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Signature Verification Based on Texture Features of Image

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***Abstract*– Signatures are one of the most important and commonly used tools for human identification. This paper proposes an offline signature verification method based on texture analysis of the image. A sample of signatures is used to represent a particular person. For each known writer sample of fifteen genuine signatures are taken. Forged signatures are also used to test the efficiency of the system. For each signature gray level run length matrix features are extracted and the inter-class distances and intra class distances have been calculated. For each test signature the intra-class threshold is compared to the inter-class threshold for the claimed signature to be verified using Euclidean distance model. Results showed that signature texture feature can be reasonably used for personal verification. Texture based feature extraction technique consistently outperformed the traditional grid based feature extraction technique. Accuracy of 85% was achieved with the Euclidean distance classifier with FAR and FRR as low 13.33% and 16.4%.**

***Index Terms*– Accuracy, FAR, FRR, Signature Verification and Texture Analysis**

I. INTRODUCTION

BIOMETRIC authentication supports the facet of identification, authentication and non-repudiation in information security [1]. Handwritten signatures, henceforth referred to only as signatures, have been considered valid proof of identity and consent for centuries. Even in our present day and age, dominated by advanced technological systems and protocols, signatures remain the preferred method for identity verification, as they are both nonintrusive and easily collectable. Many documents such as bank cheques, forms, and legal documents necessitate the signing of a signature.

Therefore it is essential to verify the signatures, with high accuracy and less time consuming processes. As a result, signature verification systems have experienced quantum leaps regarding both complexity and efficiency at a continuous and relentless pace. The objective of the signature verification system is to discriminate between two classes: the original and the forgery, which are related to intra and interpersonal variability [2]. The variation between signatures of same person is called intrapersonal variation and between original and forgeries is called inter personal variations.

Signature verification can be divided into on-line and off-line verification depending on the method of data acquisition. In on-line verification signer uses special hardware like pressure tablets or special pen called stylus to create his or her signature, producing the pen locations, speeds and pressures. In off-line signature verification, signature is available on a document which is scanned to get the digital image representation. Unlike the on-line signature, where dynamic aspects of the signing action are captured directly as the handwriting trajectory, in offline signature verification writing features, such as the handwriting order, writing-speed variation, and skillfulness, need to be recovered from the grey-level pixels [3], [4]. In this paper a robust model for offline signature verification is proposed based on texture features of the signature image.

II. RELATED WORK

All the aforementioned factors suggest that effective automatic handwritten signature verification systems are no longer a technological luxury as in years past, but have in fact become a true necessity in the modern document processing environment. According to Schmidt (1994), an individual's signature is usually composed of stroke sequences much unlike those used in ordinary handwriting and, in addition, tends to evolve towards a single, unique design. This is not only as a result of repetition, but also the innate desire of each person to create a unique signature. Signatures are therefore able to reflect a writer's subtle idiosyncrasies to a much greater extent than ordinary handwriting [5].

The available methods for off-line signature recognition are based on a vast range of concepts. Buddhika Jayasekara proposed a signature recognition method based on the fuzzy logic and genetic algorithm (GA) methodologies [6]. It consists of two phases; the fuzzy inference system training using GA and the signature recognition. Signature recognition rate of about 90% was obtained and handled the random forgeries with 77 % accuracy and skilled forgeries with 70% accuracy but the system performance highly depends on the fuzzy inference system capabilities and therefore relies on the fuzzy rule base [6]. Banshider Majhi gave a novel feature extraction method based on geometric centers. Features are obtained by recursively dividing a signature image into sub-images along horizontal and vertical axes located on the geometric centre of the parent image. Geometric centers of the final sub-images subsequently form the feature vector but this method did not classify skilled forgeries [7]. Fuzzy min-max algorithm was applied to classify the signature pattern and this fuzzy min-max algorithm totally fit to the neural network framework. The neural network middle layer work as fuzzified neuron and because of this the output can be correctly classified but error rate depend on expansion coefficients [8]. Debnath Bhattacharyya proposed an algorithmic approach for the verification of handwritten signatures by applying some statistical methods. The research work was based on the collection of set of signatures from which an average signature was obtained and then taking decision of acceptance after analyzing the correlation in between the sample signature and the average signature [9]. Reza Ebrahimpour introduced a new and robust model for signature recognition by means of features inspired by the human's visual ventral stream [10]. The proposed method leads to robust and accurate signature verification, which has not been studied and used .It is based on Euclidean distance model. After extracting GLRLM (gray level run length matrix) texture features simple statistical classifier and the Euclidean classifier is employed to verify the signature images.

III. TEXTURE FEATURE EXTRACTION USING GLRLM

Texture is one of the most important characteristics of an image. It is used to describe the local spatial variations in image brightness which is related to image properties such as coarseness, and regularity. This is achieved by performing numerical manipulation of digitized images to get quantitative measurements. Normally texture analysis can be grouped into four categories: model-based, statistical-based, structural-based and transform-based methods. Model-based methods are based on the concept of predicting pixel values based on a mathematical model. Statistical methods describe the image using pure numerical analysis of pixel intensity values. Structural approaches seek to understand the hierarchal structure of the image.

Transform approaches generally perform some kind of modification to the image, obtaining a new "response" image that is then analyzed as a representative proxy for the original image. This paper only focuses on statistical approaches, which represent texture with features that depend on relationships between the grey levels of the image. In this paper, preprocessed image (ROI) is utilized to construct the feature sets using Gray-Level Run-Length Method (GLRLM). And then each features set is used for the classification. Gray-Level Run-Length Matrix Texture is understood as a pattern of grey intensity pixel in a particular direction from the reference pixels [12].

Grey- Level Run-Length Matrix (GRLM) is a matrix from which the texture features can be extracted for texture analysis. It is a way of searching the image, always across a given direction, for runs of pixels having the same gray level value. Run length is the number of adjacent pixels that have the same grey intensity in a particular direction. Gray-level run-length matrix is a two-dimensional matrix where each element is the number of elements j with the intensity i, in the direction θ. The Gray Level Run Length matrix is constructed as follows:

$$R(\theta) = (g (i,j) \mid \theta),\ 0 \le I \le Ng ,\ 0 \le I \le Rmax \qquad (1)$$

where Ng is the maximum gray level and Rmax is the maximum length. Let p (i, j) be the number of times there is a run of length j having gray level i. There are five Run Length Matrix based features computed for 4 directions of run (0°, 45°, 90° , 135°). The Figure 1 shows the sub image with 4 gray levels for constructing the GLRLM. Figure 2 shows that the GLRLM in the direction of 0^0 of the sub image. In addition to 0^0 direction GLRLM can be calculated in all four directions.

1	**2**	**3**	**4**
1	**3**	**4**	**4**
3	**2**	**2**	**2**
4	**1**	**4**	**1**

Figure 1: Matrix of image

Gray Levels	**Run Length(j)**			
	1	**2**		**4**
1	**4**	**0**	**0**	**0**
2	**1**	**0**	**1**	**0**
3	**3**	**0**	**0**	**0**
4	**3**	**1**	**0**	**0**

Figure 2: GLRLM of Image

Seven texture features can be extracted from the GLRLM [12]. These features use grey level of pixel in sequence.

IV. IMPLEMENTATION

A. Image acquisition

The signature database used in this experiment is an experimental database. The signatures are collected using any color ink blue, black, green and red on a white A4 sheet paper. Random sample of 35 signers was used each signer contributed 15 signatures giving a total of 525 genuine signatures, collected from students of National Institute of technology, Srinagar. Some students were asked to forge other writers' signature. These Forged signatures were used to test the accuracy of the system.

B. Image Preprocessing

Each signature image is scanned at a resolution of 200 dpi, 16-bit grey-scale and stored in tiff format. The texture features do not require preprocessing like filtering, smoothening, enhancement etc. as it may damage the texture feature details. This feature makes its processing even simpler. Before finding features we have to do some adjustments to the signature image. In our experiment we fixed a standard box of size 380x380 pixels in which all signatures fitted properly. After cropping P-tile thresholding was chosen to capture signature from background. After thresholding the pixels of the signature would be "1" and that of background would be "0" eliminating the background.

C. Feature Extraction

Two dimensional gray level run length matrix for each signature image were calculated and their seven GLRLM features viz SRE, LRE, GLN, RLN, RP, LGLRE, HGLRE obtained. To check efficacy of the features so extracted and to find a suitable feature vector for classification we used statistical measure like mean and standard deviation.

The mean(μ) and standard deviation(σ) of each of seven features for training signature of every individual signer are calculated. It was found out that the mean of feature LRE showed a large discrepancy between signature of different signers but for a particular signer LRE of all the training signatures was in the range $\mu \pm \sigma$. LRE feature showed a large inter personal variation and a very small intra personal variation among the other 6 features thus a potential feature to verify a particular signature as genuine or forgery.

D. Classification

Measuring the similarity or distance between two signatures in feature space is essential for classification. Euclidean distance classifier has been used. This is a simple distance between a pair of vectors. Here vectors are LRE feature points.

Euclidean distance classifier for verification

The verification approach is based on distribution of distances genuine- genuine and genuine – forgery. The objective is to determine whether pair (A,T) belong to same individual, where T is a test signature and A is a set of known signatures from that individual . Algorithm to verify a given signature as genuine or forgery is as follows:

Algorithm

1. Given the set of known signatures perform the required preprocessing.
2. For each signature in the class of known signatures say A, B, C and test signature T, perform the GLRLM feature extraction.
3. For each pair of known signatures A,B Let Ai be the LRE feature in signature A and Bj be the LRE feature in signature B. Calculate Euclidean distance D(Ai,Bj) and the distance between A and the rest of training signature data. Create the template of known signatures class consisting of writer ID, distance parameter and intra -class thresholds. Threshold that will be used to determine the classification is produced from the average similarity score of the training signatures when they are compared to each other.

Verification: Verification is the process of testing whether a claimed signature is of the same (class) writer as the set of signatures enrolled in the system for that class.

4. For a given test signature T claimed to be of a known writer, Calculate the inter- class distances between T and each training signature in the class of known in the template.

The comparison between the distance parameters of the GLRLM features of the claimed test signature was done with those of the stored template. We let W be (D(T,A),D(T,B),D(T,C)) and Z be (D(A,B),D(A,C),D(B,C)):

Test 1: Comparing inter-class maximum distance with intra-class maximum distance as threshold.

We classify T as genuine if the condition

max(Z) > max(W) ,holds, otherwise we classify T as not genuine.

Test 2: Comparing average of inter-class distances with the average of intra-class distance as threshold.

We classify T as genuine if the condition

avg (Z) > avg ,holds, otherwise we classify T as not genuine.

Test 3: Comparing inter-class minimum distance with intra-class minimum distance as threshold.

We classify T as genuine if the condition

min (Z) > min (W),holds, otherwise we classify T as not genuine.

V. RESULTS

The proposed verification model was evaluated using the experimental database of 525 genuine signatures and their forgeries. Performance of the classifiers is analyzed by using statistical parameters such as sensitivity, specificity, accuracy. The statistical parameters with formula are given in Table 1.

TABLE I: TABLE OF FORMULAS

Measure	Formula
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Accuracy	[(1-FAR)+(1-FRR)]/2

TP-genuine signature ascertained as genuine.
FN-forgery claimed as genuine.
TN-forgery ascertained as forgery.
FN-genuine claimed as forgery.

Sensitivity and Specificity are the two most important characteristics of a signature verification model [16]. Sensitivity is proportion of actual positives (genuine signatures), which are correctly verified as positive and Specificity is proportion of actual negatives (forgeries) which are correctly verified as negative. Accuracy measures the quality of the classification. It takes into account true and false positives and negatives. Accuracy is generally regarded with balanced measure whereas sensitivity deals with only positive cases and specificity deals with only negative cases.

The results obtained with Euclidean distance classifier are given below in Table II. As explained in the previous section three decision criteria were used and accuracy of all three was also measured. A system with higher values of both sensitivity and specificity show better performance.

TABLE II: PERFORMANCE STATISTICS OBTAINED USING DISTANCE CLASSIFIER

Distance used for classifier	Sensitivity	Specificity	FAR	FRR	Accuracy
Max class distances	77.77%	86.66%	13.33%	23%	82%
Average class distance	78.8%	80%	20%	21.11%	79.45%
Min class distance	83.33%	86.66%	13.33%	16.4%	85.15%

The final results are obtained by finding the FAR, FRR and equal error rates at different threshold values. The threshold can be adjusted as per the application requirement whether a higher FAR or FRR is acceptable because these parameters are inversely proportional to each other. There is no single set of FAR and FRR specifications useful for all different applications. If the signature system is specified for very high security situations such as military installations then FAR will be chosen to be very low else for typical customer applications such as for automatic teller machines cannot afford to alienate users with such a high FRR therefore the choice in these applications is low FRR at the sacrifice of higher FAR. The choice of the threshold value is made easier by determining the Equal Error Rate (EER).

As the name implies, EER is the value where the FAR and the FRR overlaps and the value is equal for both rate. The EER of a system can be used to give a threshold independent performance measure. The lower the EER is, the better is the system's performance, as the total error rate which is the sum of the FAR and the FRR at the point of the EER decreases. The EER of this system is shown in Fig. 3. From Fig. 3, the EER of the system is approximately 22%.

The Fig. 4 shows the plot of genuine acceptance rate and false acceptance rate for the same classifier i.e., the ROC plot.

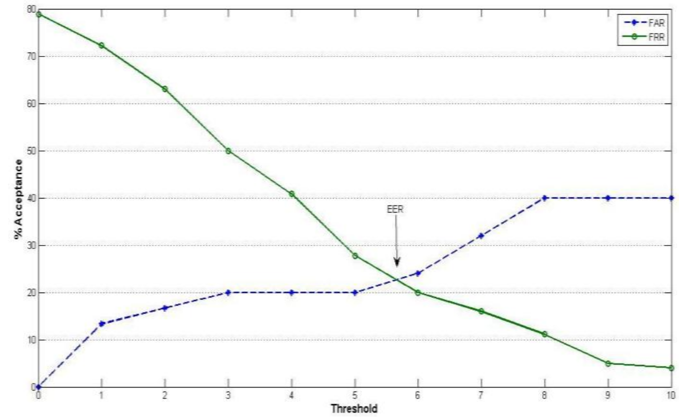

Figure 3: FAR-FRR plot for signature verification system. At selected matching threshold level of 50% we have achieved EER OF 21%

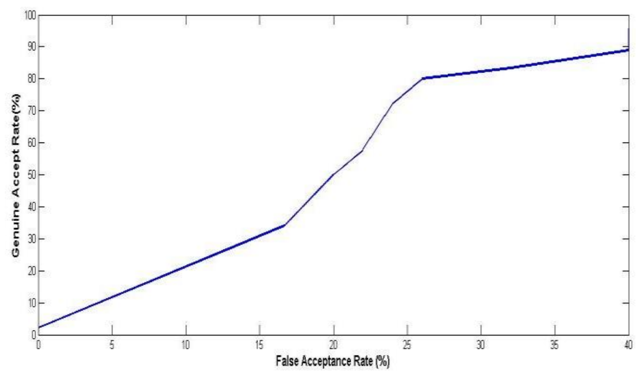

Figure 4: ROC plot

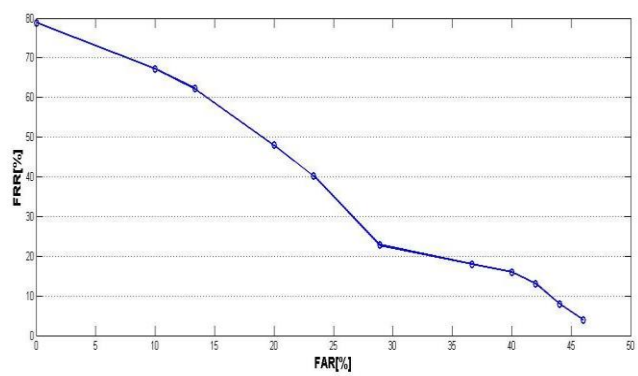

Figure 5: FAR vs FRR plot

Fig. 5 shows FAR Vs FRR plot for the given system eliminating the threshold. System performance can be tuned by setting the match score threshold to achieve a specific FAR, which will yield a specific FRR.

VI. COMPARISON

The performance of our proposed method is compared with the performance of other models in Table III on the basis of

FAR, FRR and accuracy. FAR of 13.33 % and FRR of 16.4 % and accuracy of 85 % is obtained using GLRLM feature LRE and the distance classifier with min class distance as threshold. With average class distance and maximum class distance accuracy of 82% and 79.45% was obtained which is better than other methods that have been use.

TABLE III: PERFORMANCE COMPARISON WITH OFF LINE SIGNATURE RECOGNITION SYSTEMS

Method	FAR	FRR	Accuracy
GLRLM Features(Max class distance)	13.33%	23%	82%
GLRLM Features(Average class distance	20%	21.11%	79.45%
GLRLM Features(Min class distance	13.33%	16.4%	85.15%
Walsh Coefficient[13]	40%	42%	59%
Vector histogram[13]	12%	22%	83%
GSC[14]	20.7%	17.6%	80.85%
Zernike[15]	16.3%	16.6%	83.6%
Clustering technique[13]	2.5%	6.5%	95%

VII. CONCLUSION & FUTURE WORK

This paper presented an efficient and economically viable offline handwritten signature verifier with the use of GLRLM texture features as image descriptors.

The efficiency of the verifier was tested and FAR, FRR, specificity and the sensitivity were measured for each test taken. We used Euclidean distance classifier for verification which gave FAR of 13.33% and FRR of 16.4% and accuracy 85.15%.It was noted that some writers have large discrepancies between their sample signatures such that even a forgery may fall within the intra class distances which may result to a false negative notification.

Many areas of study related to GLRLM features and various distance measures are still open. As future work further investigation can be done to explore the run length statistics in all four directions for signature verification and determine more relevant features other than LRE among the seven features. Using a mixture of features may lead to high performance signature verification system. Use of GLRLM in other areas of research is also possible due to its generalist nature and may prove to be beneficial. Mahalanobis distance is another measure that can be used to find patterns in GLRLM features. The experiments can also be extended to combine two or more of these distance measures and compare their efficiency. Further more for better classification classifiers like SVM, HMM, NN can be used.

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