Offline Signature Verification & Recognition Using Angle Based Feature Extraction & Neural Network Classifier

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Abstract

The concept of the signature is wide used as a means of individual verification emphasizes the need for an automatic verification system because of the individual aspect effect of being easily misused by those who would pretend the Identification of an individual. A great deal of work has been done in the area of off-line signature verification over the past few decades. Verification can be performed either Offline or Online based on the application. In this paper, we present a method for Offline Verification of signatures by calculating the angle curvature of each direction in signature samples. Here we have taken 8bins and calculated in all directions and extracted the features and stored in templates. The features that are used are Area, Centre of gravity, Eccentricity and Skewness along with angle based features. Earlier the features are extracted, pre-processed a scanned image to isolate the signature part and to remove any false noise present. The system is initially trained using a database of signatures. In our experimentation MCYT signature database is used. An accuracy of 97.61 % with Feed forward Back Propagation is observed in identifying the test signatures.
INTRODUCTION

Human signature is a biometric measure of person’s identification. In many sectors like banks, official documents, receipts etc., handwritten signature are verified to secure and identify the concerned person. Each individual has his own signature different with others but people unable do exactly the same signature every time. The signature verification problem aims to minimize the intrapersonal differences. Signature verification can be categorized into following two parts: online and offline. Online handwritten signature verification deals with automatic conversion of signature which are written on a special digitizer, tablet PC or PDA, sensor picks up the pen-tip movements as well as pen-up/pen-down switching. However, in offline technique just scanned images of signatures are available. Signature verification is an important research area in the field of authentication of a person as well as documents [1] in e-Commerce and banking. The importance of signature verification arises from the fact that it has long been accepted in government, legal, and commercial transactions as an acceptable method of verification [2]. The problem of offline signature verification has been faced by taking into account three different types of forgeries: random forgeries, Simple forgeries and skilled forgeries. Traditional bank checks, bank credits, credit cards and various legal documents are an integral part of the modern economy. They are one of the primary mediums by which individuals and organizations transfer money and pay bills. Even today all these transactions especially financial require our signatures to be authenticated. The inevitable side-effect of signatures is that they can be exploited for the purpose of forging a document’s authenticity.

RELATED EARLY WORK

Signature verification is a complex classification problem which deals with the variation among intrapersonal signatures and interpersonal signatures. O.C Abikoye using backpropogation network solve this problem by applying Mask, extracting global and grid features to trained the Neural Network. The developed system exhibits 100% success rate by identifying correctly all the signatures. Emre zgnduz, Tlin Enturk proposed handwritten signature verification system based on one-against-all support vector machine. This system is tested for 1320 signatures with classification ratio of 0.95. A Moment invariant method proposed by Suhail M. Odeh, Manal Khalil [3] for signature recognition and verification purpose utilized four main features like eccentricity, skewness, kurtosis and orientation. Multi Layer Perceptron neural network structure employed for examination. The system tested on more than 200 samples and obtained 78.8% accuracy rate.H.B. Kekre, V A Bharadi, S Gupta, A A Ambardekar, V B Kulkarni [4] introduced Morphological Pixel Variance Analysis technique for the same problem. In which morphology dilation is applied on signature templates with different structuring elements. The system designed by means of EX-OR template matching. Several work [5]–[16] deals with various features and classifiers used in signature verification and recognition system.
PATH IN OFFLINE SIGNATURE VERIFICATION

An offline signature verification scheme basically uses some network or mechanism as a classifier and a database in which some specimen signatures are stored. Features are extracted for each stored signature and when a new signature is employed it is matched using the classifier which classify it as genuine or forgery.

1) Acquire the signature images to create a database.
2) Execute image pre-processing to remove noise and blurring.
3) Compute the various features of stored images.
4) Use these features to train the classifier.
5) Carry out the classification and classify as genuine or forged.

![Flowchart](image)

**Fig No 1**: Duplicate Signature Sample

PROPOSED SYSTEM

The overall architecture of our signature recognition system follows: Signature acquiring, Preprocessing, Feature extraction, and classification. This requires specifying the resolution, image type and format to be used in scanning each image. So, in any offline signature verification system. The sheet on which signature is made is provided to scanner which gives scanned image of the signature. The RGB image of the signature is converted into grayscale and then to binary image. Thinning is applied to make the signature lines as single thickness lines and any noise present in
scanned images are removed thus making the signature image ready to extract features. Features available to extract in offline signatures can be either global features i.e. features extracted from whole images or local features i.e. features extracted from local region of the signature. In this system, the features extracted are Stroke angle. These extracted features form the basis to compare and thereby classify signatures either genuine or forgery.

(a) Duplicate Signature Sample

(b) Original Signature Sample

(c) Duplicate Signature Sample

(d) Original Signature Sample

Fig. 2. Sample signatures of the MCYT database
Error Rates

i) **False rejection rate (FRR)** is one of the most important specifications in any biometric system. The FRR is defined as the percentage of identification instances in which false rejection occurs. It is also known as Type- I error.

ii) **False acceptance rate (FAR)**: is the measure of the likelihood that the biometric security system will incorrectly accept an access attempt by an unauthorized user. A system FAR typically is stated as the ratio of the number of false acceptances divided by the number of identification attempts. It is also known as Type- II error.

iii) **Average Error Rate (AER)**: is the average of type 1 and type 2 errors.

iv) **Equal Error Rate (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.

PREPROCESSING

Image preprocessing represents a wide range of techniques that exist for the manipulation and modification of images pixels. Preprocessing step is applied on both training and testing phase. First the Signatures are converted into grayscale and then converted into binary format. The resizing and cropping of signature are performed. To remove the unwanted area cropping must performed and then resize the signature in particular format. The purpose in this phase is to make signatures standard and ready for feature extraction.

EXPERIMENTAL METHOD

The system has been tested for its accuracy and effectively on database of 100 users which contains both genuine and skilled forged signature sample counterparts. The MCYT database consists of signatures done with different pens. The signature samples from the data base are shown in Figure 2.

FEATURE EXTRACTION

This task requires an initial pixel labelling process according to some predetermined orientations. Then, a pixel-tracing technique used for the estimated prearranged pixel orientations. As a result of this feature extraction, the set of strokes for a given signature is obtained. Finally, a stroke normalization process is carried out prior to the recognition stage.
**Pixel labelling.** The initial pixel labelling process considers four predetermined directions $0^\circ$, $40^\circ$, $60^\circ$, $80^\circ$, $100^\circ$, $120^\circ$, $140^\circ$, $160^\circ$, and $180^\circ$ respectively. This task is performed by the application of the respective $2\times2$ convolution masks (associated to these directions) to each pixel in the signature skeleton. The obtained visual results for a random test signature are shown in Figure 3. As it can be noticed, a same pixel can be initially labelled as belonging to more than one possible direction. These labelling conflicts are solved during the tracking stage.

![Fig. 3 Pixel labelling using convolution mask](image)

The aim of pixel tracking process is to extract the component strokes of a given signature. The proposed tracking method is similar to the iterative version of connected components algorithm for binary images. This algorithm has been adapted to the specific aspects of our signature problem. As we consider four predominant angles, the pixel tracking algorithm is independently applied four times for each set $ai$ of labelled pixels ($0^\circ$, $40^\circ$, $60^\circ$, $80^\circ$, $100^\circ$, $120^\circ$, $140^\circ$, $160^\circ$,and $180^\circ$) in the four different orientations. $\{\text{SW}, \text{W}, \text{S}, \text{SE}, \text{NW}, \text{E}, \text{N}, \text{NE}\}$ Some problems could happen during the pixel tracking process. For example, it is possible to have intermediate unlabelled pixels that clearly are part of a given stroke (where the surrounding pixels are labelled as belonging to this stroke). We solved this problem by searching in the neighbourhood of border-labelled pixels (at a distance of about 6 pixels) other pixels labelled as border. If this happens, then the intermediate pixels are also classified as being part of the same stroke.
Area: Actual number of pixels in the region.

Centroid: Horizontal and vertical centres of gravity of the signature.

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.

Kurtosis: Kurtosis is any measure of the "peakedness" of the probability distribution of a real-valued random variable. In a similar 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.

Skewness: It is a measure of asymmetry of distribution. A distribution, or data set, is symmetric if it looks the same to the left and right of the centre point.

NEURAL NETWORK CLASSIFIER

Interconnecting artificial neurons are a very accurate and effective technique for pattern recognition purpose. From the literature review, best suitable techniques are adopted for the signature recognition problem. Feed forward back propagation neural network are employed for analysis. Finally, confirm the results of the methods.

Feed forward back propagation.

The generalized three layers structure of Feed Forward back Propagation network is shown in Fig.5. The function of Input layer is to holds the input for the network, second is hidden layer which serve as a propagation point for sending data from the previous layer to the next layer, whereas output layer holds the output data, usually an identifier for the input. In this network, inputs are propagated forward direction and compute the outputs for each output node. Then, each of these outputs is subtracted from its desired output, causing an error. In the second phase, each of these output errors is passed backward and the weights are fixed. These two segments are continued until the sum of square of output errors reaches an acceptable value. The created database divides in two parts, to perform the training and testing of the
network. Three layered feed forward back propagation (FFBP) network is created which has two hidden layers along with input/output layer.

(a) Feed-forward Back Propagation Neural Network

(b) Neural Network Diagram

Fig. 5 Neural Network feed forward back propagation

RESULTS CARRIED OUT

False Acceptance Rate (FAR): Accepting the forgery signature thinking it is a genuine signature. It is given by an equation (1)

\[
FAR = \frac{\text{Number of forgery signature accepted}}{\text{Number of forgeries tested}}
\]  

(1)

False Rejection Rate (FRR): Rejecting a signature even though it is genuine signature thinking it is a forgery signature. It is given by equation (2)
Offline Signature Verification & Recognition Using Angle Based Feature

\[
FAR = \frac{\text{Number of Originals signature rejected}}{\text{Number of Originals tested}}
\]  \hspace{1cm} (2)

Input image and identification of signature is shown in Fig 6.

Table 1 contains all the information related to the design of the neural network. Both original and forgery signatures are used for training the network. Testing signatures are also available.

<table>
<thead>
<tr>
<th>Learning Rate</th>
<th>Default</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Weights</td>
<td>Randomized</td>
</tr>
<tr>
<td>Max number of epochs</td>
<td>1000</td>
</tr>
<tr>
<td>Momentum Constant</td>
<td>Default</td>
</tr>
<tr>
<td>Error Area</td>
<td>0.0001</td>
</tr>
<tr>
<td>Number of patterns for original signature</td>
<td>15</td>
</tr>
<tr>
<td>Number of patterns for fake signature</td>
<td>10</td>
</tr>
<tr>
<td>Number of tested signatures</td>
<td>1875</td>
</tr>
<tr>
<td>Number of tested original signatures</td>
<td>1125</td>
</tr>
<tr>
<td>Number of tested fake signatures</td>
<td>750</td>
</tr>
</tbody>
</table>

Recognition results are based on a set of 1875 signatures. This sample has been partitioned into two disjoint sets: 1125 signatures are in the reference database set and 750 in the test set. Signatures of the reference database were collected under no constrains. Test set includes 50 original signatures (corresponding to writers present in the reference database) and 34 forgeries (28 are simple forgeries and 6 are skilled forgeries) for evaluating the system. Recognition rates are controlled by a threshold parameter (percentage) RT that serves to achieve a balance among accepted, rejected and difficult-to-classify signatures. We obtain taking a threshold of 90% a FAR of 1.6% and a FRR of 3%.

(a) Input image
Fig. 6. The caption for all the subfigures (FirstFigure through Secondfigure) goes here.

Fig. 7(a). Mean error of the signature
Fig. 7(b). Signature verification: Training and performance

Fig7(c) Regression of sample
Fig 7(d) : Target Sample

Fig 7 (e) Training image
Fig 7 (f) Validation Checks

Fig 7(S) MeanSquare Error
REFERENCES


