The features used for classification are horizontal projection moments, vertical projection moments, upper and lower envelopes and area of black pixels .The other challenging problem in offline signature verification is the feature extraction process.

The inference taken form [4], a robust signature verification system has been proposed, based on DCT coefficients and the parzen window classifier. Method can extract basic dynamic features from signature time signals, and compress signature data, while keeping the rough form and basic information of signatures. Especially in the context of skilled forgery, where inter-personal variability in the number of features becomes negligible, an effective analysis of features based on time signals is essential for attainment of a suitable performance. The proposed method is very fast in training, feature extraction, and matching, in comparison with the DTW[7] system. Another method was proposed that uses the 1-D vertical projection feature in conjunction with DTW.The system based on the modified DTW algorithm performed significantly better than the basic system. The method is computationally efficient and runs in real-time.

The inference taken form [5], Use of simple features, different cell resolutions and multiple codebooks in an HMM framework. The simple and random forgery error rates have shown to be low and close of each other. This demonstrates the potential of the system in a real application. It is important to observe that there is no forgery sample in the learning database. The high type II error rate in skilled forgery signatures demonstrates that is necessary to evaluate more accurate results.

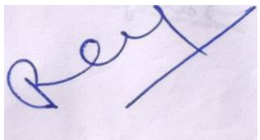
In signature verification systems, the performance is evaluated in terms of error rates [6]. There are two types of errors: False Rejection and False Acceptance. Also, there are two types of error rates: False Rejection Rate (FRR) and False Acceptance Rate (FAR). The false rejection rate (FRR) is related to genuine signatures that were rejected by the system; that is, classified as forgeries, whereas the false acceptance rate (FAR) is related to forgeries that were misclassified as genuine signatures. FRR is known as type 1 and FAR is known as type 2 error. The Average Error Rate (AER) is the average of type 1 and type 2 errors [7]. Another factor that determines the efficiency of the system is the Equal Error Rate (EER). The EER is the location on a ROC or Detection Error Trade-off curve where the FAR and FRR are equal. Smaller the value of EER better is the performance of the system.

IV.STEPS IN OFFLINE SIGNATURE VERIFICATION

Offline signature verification is a pattern recognition problem and a typical pattern recognition system has the following steps**:-**
(i) **Data Acquisition** – to capture the signature image.
(ii **Preprocessing** – to simplify subsequent operations without loosing relevant processing.
(iii)**Feature Extraction -** to reduce the data by measuring certain “features” or “properties”.
(iv)**Classification** (called verification in the signature verification field) – to evaluate the evidence presented in the value of the feature obtained from feature extraction and makes a final decision for classification
(v)**Performance Evaluation** – to evaluate the efficiency of the signature verification system.

Data Acquisition **:** Images of the signatures are scanned using a digital scanner for offline processing. Each signature is scanned into a binary image at a resolution of 300 dots per inch, after which median filtering is applied for removal of noise. On average, a signature image has a width of 400 to 600 pixels and a height of 200 to 400 pixels.Using a database of 150 signature,90 signatures were used in the training phase and the rest 60 were used for testing. The images are in RGB color scale. In this we used .jpg color images (RGB images).

Signature Preprocessing : The purpose of pre-processing phase is to make signatures standard and ready for feature extraction In this, first we find out threshold level of the digital scanned image of signature by Otsu method for converting digital colour image to binary image i.e signature in black on white background as shown in figure 2(a). As soon the binary image was obtained inversion was performed i.e signature in white on black background as shown in figure 2(b). The automatic cropping system eliminates all rows and columns which have all 0's values from the inverse binary matrix of the image where 1's represents signature and 0's represents background as shown in figure 2(c). The largest rectangular dimension of the signature image is rescaled to 512 pixels.



(a)

(b)

(c)

Feature Extraction :Features extracted for off-line signature verification can be broadly divided into three main categories:

1. Global Features 2. Local Features 3. Geometric Features

Global features – The signature is viewed as a whole and features are extracted from all the pixels confining the signature image. Based on the style of the signature, different types of Global features are extracted Signature area (Signature Occupancy Ratio), Signature height-to-width ratio (Aspect Ratio), Maximum horizontal histogram and maximum vertical histogram, Image area, Signature height , Horizontal and vertical center of the signature Image area, Pure width ,Pure height ,Vertical projection peaks ,Horizontal projection peaks .

Local features – Local features are extracted from a portion or a limited area of the signature image. It applied to the cells of a grid virtually super imposed on a signature image or to particular elements obtained after signature segmentation. These features are calculated to describe the geometrical and topological characteristics of local segments, such as position, tangent direction, and curvature.

Geometric features – These features describe the characteristic geometry and topology of a signature and preserve their global as well as local properties. Geometrical features have the ability to tolerate with distortion, style variations, rotation variations and certain degree of translation.

After feature extraction, classification and verification process is carried out. The choice of the HMM along with viterbi re-estimate is successfully used for biometric verification.

V.FEATURE EXTRACTION

Signature Zoning is the process of dividing a signature into regions, primarily to define areas from which local features can be extracted. A bounding box is defined around the signature and said box is divided into a number of vertical and horizontal strips of uniform width and height. This scheme is fixed in the sense that every signature is divided into a grid containing the same number of cells.Again the bounding box is divided into uniform vertical and horizontal strips, but the centre of the grid is now translated to correspond to the gravity centre of the signature.

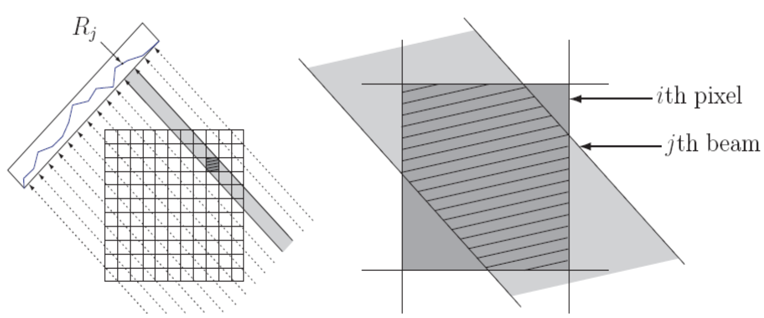
The standard grid-based zoning scheme can be modified by defining a point at the intersection of each pair of vertical and horizontal dividing lines. These points are then used as centroids for circular retinas. The flexible grid-based zoning scheme calculates the location of the vertical and horizontal dividing lines based on the percentage of the total number of black pixels contained in each strip. We define two parameter sets, Zh and Zv, which contain the intervals for the horizontal and vertical divisions respectively.The gravity centre, Gμ = (Gx,Gy), is used as a reference point.

Discrete Radon Transform of an image (or any matrix) is calculated by taking the d-dimensional projection of the image from Nθ equally distributed angles, ranging from 0◦ to 180◦. The DRT[6] is therefore a Nθ × d image, where each column of the DRT image represents the projection of the original image at a certain angle. The DRT, when converted to a grayscale image, is known as a sinogram. The DRT of an image consisting of Ξ pixels, where the intensity of the ith pixel is denoted by Ii, for i = 1, ... Ξ , is calculated using d (the number of beams per angle) and Nθ angles in total.The jth beam-sum, which is the cumulative intensity of the pixels that are within the jth beam, is denoted by Rj , where j = 1, . .,Nθ.d.

The DRT can therefore be expressed as

$$\mathbf{Rj = \sum \alpha ij,Ij,\ j = 1, 2, . . . ,N\theta.d} \qquad 5.2.1$$

where ij denotes the weight of the contribution of the ith pixel to the jth beam-sum.



The DRT model of Eq. 5.2.1. In this case, **αij**, that is, the weight of the contribution of the ith pixel to the jth beam-sum is approximately 0.6 (indicated by the patterned region). This means that the jth beam overlaps 60% of the ith pixel.

Although the projections at angles ranging from 180◦ to 360◦ contain no additional information over the projections at angles ranging from 0◦ to 180◦,these additional angles are appended to the preliminary observation sequence.This is done to aid the construction of a rotation invariant system. The additional projections are simply the reflections of the projections which form the preliminary observation sequence; no additional calculations are necessary.The final observation sequence therefore has length T = 2Nθ.The final modification made to the observation sequence is the normalization of each feature vector by the standard deviation of the intensity of the entire set of T feature vectors.

Signature Modelling Once the DRT-based observation sequences have been extracted, Nr different HMMs [6][8][10] are initialized and trained for each writer (i.e. one model for each retina).

(a) ***HMM notation*** In this paper, each retina is represented by a continuous observation, *ring-structured* HMM, with N states and no state skips. The similarity between an observation sequence X and HMM λ is obtained via Viterbi alignment [9] and denoted by the likelihood f(X|λ).

(b) ***Training*** Each HMM λ^r_w is initialised using uniform initial and state transition probabilities. i.e., the probability of entering the HMM at any state is 1/N. The training set{Xrw,1,Xrw,2,...,Xrw,NT } for a specific retina r, belonging to a specific writer w, contains NT training samples, and is used to train the HMM λ^r_w . The probability density functions (PDFs) that represent each state in the HMM, are initially estimated by assigning an equal number of feature vectors to each state.For each PDF, only the mean vector is estimated, while the covariance matrix is kept fixed. Once each HMM has been initialised,it is trained using the Viterbi re-estimation technique[9].The dissimilarity between an observation sequence X and a HMM λ is expressed as follows,

$$D(X, \lambda) = -\ln(f(X|\lambda)) \qquad (1)$$

The mean dissimilarity value of the training samples for retina r, associated with writer w, is denoted by μ^r_w and calculated as

$$\mu^r_w = \frac{1}{N_T}\sum_{i=1}^{N_T} D(\mathbf{X}^r_{w,i}, \lambda^r_w).$$

The standard deviation of the dissimilarity values of the training samples for retina r, associated with writer w, is denoted by σ^r_w,and calculated as follows,

$$\sigma_w^r = \sqrt{\frac{1}{N_T - 1}\sum_{i=1}^{N_T}(D(\mathbf{X}^r_{w,i}, \lambda^r_w) - \mu^r_w)^2}.$$

The statistics defined are used for score normalization.

Thresholding and score normalization When a test sequence X^r_w where r indicates a specific retina, is claimed to belong to a specific writer w, X^r_w is matched to the appropriate HMM λ^r_w through Viterbi alignment. The dissimilarity between the test sequence and the HMM (Eq. 1), therefore becomes

$$D(\mathbf{X}^r_{(w)}, \lambda^r_w) = -\ln(f(\mathbf{X}^r_{(w)}|\lambda^r_w)).$$

Each dissimilarity value is subsequently normalised using zscore normalisation. A normalized dissimilarity value, denoted by DZ(X^r_w, λ^r_w), is obtained as follows,

$$D_Z(\mathbf{X}^r_{(w)}, \lambda^r_w) = \frac{D(\mathbf{X}^r_{(w)}, \lambda^r_w) - \mu^r_w}{\sigma^r_w},$$

We now define a sliding threshold T ∈ [−3,∞), so that a claim is accepted (for the specific classifier associated with retina r) when

Dz (X^r_w, λ^r_w) < T, i.e.

When Dz (X^r_w, λ^r_w) < $\mu^r_w + \sigma^r_w .T$,

Otherwise, the claim is rejected.

VI. EXPERIMENTAL SETUP

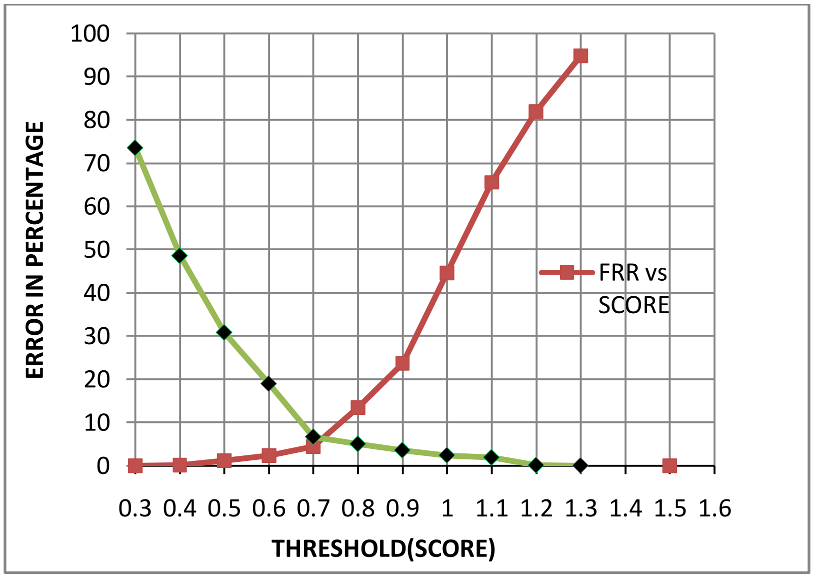
We consider 90 genuine signatures, 3 skilled forgeries,for each writer. For each writer, 3 genuine signatures are used for training and 60 for testing. No genuine signatures are used for validation purposes.

VII. RESULTS

For these experiments, we use a HMM with N = 64 states. The feature vectors are of dimension d = 512, in the case of the global retina, and of dimension d=240 (radius γ=120) for the local retinas. The observation sequences are of length T = 256 and Nr -1 = 15 retinas (Nr =16 for global retinas).

All results are reported at the EER. The results are shown in Table I, with the best result in boldface.

THRESHOLD (SCORE)	**FRR %**	**FAR %**	**TER %**
0.3	0.00	73.59	73.59
0.4	0.21	48.89	49.10
0.5	1.22	30.82	31.80
0.6	2.33	18.95	22.48
0.7	**4.44**	**6.66**	**11.10**
0.8	13.52	5.01	18.53
0.9	23.69	3.55	27.24
1.0	44.58	2.38	46.96
1.1	65.62	1.89	67.51
1.2	82.00	0.08	82.08
1.3	94.90	0.00	94.90



Graph for FRR and FAR when d = 512, Ξ = 128,N= 64 and l = 1.

VIII. CONCLUSIONS AND FURTHER RESEARCH

7.1 Conclusion

The objective of this project was mainly to offer an efficient and economically viable offline hand- written signature verifier. In order to meet the objective various existing methods of offline hand- written signature verification were reviewed and DRT features were decided as robust image de- scriptors. Also HMM model is used as a classifier.A database of signatures was collected consisting of known writers'signatures and forgeries. The efficiency of the verifier was tested and specificity and the sensitivity were measured for each test taken.The main purpose of this paper was to decrease the error rates by using local features which uses local DRT based feature extaction method and continuous observation ring-structured HMM model.

7.2 Area Of Future Research

As Discussed in the conclusion the error rates of DRT and HMM using viterbi algorithm is low as compared to LRT -SVM & HMM using global features, we can improvise the method by using other encoder and Mahalanobis distance, When parameter features are used, Support Vector Machines (SVM)[15] are another effective approach for signature verification, since they can map input vectors to a higher dimensional space, in which clusters may be determined by a maximal separation hyper-plane. Also SVM based on longest common subsequences (SVM-LCSS) will also used as they) are superior with respect to SVM based on other kernel functions.

REFRENCES

[1] MettaMadhavi, Manoj Reddy Yaram, Dr.R.V.Krishnaiah, **"Effective Implementation techniques in Offline Signature Verification"** M.Tech, Department of CSE, D.R.K. college of engineering and technology, Hyderabad, India.

[2] Bence Kovari, Hassan Charaf **"Feature matching in off-line signature verification"** Department of Automation and Applied Informatics Budapest University of Technology and Economics 1117. Budapest, Magyar Tudosok Korutja 2, Q.

[3] C. Ajoy Navin **"Offline signature Verification using Projection Moments and Envelope Characteristics",** Sri Sivasubramanya Nadar College of Engineering, Old mahabalipuram road, Kalavakkam, Chennai**.**

[4] A. Piyush Shanker "**Offline signature Verification using DTW**", Pattern Recognition 1, 2007 pp. 97-103**"**, Image Processing and Computer Vision Lab, Department of Electrical Engineering, Indian Institute of Technology Madras, Chennai, Tamil Nadu,.India.& S. Rashidi, A. Fallah, F. Towhidkhah **"Feature extraction based DCT on dynamic signature Verification"** Faculty of Biomedical Engineering, Amirkabir University of Technology, Tehran.

[5] Edson J.R. Justino a, Fla´vio Bortolozzi a, Robert Sabourin **"A comparison of SVM and HMM classifiers in the off-line signature verification"** Institute for Digital Communications,

Joint Research Institute for Signal and Image Processing, The University of Edinburgh, EH9 3JL Edinburgh.

[6] Coetzer J., Herbst B., & du Preez J. 2004. **"Off-line signature verification using the discrete random transform and a hidden Markov model"** EURASIP Journal on Applied Signal Processing.

[7] Guler I and Meghdadi M. 2008. **"A different approach to off-line handwritten signature verification using the optimal dynamic time warping algorithm"** Digital Signal Processing (Science Direct) 18 (2008) (pp 940–950)

[8]Miguel A.Ferrer**," Off-line Signature Verification using Local Patterns**", Telecommunications (CONATEL), 2011 2nd National Conference on Date of Conference: 17-20 May 2011.
.
[9] Baochang Zhang, YongshengGao, "**Local Derivative Pattern versus Local Binary Pattern: Face Recognition with high order local Pattern Descriptor**", IEEE Transactions in image processing, Vol. 19.no.2, February 2011.

[10] Edson J. R. Justino, Abdenaimel Yacoubi, Flaviob Ortolozzi and Roberts Abourin, "**An Off-Line Signature Verification System Using Hidden Markov Model and Cross-Validation**", in IEEE International Workshop on Neural Networks for Signal Processing, pp. 859–868, Sydney, Australia, December 2000.

[11] Edson J. R. Justino, Flávio Bortolozzi and Robert Sabourin ,"**Off-line Signature Verification Using HMM for Random,Simple and Skilled Forgeries**", in International Conference on Document Analysis and Recognition, vol. 1, pp. 105–110,Seattle, Wash, USA, 2001

[12] Jose' A. Sanchez, Carlos M. Travieso, Itizar G. Alonso and Miguel A. Ferrer, "**Handwritten signatures recognizer by its envelope and strokes layout using HMM's",** in proc. IEEE 35th Int carnahan Conf on Security Technology", vol 1, pp.267-271, Oct 2001.

[13] Wei Tian, Yizheng Qiao and Zhiqiang Ma, "**A New Scheme for Off-line Signature Verification Using DWT and Fuzzy Net"**, 8th ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing.

[14] Xiufen Ye, Weiping Hou and Weixing Feng, "**Off-line Handwritten Signature Verification with Inflections Feature**", Proc. of the IEEE International Conference on Mechatronics & Automation, Canada , July 2005.

[15] Emre Özgündüz, Tülin Sentürk and M. Elif Karslıgil, "**Off- Line Signature Verification and Recognition by Support Vector Machine".**