Effect of Moment Invariants on Signature Recognition Rate by using Fuzzy Min-Max Neural Networks

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ABSTRACT
This paper presents a method of recognition of signatures by Fuzzy Min-Max Neural Networks and analyses the effect of moment invariants on signature recognition by comparing the accuracy of recognition. In addition, database is also tested by fuzzy min-max neural networks for recognition of signatures resulting more accurate results. Image processing and fuzzy neural network toolboxes are used in person identification system provided by MATLAB. For the identification of signatures database is created for five persons with the thirty times repetitions. These signatures are preprocessed by scanning the images and then converting them to standard binary images. The features are selected and extracted which gives the information about the structure of signature. This paper also investigates the performance of the system by using fuzzy min max neural networks classifier.

Keywords
Fuzzy min max neural networks, handwritten signatures, artificial neural network, Multi layer perceptrons, HU's seven moment invariants.

1. INTRODUCTION
Signature recognition is an important research area in the field of person authentication. The recognition of human handwriting is important concerning about the improvement of the interface between human-beings and computers. If the computer is intelligent enough to understand human handwriting it will provide a more attractive and economic man-computer interface. In this area signature is a special case that provides secure means for authentication, attestation authorization in many high security environment. The objective of the signature recognition system is to discriminate between two classes: the original and the forgery, which are related to intra and interpersonal variability. The variation among signatures of same person is called Intra Personal Variation. The variation between originals and forgeries is called Inter Personal Variation.

Signature verification is so different with the character recognition, because signature is often unreadable, and it seems it is just an image with some particular curves that represent the writing style of the person. Signature is just a special case of handwriting and often is just a symbol. So it is wisdom and necessary to just deal with a signature as a complete image with special distribution of pixels and representing a particular writing style and not as a collection of letters and words. A signature verification system and the techniques using to solve this problem can be divided into two classes: online and off-line. In an online system, a signature data can be obtained from an electronic tablet and in this case, dynamic information about writing activity such as speed of writing, pressure applied, and number of strokes is available. In off-line systems, signatures written on paper as has been done traditionally are converted to electronic form with the help of a camera or a scanner and obviously, the dynamic information is not available. In general, the dynamic information represents the main writing style of a person. Since the volume of information available is less, the signature verification using off-line techniques is relatively more difficult. Our work is concerned with the techniques of off-line signature verification. The static information derived in an off-line signature verification system may be global, structural, geometric or statistical.

In this paper we concern with offline signature verification which is based on geometric centre and is useful in separating skilled forgeries from the originals. The algorithms used have given improved results as compared to the previously proposed algorithms based on the geometric centre.

1.1 Types of Forgeries
Distinction between signature recognition and signature verification is verification decides whether a claim that a particular signature belong to a specific class (writer) is true or false whereas recognition decides to which of a certain number of classes (writers) a particular signature belongs. Automatic handwritten signature recognition systems are classified into two categories: offline handwritten signature recognition and online handwritten signature recognition. In online system signature is captured using a special pen called a stylus and digitizing tablet and analysis is based on dynamic characteristics like pressure, velocity, acceleration and capture time of each point on the signature trajectory.

1.1.1 Random or simple forgeries
The forger doesn't have the shape of the writer signature but comes up with a scribble of his own. He may derive this from the writer's name. This forgery accounts for majority of forgery cases though it's easy to detect with naked eyes.

1.1.2 Unskilled /casual forgeries
The forger knows the writers signature shape and tries to imitate it without much practice.

1.1.3 Skilled forgeries
This is where the forger has unrestricted access to genuine signature model and comes up with a forged sample.

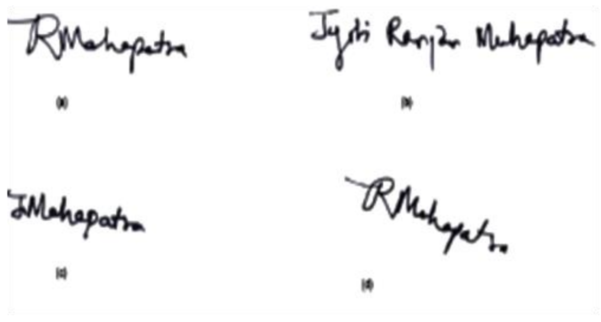

Fig. 1 (a) Original Signature (b) Random Forgery (c) Simple Forgery (d) Skilled Forgery

2. PREPROCESSING OF SIGNATURES

In order to develop the handwritten signatures-based automatic person identification system, a handwritten signature database is required. An in-house handwritten signature database is collected, which contains images of 5 persons. In this handwritten signature recognition database, IDs 001 until 005 represent the persons. Each person was asked to sign on a white sheet that contains a table with 20 cells for 30 times. It is important to highlight that all participants used a black colored pen to sign on the white sheet. Therefore, the total number of handwritten signature images in this handwritten signature database is computed as follows:

Total Handwritten Signature Images = [30 repetitions × 05 persons]

= 150 images

These 150 images are distributed into training and testing data sets, whereby the training data set contains 20 repetitions per person. In order to develop a ready to use handwritten signature images database, various pre-processing steps must be taken into consideration such as producing digitized versions of the hand signature tables, hand signature images cropping, converting input images. type to a standard binary images type, normalization of images size, and reshaping.

Once all persons finished signing on the white paper, the papers are scanned using the scanner in order to produce a digitized version of the hand signatures. The Microsoft paint tool is then used in order to crop each cell and save it into a separate (.png) file. Following figure shows an example of a cropped handwritten signature image for one of the persons.

Fig.2 Example of a Cropped Handwritten Signature Image

On every cropped image from database, the preprocessing steps are performed individually by using MATLAB commands. The preprocessing step provides the image in the state to extract its features from it.

2.1 Database Formation

First pre-processing step is converting input images type to a standard binary images type. All input images are digitized using a scanner. Therefore, the images color model is RGB (Red, Green, and Blue). To use this data in the automatic person identification system, all images should be standardized so that the color model should represent only two components, which can be achieved by converting input images to binary images. This can be performed by converting input handwritten signature images to gray scale format.

Once input handwritten signature images format is converted to gray scale format then they are converted to binary format images, whereby the output binary images are of two values: 1 that represents pixels with white color in the image, and 0 that represents pixels with black color. The image shown in figure 3 is the preprocessing steps performed on the input signature image for the best feature extraction sets and to remove noise during scanning of signature images.

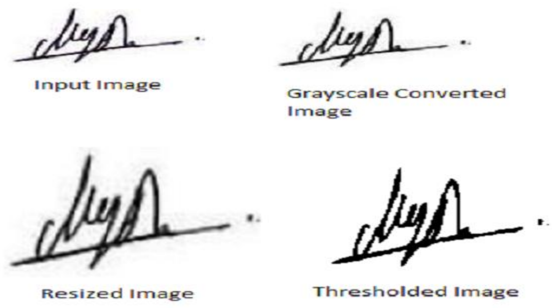

Fig.3 Preprocessing Steps performed on input signature Image

In addition, once the binary images are produced, signature area in each image is separated from the background area, which means reducing white pixels in the handwritten signature image. This process is referred to as cropping, which normally discards the white space surrounding the handwritten signature image. This process however will result in images with different sizes as shown in example in Fig 4.

Fig.4 Negative version of a Signature Image

2.2 Feature Extraction

This section deals with the selection of powerful set of features that are use for signature recognition. Feature extraction phase is essential for automatic person identification system based on handwritten signatures since selecting a powerful set of features is crucial in order to develop highly performing systems. Being able to reflect information about the structure of the hand signature image features are selected and extracted to be used in training and testing the developed system. The selected features include Energy Density and angle which are explained below:

2.2.1.1 Energy Density:

Energy density of an Image is found by simply segmenting the image into four parts and calculating energy at every part by the formula:

$$\mathbf{Energy} = \sum((\mathbf{X(n)})^2 \quad \mathbf{(1)}$$

The value of X (n) may be 0 or 1 therefore $(X(n))^2$ will be 0 or 1.Taking the mean of all the values in the matrix, the energy of the whole cropped image is calculated.

2.1.2.2 Angle:

For finding the angle feature the image will be segmented in three parts. Each segment is divided into sixteen parts. The value of angle is calculated by,

$$\mathbf{Value} = \frac{\mathbf{amax-amin}}{\mathbf{bmax-bmin}} \quad \mathbf{(2)}$$

$$\mathbf{Angle} = \mathbf{atan(value)} * \frac{\mathbf{180}}{\boldsymbol{\pi}} \quad \mathbf{(3)}$$

By using these formulae the individual angle of each segment is calculated. Taking the mean of all the angles gives total round off angle.

2.3 Feature Classification using Fuzzy min max neural networks

Implementing the fuzzy min-max classifier as a neural network, it is possible to immediately exploit the parallel nature of the classifier and provide a mechanism for fast and efficient implementation. The neural network that implements the fuzzy min-max classifier is shown in. The topology of this neural network grows to meet demands for the problem. Each FC node in this three layer neural network represents a hyper box fuzzy set where the FA to FB connection are the min-max points and the FB. Transfer function is the hyper box membership function defined by equation . The min points are stored in the matrix V and the max points are stored in the matrix W. The connection are adjusted using the learning algorithm describe in next section. The connections between the FB and FC nodes are binary valued and stored in the matrix U.

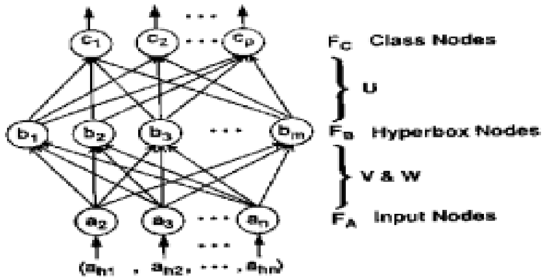

Fig.5 Architecture of fuzzy min-max neural network

3. MOMENT INVARIENTS

The method uses "moment invariants" or invariant moments (moments referred to a pair of uniquely determined principal axes).Based on normalized central moments, Hu introduced seven moment invariants.

$$M_1 = \eta_{20} + \eta_{02}$$
$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$
$$M_3 = (\eta_{30} - \eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

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$$M_7 = (3\eta_{21} - \eta_{03})(\eta_{30} - \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(3\eta_{21} + \eta_{03})^2]$$

Hu's seven moments invariant have desirable properties of being invariant under image scaling, translation, rotation, and shear. So from this study we can conclude that when the input signature pattern has some affine transformation like change of their scale or translation in their central axis or shearing or rotation because of the some human nature or machine error. Then this can be removed or normalized using these seven moment invariant designed by Hu's. These moment invariant are calculated with respect to the central moment which having the order of three and from that calculated values of the moment invariant the signature can be in one form and with one central moment. Because of this the classification is made easily.

4. RESULTS AND DISCUSSIONS

For obtaining the experimental results each signature is tested along with the existing database with one at a time. TABLE I shows the accuracy obtained by testing the signatures with the existing database using ANN classifier and Fuzzy min max Classifier.

TABLE I. Comparison of Performance between Fuzzy min-max Neural networks without and with HU's moments

Accuracy (%)	Number of Occurrences By FMMN (Without HU Moment)	Number of Occurrences By FMMN (Using HU Moment)
0	0	0
10	0	0
20	0	0
30	10	1
40	15	5
50	**20**	8
60	**22**	5
70	**20**	**11**
80	08	**29**
90	04	**29**
100	01	12

From above table, the accuracy of recognition of handwritten signature ranges about 60% to 70% by using simple FMMN architecture and the accuracy ranges between 85-90% by using FMMN with HUs Moment i.e. more number of signatures are been correctly identified when we use fuzzy min max neural networks with HU's Moments. Following graphical representation shows the comparison of accuracy of recognition.

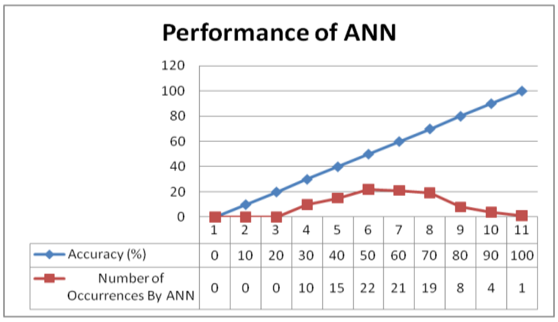

Fig.5 Performance of FMMN without HU's Moments

As shown in the above graph, the performance of recognition of signature is indicated by red line. The number of signatures recognized is in the range of about 60-70%.

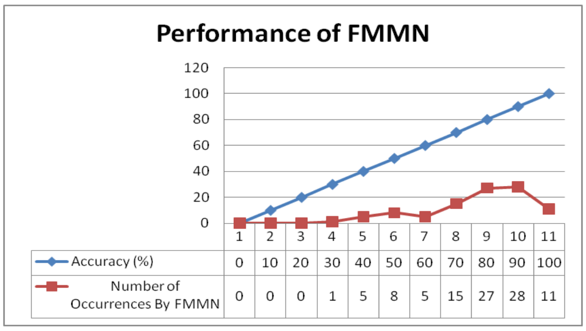

Fig.6 Performance of FMMN with HU's Moments

Fig.6 shows the performance of signature recognition by using fuzzy min max neural networks classifier. Red line shows the recognition rate lies between 85-90% which is better as compared to artificial neural network Classifier.

5. CONCLUSION

This paper gives the comparison of performances of recognition of signatures using different techniques which is based on biometric authentication of the signatures. A detailed preparation, design, and implementation of the handwritten signature-based automatic person identification system have been presented in this paper. For the calculation of accuracy the powerful set of features are selected. For getting more accurate results the existing system is tested for the huge database so that the numbers of repetitions of the signatures are increases. Thus, this technique should be verified with large data base. The comparison shows the better accurate results by using complex classifier i.e. fuzzy min max classifier. Combining the local features and global features can improve the accuracy of the existing system.

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