ENHANCED SIGNATURE VERIFICATION AND RECOGNITION USING MATLAB

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Abstract: ***Signature verification and recognition is a technology that can improve security in our day to day transaction held in society. This paper presents a novel approach for offline signature verification. In this paper offline signature verification using neural network is projected, where the signature is written on a paper are obtained using a scanner or a camera captured and presented in an image format. For authentication of signature, the proposed method is based on geometrical and statistical feature extraction and then the entire database, features are trained using neural network .The extracted features of investigation signature are compared with the previously trained features of the reference signature. This technique is suitable for various applications such as bank transactions, passports with good authentication results etc***

Keywords: False Acceptance Rate (FAR), False Rejection Rate (FRR), Signature verification.

I. INTRODUCTION

Biometrics based verification systems are improved systems in terms of security than traditional verification techniques such as passwords etc. It is due to the fact that biometric characteristics of every person are unique and cannot be lost, stolen or broken. There are two types of biometrics:

1. Behavioral
2. Physiological.

Handwriting, speech etc. come under behavioral biometrics. Iris pattern, fingerprint etc. are part of physiological biometrics.

On the basis of acquisition there are two main types of signature authentication either its Offline or Online.

Off-line or **static** signatures are scanned from paper documents, where they were written in conventional way. Off-line

Signature analysis can be carried out with a scanned image of the signature using a standard camera or scanner.

On-line or **dynamic** signatures are written with an electronically instrumented device and the dynamic information (pen tip location through time) is usually available at high resolution, even when the pen is not in contact with the paper

Depending on the forgery done by the individual they can be classified as:

1. Random
2. Skilled
3. Unskilled.

Random Forgeries: Written by that person who don't know the shape of original signature.
Simple Forgeries: Written by a person who knows the shape of original signature without much practice.
Skilled Forgeries: Written by a person who knows the shape with much practice of the signature.

There are different techniques through which we can verify the signature namely Template Matching Approach, Neural networks approach, Hidden Markov models approach, Statistical approach, Structural or syntactic approach, Wavelet- based approach. From which we have chosen neural network approach. As strenuous efforts at applying NNs for identification system have been undertaken for over a decade with varying degrees of success.

The main attractions for selecting neural network include:

1) ***Expressiveness*****:** NNs are an attribute-based representation and are well-suited for continuous inputs and outputs.
2) ***Ability to generalize:*** NNs are an excellent generalization tool (under normal conditions) and are a useful means of coping with the diversity and variations inherent in handwritten signatures.
3) ***Sensitivity to noise*****:** NNs are designed to simply find the best fit through the input points within the constraints of the network topology (using nonlinear regression). As a result, NNs are very tolerant of noise in the input data.
4) ***Graceful degradation*****:** NNs tend to display graceful degradation rather than a sharp drop-off in performance as conditions worsen.
5) ***Execution speed*****:** The NN training phase can take a large amount of time. In HSV this training is a one-off cost undertaken off-line (i.e., rarely performed while a user waits for verification results). The paper is organized as:

Section II describes the proposed idea of this paper which includes signature acquisition, signature preprocessing, feature extraction and recognition technique .and experimental results have been presented including the results of the proposed technique and comparison with existing techniques. Section III concludes the technique discussed in the paper.

II. PROJECTED METHODOLOGY

This section describes the projected method behind the system development. It describes the following points:

1. Signature Acquisition
2. Signature Preprocessing
3. Feature Extraction
4. Proceesing of signature
5. Signature Verification

I. Signature Acquisition:

Signatures are scanned with 200dpi resolution, resulting in an average image size of 1000*250 pixels. This resolution has shown to be necessary to correctly interpret the line crossings

Fig.1. Template of Signature Database

Figure 1 shows a template of signature database of few signers taken on the same day which is ready for preprocessing. **Inclusion of skilled forgeries:** It is more difficult to obtain skilled forgeries than genuine signatures, but without the inclusion of skilled forgeries, quoting false rejection rates is far less meaningful.

II. Signature Preprocessing:

Signature preprocessing is a necessary step to improve the accuracy of the latter algorithm, and to reduce their computational needs..Following preprocessing steps are taken into consideration:

1. Transformation from color to grayscale, and finally to black and white.
2. Resizing the image, so that all images have a same and secure size.
3. Thinning the black and white image results always in a huge information loss.

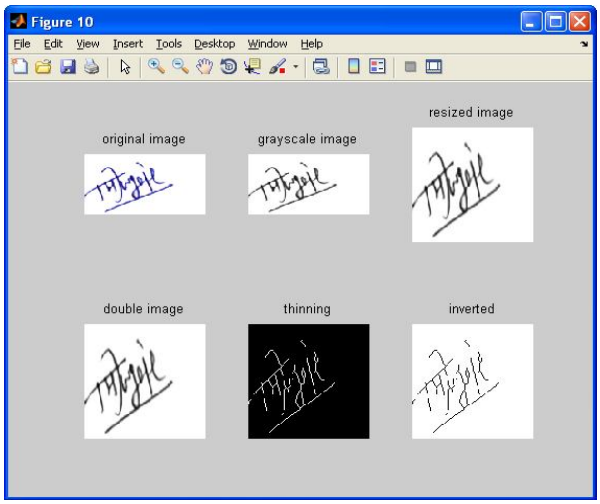

Fig 2.Various preprocessing steps

It is essential to select a thinning algorithm which gives a good abstraction of the original signature, with a low noise level.

III. Feature Extraction:

The features extracted from handwritten signature play a vital role in authentication process. A large number of features are extracted from signatures but not all features can be used in the feature set A good feature set would result in an successful system. It is really important to have an meaningful feature set for assurance of proper learning by NN. Feature set consist of different types of features .For offline signature verification types of features used are discussed below Statistical features that are derived from the distribution of pixels of a signature, e.g. statistics of high gray-level pixels to identify pseudo-dynamic characteristics of signatures Global features describe or identify the signature as a whole. They are extracted from every pixel that lies within a rectangle circumscribing the signature Geometrical and topological features that describe the characteristic geometry and topology of a signature and thereby preserve the signatures global and local properties, e.g. local correspondence of stroke segments to trace signature Various features used in the feature set of the proposed method are explained as follows

I. ECCENTRICITY

An eccentricity in the mathematics is denoted by *e*, a parameter associated with every conic section. It can be thought of as a measure of how much the conic section deviates from being circular .In particular, the eccentricity of a circle is zero. Ellipses, hyperbolas with all possible eccentricities from zero to infinity and a parabola on one cubic surface. The eccentricity of an ellipse which is not a circle is greater than zero but less than 1. The eccentricity of a parabola is 1.The eccentricity of a hyperbola is greater than 1.Eccentricity is defined as the central point in an object. Importance: We need to know the central point of 2 images in order to compare them. After identifying the central point, we can then compare the features around them. Central point:-The central point is acquired by applying the ratio of the major to the minor axes of an image.

II. SKEWNESS

In everyday language, the terms “skewed” and “askew” are used to refer to something that is out of line or distorted on one side. “Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point”. Skewness can range from minus infinity to positive infinity.A distribution with an asymmetric tail extending out to the right is referred to as “positively skewed” or “skewed to the right,” while a distribution with an asymmetric tail extending out to the left is referred to as “negatively skewed” or “skewed to the left.”

III. KURTOSIS

Kurtosis is any measure of the "peakedness" of the probability_distribution of a real-valued random_variable. In asimilar way to the concept of skewness. Kurtosis is a descriptor of the shape of a probability distribution and, just as for skewness; there are different ways of quantifying it for a theoretical distribution and corresponding ways of

estimating it from a sample from a population. The measurement of skewness allows us to determine how bowed are the lines in each segment of the signature. There are various interpretations of kurtosis these are primarily peakedness (width of peak), tail weight etc.

IV. ORIENTATION

It allows us to know how the signer wrote down the signature. Which letters came first emphasizing the direction of angles and peaks. Orientation' — Scalar; the angle (in degrees ranging from -90 to 90 degrees) between the *x*-axis and the major axis of the ellipse that has the same second-moments as the region.

V. ENTROPY

E = entropy (I)

Returns E, a scalar value representing the entropy of grayscale image I. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image

VI. EULER NUMBER

eul = bweuler (BW ,n) returns the Euler number for the binary image BW.
The return value eul is a scalar whose value is the total number of objects in the image minus the total number of holes in those objects. BW can be numeric or logical and it must be real, and two-dimensional. The return value eul is of classdouble.

VII. SOLIDITY

Scalar specifying the proportion of the pixels in the convex hull that are also in the region. Computed as Area/Convex Area. This property is supported only for 2-D input label matrices. Also some statistical features like mean, variance, and standard deviation are also used.

VIII. MEAN

Average or mean value. For vectors, mean(X) is the mean value of the elements in X. For matrices, mean(X) is a row vector containing the mean value of each column. For N-D arrays, mean(X) is the mean value of the elements along the first non-singleton dimension of X.

B = mean2(A) computes the mean of the values in A.

IX. STANDARD DEVIATION

Standard deviation of matrix elements s = std(X), where X is a vector, returns the standard deviation using (1) above. The result s is the square root of an unbiased estimator of the variance of the population from which X is drawn, as long as X consists of independent, identically distributed samples. b = std2(A) computes the standard deviation of the values in A.

IV. PROCESSING OF SIGNATURE

Processing of signature consists of two main parts:
1. Trainning phase
2. Testing phase

In experiment of proposed method, eight genuine signatures of 12 individual are used to train the network, and also some skilled forgeries are introduced in the training dataset.
There are different neural networks through which we are gone through such as back propagation, self-organizing map etc. but found Cascaded feed-forward back-propagation networks giving best results. As back-propagation is having the highest classification accuracy as compared with other implemented algorithms. Feed-forward networks have the following characteristics: Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence are called hidden layers. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed- forward" from one layer to the next., and this explains why these networks are called feed-forward networks. There is no connection among perceptrons in the same layer. Back-propagation is used for its simplicity, efficiency and performance measure. Different types of Back propagation are studied .From which Feed-forward back-propagation network, Cascade-forward back-propagation network are giving the finest results .Diagrams of those neural networks are shown below.
The execution of back propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly, the negative of the gradient. Equation for the back-propagation for one iteration, can be written as follows

$$X_{k+1} = X_k - \alpha_k g_k$$

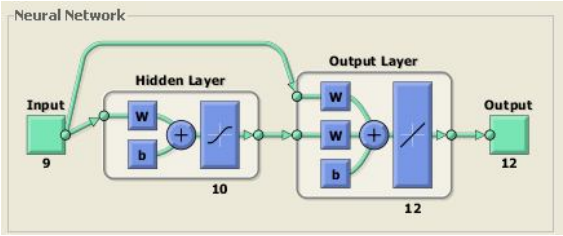

Fig. 3 Cascaded feed-forward back propagation

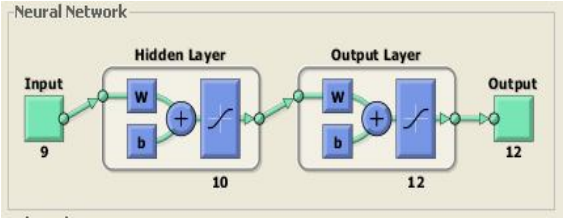

Fig .4 Pattern recognition network

The following performance metrics are used throughout this section: **FAR (**false acceptance rate**)***:* It is the rate of forgeries accepted as genuine. False acceptance rate expressed as a percentage.**FRR (**false rejection rate**)***:* False rejection rate expressed as a percentage.**EER** (Equal Error Rate): Equal error rate for evaluation comes when FRR=FAR i.e. false acceptance rate is equal to false rejection rate.**OER***:* overall error rate (FAR + FRR).The proposed method outperforms very well in all the performance measures.

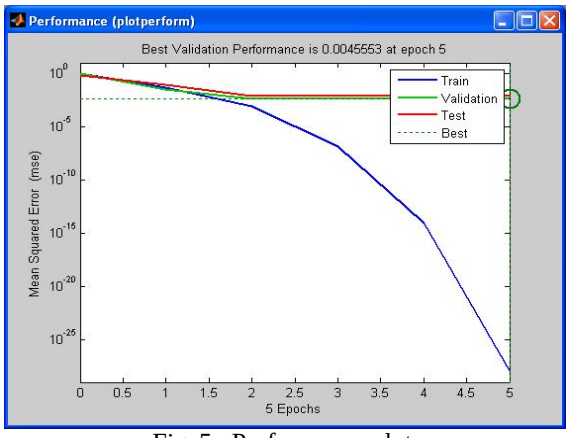

Fig. 5 Performance plot

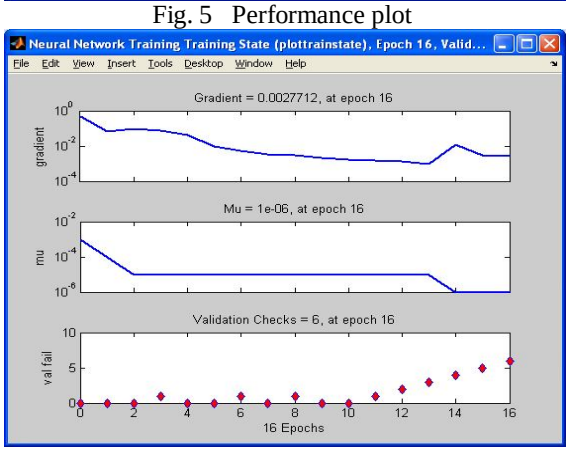

Fig. 6 Template of training state

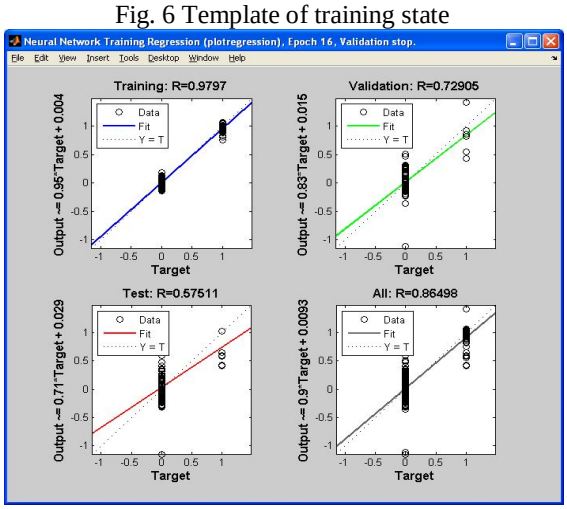

Fig .7 Template of regression plot

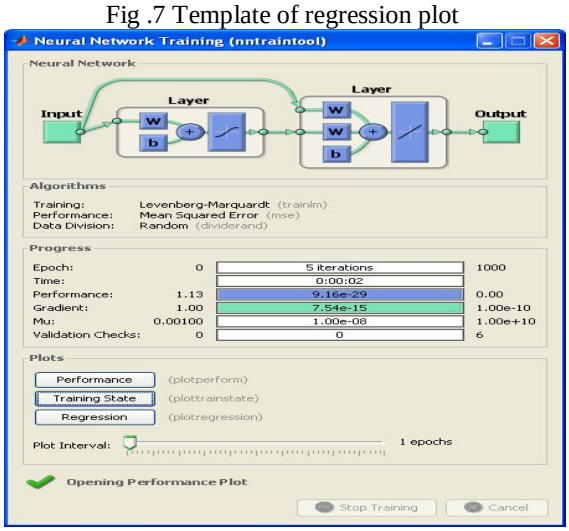

Fig .8 Neural Network Training

SECTION III

CONCLUSION: This paper presents neural network for authentication and verification of individual signature. Neural networks are highly reliable when trained using a large amount of data. This paper helps in detecting the exact person and it provides more accuracy of verifying signatures.
We have achieved 85-100% efficiency for various test data's.

FUTURE WORK:
Offline signature verification can be absolute to other biometric authentication system like handwriting analysis, and when combined with other biometric aspects such as speech and face recognition can present a far better result than any individual system.

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