



An Offline Signature Verification System Using Neural Network Based on Angle Feature and Energy Density

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ABSTRACT : Hand written signature used every day at various places for the authentication of a person, but a signature of a person may not be same at different time or it may be generated by some fraud way. So, a system is required for verification of the signature. The signature verification can be done either online or offline, here we are using offline signature verification network. In the proposed system the signatures is taking as an image and apply image processing technique to make the system effective. Here we propose an intelligent network that works on the features like angle feature and energy density of the signature for the verification and also a comparative statement is made between them in order to see which method provides better results.

I. INTRODUCTION

Human signature are used every day for the identification of a person in various work like for processing Bank checks etc., but along with the signature it is also required to verify that the signature on the paper is signed by the genuine signer or a forgery signature. Also the signature signed by a genuine signer may be different depends upon various conditions like his mood, health etc, and also there is a variation in the signature according to age. So it is required to keenly observe the signature before reaching to any conclusion.

This give rise to make a computerized signature verification system .and also it become the subject of continue research until a purely faithful system is found to rely on. This paper is like one of a small step forward towards achieving the goal of a developed system for signature verification.

Before modeling the system it is required to know about the signature characteristics [1], Types of forgeries [2] and also the signature verification systems.

Signature characteristics

Signatures of a person may be different in shapes and size and it is difficult for a human being to separate a genuine signature from the forged one by only visual analysis of the signatures. Signatures may be simple like a signer writes his name in a simple way, cursive when written in cursive way or graphical that contents some geometric patterns. So for making the automatic offline signature verification system, signature must be treating as an image and extracting features from the image. But before modeling such system some essential characteristics are keep in mind like:

- (a) *Invariant:* It should not change with the time.
- (b) *Uniqueness:* It must be unique to the individual.

(c) *Inimitable:* Signature may not be produced by other means.

(d) *Reducible and comparable:* Capable of being convert in the format that is easy to store or handle and also easily comparable with the others [3].

Types of Forgeries:

There are three kinds of forgeries -Random, Unskilled and Skilled (Fig. 1).

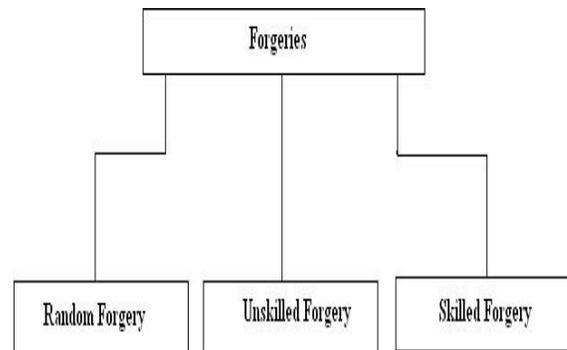


Fig. 1.

1. Random forgery. It is produced when the signer knowing the name of the victim and produced signature in his own style. This forgery is easily detected by the visual analysis.

2. Unskilled forgery. It is produced when the signer copy the signature in his own style without having any previous experience.

3. Skilled forgery. It is produced by looking the original signature or by having idea about the signature of the victim. Generally this kind of forgery is generated by the professional persons who have experience in copying the signature.

The Random and Unskilled forgeries are easy to catch but the skilled forgery is hard to detect. So this paper is based for detecting the skilled forgery.

Signature Verification Systems [4][5]

Automated handwritten signature verification can be divided into two classes, namely, on- and off-line. On-line data records the motion of the stylus while the signature is produced, and includes location, and possibly velocity, acceleration and pen pressure, as functions of time. Online systems use this information captured during acquisition. These dynamic characteristics are specific to each individual and sufficiently stable as well as repetitive. In the off-line signature verification systems, the signature is captured once the writing process is over and thus only a static image is available. As compared to on-line signature verification systems, off-line systems are difficult to design as many desirable characteristics such as the order of strokes, the velocity and other dynamic information are not available in the off-line case. The verification process has to wholly rely on the features that can be extracted from the trace of the static signature image only. Although difficult to design, off-line

Signature verification is crucial for determining the writer identification as most of the financial transactions in present times are still carried out on paper. Therefore, it becomes all the more essential to verify a signature for its authenticity.

The design of any signature verification system generally requires the solution of five sub-problems [6][9]:

Data acquisition, Pre-processing, Feature extraction, Comparison process, Performance evaluation.

A robust system has to be designed which should not only be able to consider these factors but also detect various types of forgeries. The system should neither be too sensitive nor too coarse. It should have an acceptable trade-off between a low False Acceptance Rate (FAR) and a low False Rejection Rate (FRR)[7][8].

II. PROPOSED SYSTEM [6][17]

Signature is a special arrangement of symbols, characters, etc., and may be simple, cursive or geometric. Generally the static feature *i.e.*, the image of the signature is available for the verification and authentication of a genuine person because it is not possible everywhere to capture the dynamic feature. So here we propose a system that works on the static features. The static features that consider of the signature for modeling an offline verification system are an Angular feature in the combination of the Energy density feature which extract locally and the feed forward back propagation neural network use as a classifier. Aspect ratio is also included as a global feature in energy density method. The proposed system includes both signature verification and forgery detection parts. The difference between the two parts is that verification is based on inherent characteristics of a signer whereas the detection is based on specification of a limit, which exceeds the inherent variation in the genuine Signatures of a signer.

The performance of the offline system is evaluate on the basis of angular features, then evaluate the performance by using the energy density method with aspect ratio and the result obtained from the above methods is compared with the proposed Angular feature with energy density method so that it may be clear that is it worth to improve the accuracy on the cost of memory and time ?

A. Data acquisition

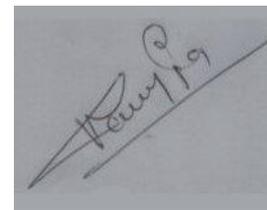
The data for the offline signature verification system may be acquire from various ways like by optical pad, scanner etc. here for making the data base we collect the samples of signature written on the white paper by using the black/ blue pen. The signature samples are then scanned and then fix in the proper box size. Some typical signatures along with forgery are as shown in Fig. 2.



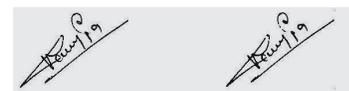
Fig. 2.

B. Pre-Processing

Before processing the image for feature extracting some preprocessing algorithms are applied on the scanned image like Binarization, Denoising, Thinning algorithm because thin image required less storage memory as compared to original image also skew removal .Shown in Fig. 3.



(a) Original Signature Image



(b) Binarization (c) Denoising



(d) Thinning



(e) Skew Removal

Fig. 3. Pre-process Image.

C. Feature Extraction

It is the important part where we decide which portion or part or characteristics are extracted those are useful for our system and on which the designed system give optimum result. For the proposed system the features which are extracted are The Energy density of the signature and the Angle feature of the signature.

(a) Energy Density [1]

Energy density is defined as the total energy present in each segment which is used as a local feature. In this method the image is divided in various segments and energy density of each segment [14] is calculated by counting the total number of ones i.e., total no of white pixels in a segments. In the proposed system the signature image is segmented in to the 4 equal parts and calculating the number of ones in each of them. Also we are considering the Aspect ratio which is used as a global feature but here we normalize it for all segments. Aspect ratio is the ratio of Height (maximum vertical distance) to length (maximum horizontal distance) of the signature. We have calculated it after skew removal. Thus, we have a feature vector of size 1*4 for a single signature image and it is used as a final database in an energy density method. For 100 signature image we have feature vector of size 100*4. This final database is fed to the neural network to perform the desired function i.e. training or classification as shown in Fig. 4.

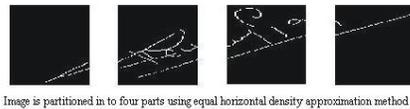


Fig. 4.

(b) Angle Feature [10]

In this method first the Pre-processing image is resized and partitioned into four portion or cell using the equal horizontal method after that each partition(cell) are divided in to 3 row and 3 column of equal size so we have total nine sub cell of each cell. After that consider the sub cell one by one and calculate the angle of each with pixels by considering the bottom left corner after that calculate the mean value of the angles this process is repeat for all the sub cells. Once the value of angles for each sub cell is found then calculating the mean value from that to determine the value of angle for that cell or partition. This process is repeat for the reaming three partitions, so at the end we have the angle vector of size 1*4. This is given as an input to the neural network. For example the data base used consist 100 signature samples. For one sample we have angle vector of size 1*4 so for all 100 sample we have feature vector of size 100 *4 which is used as a final data base for training the neural network and also for classification. The process of angle calculation is shown in Figs. 5, 6, 7, 8 and 9.



Fig. 5. Pre-Processed Signature Image.



Image is partitioned in to four parts using equal horizontal density approximation method

Fig. 6.



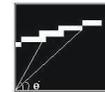
Each partition is resized to a fixed size window/box

Fig. 7.



Each box is then partitioned into 3 rows and 3 column total nine partition of a box. So there are total 36 partition of the signature we have

Fig. 8.



Finding the angle of each white pixels and calculate the mean value

Fig. 9.

III. IMPLEMENTATION

This part is subdivided into two phases first one is the training and the second one is the classification. During the training phase the neural network is prepared and trained for doing the classification work with optimum accuracy and during the classification phase the proposed system takes the signature (signature image) and check whether the image given to the input is a genuine or the forged one by comparing with the database. The system can be broadly categorized on the basis of method used for pre-processing and feature extraction from the image database and final input given to the neural network.

During training phase the data base is first prepared or acquire from the various methods and pre-process as stated above.

Here the data base of signature of 10 persons are

gathered which consist of 50 genuine and 50 forged signature of an individual person. (i.e. 1000 Signature Samples) and digitized using scanner and perform the preprocessing techniques like Binarization which produce binary image i.e. to convert colored (if any) image in black & white (i.e. in 0 or 1) format, Noise removal or Filtering using median filter, Thinning by Morphological operations (in MATLAB). Skew removal is carried out by the concept of trigonometry. After that the signature is extracted from the available image and the signature image is again resized. Then the pre-processed image is used for features extraction as stated above. The features that are extracted are the angle feature and the energy density feature (as a local feature) also aspect ratio as a global feature. Once the features are extracted the data base is fed to the neural network for training and classification.

In the proposed system the angle and the energy density method for extracting the feature and prepare the database for training and classification of neural network and observe the result.

IV. NEURAL NETWORK [11][12][15][16]

The main reasons for the widespread usage of neural networks (NNs) in pattern recognition are their power (the sophisticated techniques used in NNs allow a capability of modeling quite complex functions) and ease of use (as NNs learn by example it is only necessary for a user to gather a highly representative data set and then invoke training algorithms to learn the underlying structure of the data). The signature verification process parallels this learning mechanism [1-12][15-16]. There are many ways to structure the NN training, but a very simple approach is to firstly extract a feature set representing the signature (details like length, height, duration, etc.), with several samples from different signers. The second step is for the NN to learn the relationship between a signature and its class (either "genuine" or "forgery"). Once this relationship has been learned, the network can be presented with test signatures that can be classified as belonging to a particular signer. NNs therefore are highly suited to modeling global aspects of handwritten signatures.

Once a network has been structured for a particular application, that network is ready to be trained. To start this process the initial weights are chosen randomly. Then, the training, or learning, begins.

There are two approaches to training - supervised and unsupervised. Supervised training involves a mechanism of providing the network with the desired output either by manually "grading" the network's performance or by providing the desired outputs with the inputs. Unsupervised training is where the network has to make sense of the inputs without outside help.

For any neural network the output layer consists of a

single neuron that gives the degree of confidence of the genuineness of the signature presented to the net. The degree of confidence range from 0 to 1. With '0' meaning absolutely confident of the signature being forged and '1' meaning absolutely confident of it being genuine. The proposed architecture of back propagation feed forward neural network is as shown in Fig. 9.

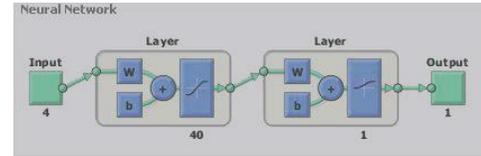


Fig. 10. Proposed Network.

The proposed ANN scheme uses a multi layer feed forward network employing a back propagation learning algorithm with 4 Neurons in input layer and 1 Neuron in output layer. One hidden layer is present with 40 Neurons. The transfer function used for all the three layers are Hyperbolic Tangent Sigmoid (tansig). Total 4 inputs is given to this neural network.

V. RESULTS (COMPARISON PROCESS AND PERFORMANCE EVALUATION)

For the proposed neural network based signature verification system the results are calculated on the basis of False Rejection Ratio (FRR), False Acceptance Ratio (FAR) and on the basis of Time and the training performance of neural network is also check. The following plots are obtained during training is as shown in Fig. 11 and 12.

(a) Training performance Energy Density

(b) Training performance Angle Feature

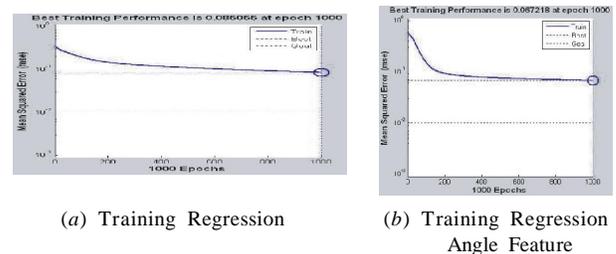


Fig. 11.

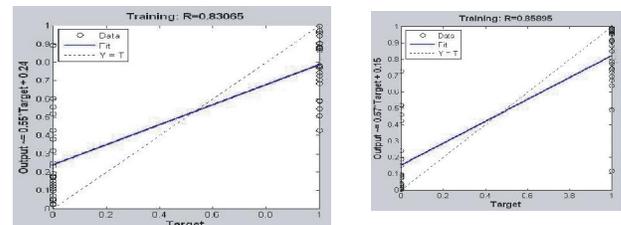


Fig. 12.

Gradient descent with momentum weight and bias learning function (learngdm) is used by default. Mean square error (mse) is network performance function. It

measures the network's performance according to the mean of squared errors. As the numbers of epochs are increasing during training then accordingly the mean square error is reducing. The black horizontal line is showing the reference and the blue is denoting the reducing mse i.e. actual mse. The goal of training is to reduce mse till the extent that it will meet the reference. The training will stop when either the set goal has achieved or the maximum number of epochs reached. The plot of regression shows that up to what extent the target is achieved.

Now during classification or verification phase the performance is calculated on the basis of FRR, FAR and on the basis of time and also the result obtained from the proposed technique (Angle feature with Energy density) is compared with basic Angle Feature Method or With Basic Energy Density Method as shown in Table 1-5.

Table 1: (For Sample-A).

No. of samples (Original Forgery)	Methods of feature extraction			
	Energy Density		Angle Feature	
	FRR	FAR	FRR	FAR
10o, 40f	0.20	0.10	0.15	0.02
20o, 30f	0.15	0.06	0.10	0.03
25o, 25f	0.08	0.16	0.08	0.04
30o, 20f	0.03	0.20	0.06	0.10
40o, 10f	0.025	0.20	0.025	0.10
50o, 50f	0.12	0.16	0.06	0.14

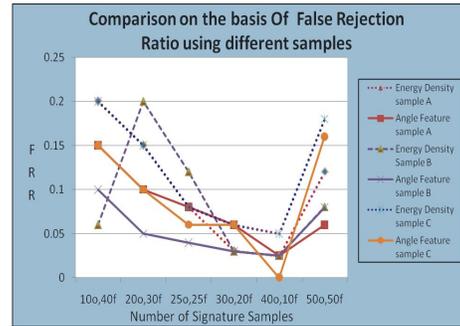
Table 2: (For Sample-B).

No. of samples (Original Forgery)	Methods of feature extraction			
	Energy Density		Angle Feature	
	FRR	FAR	FRR	FAR
10o, 40f	0.06	0.05	0.10	0
20o, 30f	0.20	0.16	0.05	0.03
25o, 25f	0.12	0.16	0.04	0.08
30o, 20f	0.03	0.20	0.03	0.05
40o, 10f	0.025	0.30	0.025	0.10
50o, 50f	0.08	0.12	0.08	0.04

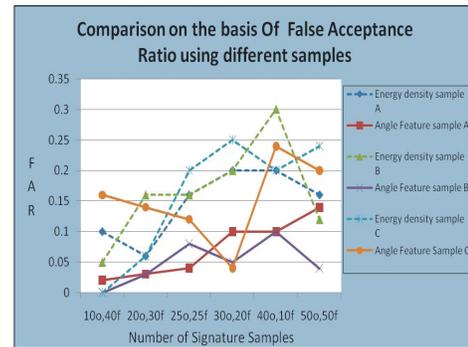
Table 3: (For Sample-C).

No. of samples (Original Forgery)	Methods of feature extraction			
	Energy Density		Angle Feature	
	FRR	FAR	FRR	FAR
10o, 40f	0.20	0	0.15	0
20o, 30f	0.15	0.06	0.10	0.03
25o, 25f	0.08	0.20	0.06	0.12
30o, 20f	0.06	0.25	0.06	0.20

40o, 10f	0.05	0.20	0	0.10
50o, 50f	0.18	0.24	0.16	0.20



Plot - I



Plot - II

Comparison on the basis of Time:

Number of Samples	Time required for Feature Extraction and Training (Energy Density)	Feature required for Feature Extraction and Training (Angle Feature)
50	21.94 Sec.	49.82 Sec.
100	36.56 Sec.	92.33 Sec.

VI. CONCLUSION

It is observed from the analysis of the result tables that the Angular feature based method of feature extraction for the design of off-line signature verification gives better result than that of basic energy density method in terms of accuracy i.e. better FRR and FAR but at the cost of time i.e., the time required for the proposed method is greater than that of basic energy density method.

It is also observed that for any method when the system is trained with signature samples contain more genuine signature and less forged signature then the probability of false acceptance is high (i.e., greater FAR) and when the system is trained with sample in which genuine signature is less and forged signature is more than the probability of False rejection is high (i.e., greater FRR). False rejection is not a crucial issue but the false acceptance create major problem in various cases. So for making the tradeoff between this two uses signature samples contain equal ratio of Genuine and Forged signature for Training the system.

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