SIGNATURE RECOGNITION AND VERIFICATION USING CASCADING OF TCHEBICHEF MOMENT AND CONTOUR CURVATURE FEATURES IN MATLAB

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ABSTRACT

Signature verification is most commonly used as an authorization tool from the beginning till now. Many people uses bank cheques for most of their transactions. Although banks are computerized, but still verification process of signature in cheques is done manually which consumes time and even misleads sometimes. Signatures verification process can be done online or off-line depending upon the application. In this paper, model is proposed for the signature verification and testing using the Offline Signature Verification System. The acquired signature from the bank cheque is preprocessed for the purpose of feature extraction. Here tchebichef moment feature and contour curvature features of the signature are extracted and cascaded for increasing accuracy. The extracted features are used to train a multilayer Feed Forward Neural Network. The signature features, to be tested, are fed to the trained neural network to find whether the signature is genuine or a forged one.

Keywords: Feature Cascading, Contour Curvature Feature, Tchebichef Moment Based Feature, ANN and Signature Recognition

I. INTRODUCTION

The need to make sure that only the right people are authorized to access high-security systems has paved the way for the development of systems for automatic personal authentication. Handwritten signature verification has been identified as a main contender in the search for a secure personal verification system. Signatures in offline systems are based on the scanned image of the signature and verification of signature is based on extracted features of signature. Here multi-features will be used for the process of feature extraction of signature from the preprocessed scanned image of a signature.

Here two methods were used for the process of feature extraction of signature from the preprocessed scanned image of a signature. One of the method is moment based method. Many moment based methods are used for extracting feature of a signature but we have used tchebichef moment feature. The second method is based on contour curvature. Contour is very important boundary feature used for finding similarity between shapes. The objective of this paper is to emphasize the importance of the use of biometrics in the area of secure person authentication. In this paper the efficiency of these features for signature Recognition is studied. This provides a biometrics accuracy as a highest level of network security with the fusion of multiple feature extraction. Based on the analysis of reconstructed images with tchebichef moment feature and contour feature, it is recommended to compose the feature vectors in order to achieve image recognition results. The classification was done individually with two extracted features and finally features were cascaded to increase the accuracy. The proposed method is tested on database.

Tchebichef moments are having good energy compaction property that made them useful in image compression and dimensionality reduction operations. Moreover the translation and scale invariant properties of Tchebichef moments are very much useful in almost all pattern recognition applications. The proposed method gives fast and better recognition rate when compared to other classifiers. The main advantage of this method is its high speed processing capability and low computational requirements.

1.2 Types of Forgeries

There are three types of forgery these are as follows [15].

1. Random Forgery: Random Forgery is the type of signature forgery in which the victim's identity is not known.

2. Simple Forgery: Simple Forgery is the type of signature forgery in which a person knows victim signature's shape. Its is done without practicing the signature.

3. Skilled Forgery: Skilled Forgery is the type of signature forgery which is a kind of genuine signatures.

II. LITERATURE REVIEW

The Literature study is in category namely research work in signature recognition. Since 1990 a large amount of work has been carried out in signature recognition. The different existing techniques of preprocessing, feature extraction and signature verification for offline signature verification systems are discussed below.

Bank cheques are widely used for financial transactions all over the world. Large volumes of handwritten bank cheques are processed manually every day in developing countries. In such a manual verification, user written information including signature has to be visually verified. As many countries use cheque truncation systems (CTS) nowadays, much time, effort and money can be saved if this entire process of recognition, verification is done automatically using images of cheques. To save time and processing costs in clearing the cheques and to offer better customer services, many countries around the world have implemented cheque truncation systems (CTS) [or image-based clearing system (ICS)]. Instead of sending a physical cheque for clearance, the presenting bank captures the image of the paper cheque using suitable hardware and software. The image then will go through various clearing steps, and the transaction will be settled based on the image data [8.].

There are two approaches to signature verification, online and offline differentiated by the way data is acquired. Offline signature verification deals with a 2D static image record of the signature. It is useful in automatic signature verification found on bank checks and documents authentication. Whereas online signature require the presence of the author during both the acquisition of the reference data and the verification process.Online handwritten signature is usually obtained on an electronic tablet and pen [9.].

The first stage of the proposed system is related to data preprocessing [1.]. Background elimination, noise reduction, width normalization and thinning/skeletonization are the various

Preprocessing operations[3.]. The second stage of the proposed system is focused on obtaining a selection of global features-based (commonly known as global) and time functions-based (commonly known as local) [1.]. Signature recognition algorithm relying on pixel-to-pixel relationship between signature images based on extensive statistical analysis, standard deviation, variance, and theory of cross-correlation is discussed in [10.].

For the intrapersonal features extraction of signature Tchebichef moments, contour curvature and moment invariant can be effectively used as pattern features inthe analysis of two-dimensional images[12.]. MOMENTS and moment functions have been extensively used for feature extraction in pattern recognition and object classification [12.]. One important property of the moments is their invariance under affine transformation. The pioneering work on this subject was by Hu[12.]. The paper [7.] presents a new fuzzy approach to off-line handwritten signature recognition. The solution is based on characteristic feature extraction. After finding signature’s center of gravity a number of lines are drawn through it at different angles. Cross points of generated lines and signature sample, which are further grouped and sorted, are treated as the set of features. In [4.] authors provide an approach to determine whether a particular signature truly belongs to a person or not by using two classifiers i.e. DTI and Guided DTI. With addition of that digital encryption is also implemented to encrypt the signature to ensure the security purpose so that no one can copy the signature of another person. In [5.] authors uses Surf features and neural-fuzzy techniques for recognition of offline signatures system that is trained with low-resolution scanned signature images. Off-line signature recognition & verification is done using neural-fuzzy in ANFIS in MATLAB. The proposed algorithm was successfully made rotation invariant by the rotation of the image. In paper [6.] the texture and topological features of signature recognition includes baseline slant angle, aspect ratio, and normalized area, center of gravity of the whole signature image and the slope of the line joining the center of gravities of the two halves of the signature image. The set of the original signatures is obtained from which the mean values and standard deviations of are computed. The mean signature acts as the template for verification against the claim test signature. In [11.] paper presents a set of geometric signature features for offline automatic signature verification based on the description of the signature envelope and the interior stroke distribution in polar and Cartesian coordinates. The features have been calculated using 16 bits fixed-point arithmetic and tested with differentClassifiers, such as hidden Markov models, support vector machines, and Euclidean distance classifier.

The classification step in offline handwritten signature identification systems is in fact a feature matching process between the features of a new handwritten signature and the features saved in the database. For successful classification, each handwritten signature is modeled using a set of data samples in the training mode, from which a set of feature vectors is generated and saved in a database. Common classifiers in identification include Gaussian Mixture Models (GMMs), Hidden Markov Models (HMMs), Vector Quantization (VQ) and Neural Networks (NNs) which is used for classifying data. Neural networks are widely used for feature matching. The multi-layer feed-forward neural network is used for verification process. It consists mainly of an input layer, hidden layer(s), and an output layer. Each layer consists of a number of neurons. Each neuron is connected to all neurons in the next layer through weights. To determine weight values, one must have set of examples of how outputs must relate to inputs. The task of determining weights from these examples is called training or learning. Multilayer feed forward neural network with only one hidden layer and Sufficient number of neurons acts as universal approximate of nonlinear mappings. Error back-propagation learning algorithm consists mainly of two passes through the different layers of the network. In the forward pass, an input vector is applied to the sensory neurons of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs produced as the actual response of the network. During the forward pass the synaptic weights of the networks are all fixed. In the backward pass the synaptic weights are all adjusted in accordance with an error correction rule. The actual response of the network is subtracted from a target response to produce an error signal. Bayesian regularization back propagation is a training function used in this research. It updates the weight and bias values according to Levenberg–Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. It minimizes performance function during training towards zero. [9].

III. PROPOSED OFF-LINE SIGNATURE VERIFICATION MODEL

Signature verification systems are recognized and verified against available signature in existing signature databases. A signature database is a set of digitized or scanned signatures. Various public databases for off-line signature verification available are SVC2004, MCYT, GPDS, BME-AUT1 and Center of Excellence of Document Analysis and Recognition.

3.1 Image Acquisition: Image acquisition is the process of capturing the image and giving to the system as input. Signatures can be captured by a camera or it can be scanned by a scanner [9]. The proposed model uses 100 genuine and 100 forged signatures of 4 persons. It is considered as a block of single digital image as one cannot segment individual characters in a signature. The scanned image should include all the portions of the cheque[9].

Image Acquisition Preprocessing Feature Extraction Decision Making

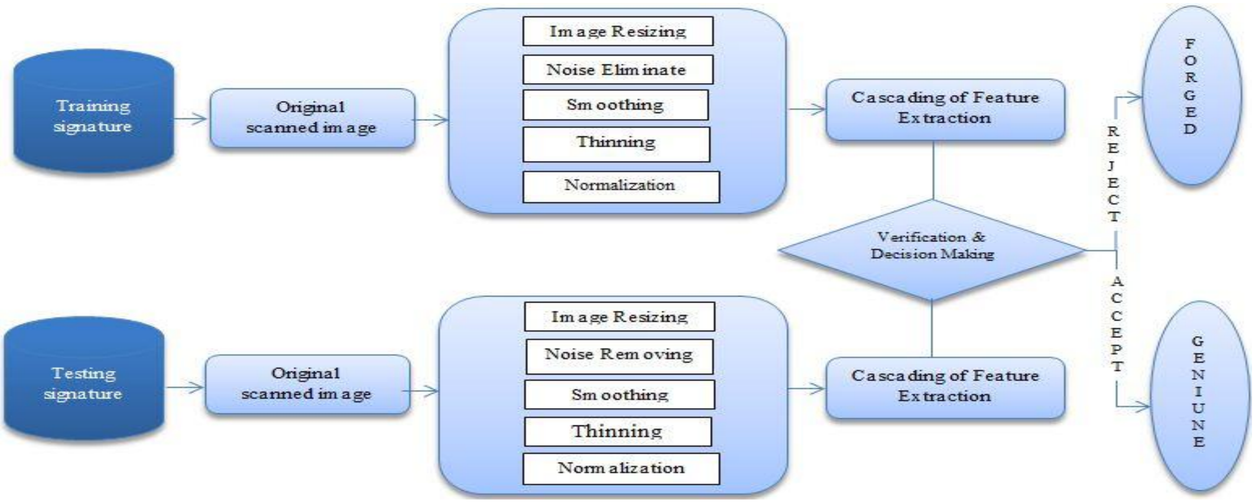

Figure 1.1: Proposed Off-Line Signature Verification Model

3.2. Pre-Processing

The signature to be recognized is acquired by using an optical scanner for the purpose of pre-processing of image.The preprocessing stage includes skew correction and normalization. Skew is basically tilting of image while scanning. Skew detection and correction plays vital role in preprocessing steps in signature recognition process.The pre-processing stage primarily involves some of the following steps:

3.2.1.) Resizing: The image is cropped. Then zoom in or zoom out, to the bounding rectangle of the signature.

3.2.2) Noise reduction: A noise filter is a normalization that applied to remove the noise caused during scanning and improves the quality of document.

3.2.3) Binarization: It is the process of transformation from color to grayscale and then converts to binary image.

3.2.4) Thinning: The goal of thinning is to eliminate the thickness differences of pen by making the image one pixel thick. The aim of this is to reduce the character features to help in feature extraction and classification.

3.2.5) Normalization: Normalization is used to remove selected foreground pixels from the binary image. So the outcome is a representation of a signature pattern by a collection of thin arcs and curves.

3.3 Segmentation

Segmentation is the process of segmenting characters in a word. Here the segmented regions are identified from the peaks of the vertical projection profile. Vertical projection of a binary image looks like a set of black hills on a white surface. After extracting the segmentation regions, characters are segmented for the further image process.

3.4. Feature Extraction

Feature extraction step employs the extraction of features of the signature for the purpose of training and recognition. The segmented signature is scaled using image resizing technique. Unwanted noise in the segmented signature is removed using median filter.Features extracted for off-line handwritten signature verification can be broadly divided into three main categories:

3.4.1) Global features– The signature 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, Maximum horizontal histogram and maximum vertical histogram, Image area, Edge point numbers of the signature, Signature height, Horizontal and vertical center of the signature Image area, Pure width, Pure height, Vertical projection peaks, Horizontal projection peaks Number of closed loops Local slant angle Number of edge points Number of cross points Global slant angle Baseline shift.

3.4.2) Local features –Local feature 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. These features are generally derived from the distribution of pixels of a signature, like local pixel density or slant.

3.4.3) 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.

(a) Tchebichef moments (TM)

For an image signature*f*(*x*, *y*) with image size *N*×*N*, the Tchebichef moments of (n+m)th order is defined as follows. [11]

$$T_{nm} = \frac{1}{\tilde{\rho}(n,N).\tilde{\rho}(m,N)} \sum_{x=0}^{N-1}\sum_{y=o}^{N-1} \tilde{t}_n(x)\tilde{t}_m(y)f(x,y),$$

Tchebichef moment is best suitable for signature recognition[11]. Tchebichef moment is described in detail below.

The 2-D Tchebichef moment of order (n+m) of a signature image intensity function f(x, y) with N x N size is defined as

$$T_{nm} = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} t_n(x)t_m(y)f(x,y) \tag{1}$$

Here $t_n(x)$ is the nth order ortho normal Tchebichef polynomial and is defined as

$$t_n(x) = \frac{(1-N)_n}{\sqrt{\rho(n,N)}}.\sum_{k=0}^{n} \frac{(-n)_k(-x)_k(1+n)_k}{(k!)^2(1-N)_k}$$
$$n, x = 0,1,\ldots\ldots,N-1. \tag{2}$$

$(a)_k$ represents Pochhammer symbol

$$(a)_k = a(a+1)(a+2)\ldots\ldots(a+K-1)$$
$$k \geq 1 and (a)_0 = 1 \tag{3}$$

And the squared-norm (n,N) is given by

$$\rho(n,N) = \frac{(N+n)!}{(2n+1)(N+n-1)!} \tag{4}$$

Equation (2) can also be written as

$$t_n(x) = \sum_{k=0}^{n} c_{n,k}(-x)_k \tag{5}$$

Where

$$c_{n,k} = \frac{(-1)^k}{\sqrt{\rho(n,N)}}.\frac{(n+k)!}{(n-k)!(k!)^2}.\frac{(1-N)_n}{(1-N)_k}$$
$$= \frac{(-1)^n}{\sqrt{\rho(n,N)}}.\frac{(n+k)!}{(n-k)!(k!)^2}.\frac{(N-k-1)!}{(N-n-1)!} \tag{6}$$

The orthogonally property leads to the following inverse moment transform

$$f(x,y)=\sum_{n=0}^{N-1}\sum_{m=0}^{N-1}T_{nm}t_n(x)t_m(y). \quad (7)$$

If only the moments of order up to (M-1, M-1) are computed,(7) is approximated by

$$\tilde{f}(x,y)=\sum_{n=0}^{M-1}\sum_{m=0}^{M-1}T_{nm}t_n(x).t_m(y). \quad (8)$$

It has been shown that the reconstruction accuracy improves significantly by renormalization of orthonormal Tchebichef moments [22]. We use this renormalized version of orthonormal Tchebichef moments in our method.

(b) Contour based method

This was the second method used for the process of feature extraction which is explained below. Shape based methods can be broadly divided into two class of methods:

Contour based methods and region-based methods. The classification is dependent on whether shape features are extracted from the contour only or are extracted from the whole shape region[8]. Under each class, the various methods are further divided into structural approaches i.e. the shape is represented by segments and global approaches where the shapecan be represented as a whole. These approaches can be further divided into space domain and transform domain.

Contour shape methods only find the shape boundary information. There are generally two types of approaches for contour detection first one is the continuous approach or global approach and second one is the discrete approach or the structural approach. In continuous approach shape is not divided into sub-parts, usually a feature vector derived from the integral boundary is used to describe the shape. The measure of shape similarity is usually a metric distance between the attained feature vectors. In discrete approaches the shape boundary is broken down into segments, called primitives using a particular criterion.

3.5 Contour Signature

The contour of an object (S) consists on a finite set of Ni points on the image (sk) [25].

S = {sk= (xk, yk); k = 1… Ni}

The contour S has the below said properties:

1. S is closed, i.e. s1is next to SNi.
2. S has a depth of one single point.
3. S is defined by accounting points in the clockwise direction.

The contour signature is defined as the polar coordinates representation of each point sk.

The polar coordinates are defined in such a way that the origin of the coordinate system is the centroid C.

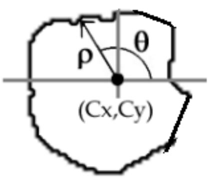

Fig. 3.2: Contour Signature

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Figure 3. 2 The Contour Signature is determined using the polar coordinates of each point on the contour of the image

In contour signature the centroid is calculated and the distance between centroid and boundary points is calculated. After that the angle which the boundary point made to the centroid is also determined according to the formula as described below.

3.5.1 Centroid

The centroid also known as centre of gravity. Its position is fixed in relation to the shape.

Suppose that shape is represented by its region function, then centroid (gx, gy) is given by:

Where N is the number of point in the shape,

The general function f(x,y) is :

$$\begin{cases} g_x = & \frac{1}{N}\sum_{i=1}^{N} x_i \\ g_y = & \frac{1}{N}\sum_{i=1}^{N} y_i \end{cases}$$

If otherwise y

$$(x_i, y_i) \in \{(x_i, y_i) \mid f(x_i, y_i) = 1\}.$$

The general function f(x,y) is:

$$f(x, y) = \begin{cases} 1 if (x,y) \varepsilon D \\ 0 otherwise \end{cases}$$

Where D is the domain of the binary shape.

3.5.2 Tangent Angle

The tangent angle function at a point $P_n(x(n), y(n))$ is given by a tangential direction of a contour at that point [12]:

$$\theta(n) = \theta_n = \arctan\frac{y(n) - y(n-w)}{x(n) - x(n-w)}$$

W is a small window to calculate θ (n)

Tangent angle has its own snags which are as follows:

1) **Noise sensitivity**- To reduce the effect of noise, we use a low-pass filter with suitable bandwidth before determining the tangent angle function.

2) **Discontinuity-** The tangent angle function value is assumed in the range of length 2π, usually in the interval of [-π, π] or [0, 2π]. So θn in general contains discontinuities of size 2π. To reduce the problem of discontinuity, the cumulative angular function φn is known as the angle differences between the tangent at any point Pn along the curve and the tangent at the starting point P0.

3.6 Ann Training: Here we use the stochastic gradient descent version of the Back propagation algorithm for feed-forward networks containing two layers of sigmoid units for training character[2]. BACKPROPAGATION (training_example η, η_{in}, η_{hidden}, η_{out}).η is the learning rate(e.g. 0.08). η_{in} is the number of network inputs.

$\eta_{hidden}$the number of units in the hidden layer and $\eta_{out}$the number of output units. Create a feed-forward network with inputs, the number of units in the hidden layer, and output units.

Types of Neural Networks

1. Multi-Layer Feed-forward Neural Networks.
2. Multi-Layer Feed-back Neural Networks

3.7 Classification: A neural network classifier is designed and trained using the extracted features set. We used transigmoid activation function[8]. The choice of classifier depends on our purpose of use. There are many existing Classical and soft computing techniques for signature identification. They are given as:

1.) Classical technique

- Template matching
- Statistical techniques
- Structural techniques

2.) Soft Computing Techniques:

- Neural networks (NNs)
- Fuzzy- logic technique
- Evolutionary computing techniques

IV. CONCLUSION

Signature Recognition has been the area of interest from past many years. The motive of this work was to develop an offline signature recognition system. Here we have used two types of features first one was contour based and second one was moment based. Prior to that basic morphological operation were performed to make the data fit for feature extraction. The work was completed by using an ANN classifier.

We assumed that there may be some hidden attributes which cannot be determined by using single type of features, so we cascaded the features obtained by both the methods to get a feature set which have some extra features. The cascading of features were used for testing and training and theperformance parameters increased significantly.

V. FUTURE WORK

The area of signature recognition is very wide. Here we have recognized offline signature.Work can be done for recognition of online signature recognition using cascading of many more different features.

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