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Neural Network Based Offline Signature Recognition and Verification System

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Abstract

Handwritten signatures are the most natural way of authenticating a person's identity. An offline signature verification system generally consists of four components: data acquisition, pre- processing, feature extraction, recognition and verification. This paper presents a method for verifying handwritten signature by using NN architecture. In proposed methods the multi-layer perceptron (MLP), modular neural networks with generalized feed-forward networks and Self Organizing Map groups (SOM) neural network with competitive learning will be considered. Self Organizing Map groups the input data into clusters which are commonly used for unsupervised training. After recognition and verification of input data FRR, FAR and TER is calculated.

Keywords: Handwritten signature, MLP neural network, FAR, FRR, TER self-organizing maps, clustering.

Introduction

With the recent advances in the computing technology, many pattern recognition tasks have become automated. These include tasks naturally performed by humans, such as speech and handwritten signature recognition.

A signature may be termed a behavioural biometric. It is mostly used to identify a person carrying out daily routine procedures, i.e. bank operations, document analysis, electronic funds transfer, and access control, by using his handwritten signature[1,2]. Automatic signature recognition system and verification system has many applications as a symbol of consented authorization, especially in the case of credit card validation, cheques, land purchases, legal documents, and security systems[3].

On the basis of static and dynamic characteristics signature verification system are two types on-line and off-line. In off-line verification, as the number of features, which may be extracted from off-line mediums, surpass those obtained from on-line verification i.e. time, pressure and velocity can be extracted from on-line modes of verification[4]. In SOM after extraction of features we used clustering techniques. A number of methods have been proposed by many authors for clustering data. Hierarchical clustering, self-organizing maps, K-means, and fuzzy c-means have all been successful in particular applications. Clustering involves dividing a set of data points into non-overlapping groups, or clusters, of points, where points in a cluster are "more similar" to one another than two points in other clusters. Any particular division of all points in a dataset into clusters is called a partitioning[5]. A common feature among those systems is that the comparison stage is trained with genuine signatures as well as with forgeries.

In this paper we propose an off-line signature recognition system, which is based on MLP'S and SOM neural network structure. We propose recognition of an individual based on behaviour biometric, specifically through his signature. In Self Organizing Map SOM was chosen as the learning algorithm because it allows analysis, including visual analysis, about the relationship data. The mappings are built by means of a process of competitive and unsupervised training (or learning). In MLP neural networks trained with feed forward back propagation for mapping problem of multi-dimensional data well given consistent data and enough neurons in its hidden layer.

This paper is organised as follows: Section II describes the methodology regarding how signatures are captured and Section III the feature extraction process. Section IV details the experimentation performed as part of the NN HSV system development. Section V provides some concluding remarks.

Data Acquisition and Pre-Processing: There are a few pre-processing steps, aimed to improve the verification performance of a system. A signature database was created in order to facilitate the HSV experimentation.

The signature samples were acquired from 10 individuals. Each individual has sign non-overlapping signatures using black pen on a white sheet of paper. A total of 20 signatures were collected from each person to have samples of intra-personal variations. All these sample signatures were scanned and stored as genuine signatures. Forgeries were obtained from volunteers who were asked to imitate genuine signatures. 20 samples for each person was collected, scanned and stored as forgery signatures. Thus the database used for testing the proposed system consists of 20 genuine samples and 20 skilled and 20 random forgery samples for each person. The size of the database is 60 samples. There are a few pre-processing steps, aimed to improve the verification performance of a system. The scanned signature is converted to a gray scale image by threshold. The image was resized to a convenient size of 128 pixels in height by 128 pixels in width. Since the signature consists of black pixels on a white background, the image is then complimented to make it a white signature on a black background. Then alignment is done on input signature. The orientation of the image was calculated and the image was rotated accordingly to align it along the axes.

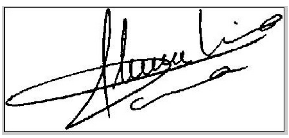

Figure-1
Original Scanned Signature

Figure-2
Segmented and binaries signature

Figure-3
Effect of alignment

The true center of the image was calculated and the image was then padded and cropped to bring the signature to the geometric center of the image.

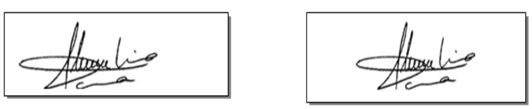

Figure-4
Effect of centring

Thinning and cropping of signature image was performed. After pre-processing of all signatures from the database various features will be extracted.

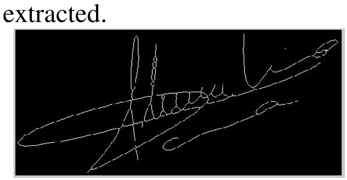

Figure-5
Thinned Signature

Feature Selection and Extraction: The features extracted from signatures or hand writing play a vital role in the success of any feature-based HSV system. They are the most important aspect, exceeding the choice of model or comparison means. Global features considered are computed after normalization and skeletonization of the signature image. In this prototype, the following features are selected.

Image area: This feature gives the number of black (foreground) pixels in the image. In Skeletonised signature images, it represents a measure of the density of the signature traces. The total area is calculated by summing the number of white pixels in each column. This is the foreground pixel area (i.e. the area of the signature only).

Pure width and height: This feature gives the width of the image with horizontal blank spaces removed. The height and width of a signature is directly measured as the size of the image after blank spaces were removed. The blank edge removal was accomplished by sequentially eliminating row (or columns) on the edge of the image if the total number of pixels in the row (or columns) was less than two.

Vertical center of the signature: The vertical centre of gravity, Cv, and the maximum horizontal projection, Pm, were used to indicate the location and strength of the signature baseline, and were obtained from the horizontal projection Ph. This is given by:

$$C_y = \frac{\sum_{y=1}^{\max y} y \sum_{x=1}^{\max x} b[x,y]}{\sum_{x=1}^{\max y} \sum_{y=1}^{\max y} b[x,y]} \qquad (1)$$

Horizontal center of the signature: The horizontal centre of gravity, **Cx**, and the maximum vertical projection were Obtained from the vertical projection **Pv**. This is given by:

$$C_x = \frac{\sum_{x=1}^{\max x} x \sum_{y=1}^{\max y} b[x,y]}{\sum_{x=1}^{\max y} \sum_{y=1}^{\max y} b[x,y]} \qquad (2)$$

Eigen value: The processing like measurement of image sharpness can be done using the concept of Eigen values[6]. The eigen values of such M rows and N columns matrix shows the main feature of the images. In image processing techniques such as image enhancement, image compression[7], pattern recognition[8] and face identification[9], calculation of eigen values and eigenvectors is required. The largest eigen value represent the important (dominant) features of the image whereas the smallest eigen value represent the less important features to find the Eigen values λ, we solve the characteristic equation,

$$|A - \lambda I| = 0 \qquad (3)$$

Where, *I* is the identity matrix of order n×n.

Methodology

This section details the experimentation performed as part of the NN HSV system development. Each signer provides six features for training. Finally, the data from the signers is combined into a single 6×60 matrix. The SOM and MLP's created earlier needs to be trained using the reference data.

SOM is a data visualization technique which reduces the dimensions of data through the use of self-organizing neural networks. SOM reduces high dimensional data into a map of usually 1 or 2 dimensions by clustering similar data groups. This makes it easy to visualize and classify data.

MLP's with two or more hidden layer were found efficient for static pattern classification. They are capable of approximating any input/output map.

Architecture of SOM: The Self Organizing Map, introduced by Teuvo Kohonen is a kind of artificial neural networks suitable to clustering tasks, which can be useful to solve pattern recognition problems[10,11]. The mappings are built by means of a process of competitive and unsupervised training (or learning).

The architecture of self organizing map is shown in figure 6. This architecture is similar to the competitive net architecture as shown in figure 9. The key principle for map formation is that training should take place over an extended region of the network centred on the maximally active mode. Hence, the concept of "neighbourhood "should be defined for the net. Thus may be fixed by the spatial relation between nodes within the self organizing layer as shown in figure 9 in all cases, neighbourhoods are shown delimited with respect to a shaded unit at distance of 1, 2 and 3 arrays from this node[12].

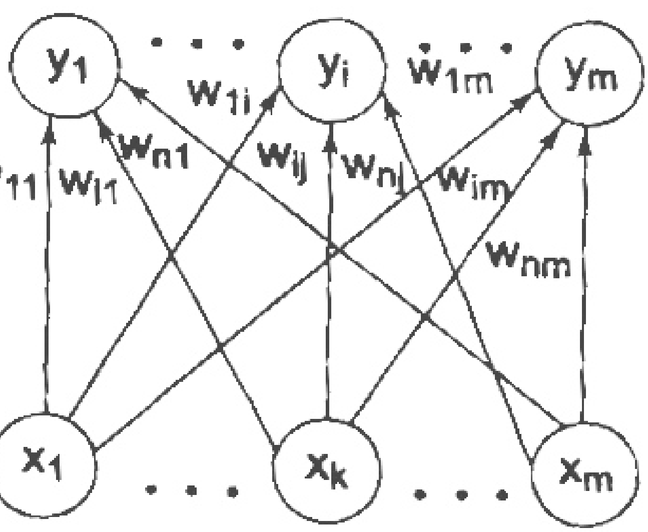

Figure-6
Kohonen Self - Organizing Map

Details of simple competitive learning SOM NN are shown in figure 7.

Each j[th] output node has connections from all input nodes , with connection strengths given by the n-dimensional vector $w_j=\{w_{j,1},........,w_{j,n}\}$.these weights are initially assigned random values , and their values change during the learning process.

The input vectors to be clustered are presented to the network. The neighbourhood $N_j(t)$ contains nodes that are within a topological distance of D(t) from node j at time t , where D(t) decrease with time and does not refer to Euclidean distance in input space. Weights change at time t at a rate η (t) which decreases with time. If j is the winner node,
N_j (t) = {j} {neighbours of j at time t},

And i is the input vector presented to the network at time t, then the weight change rule is given by the equation (4).

$$w_l(t+1) = \begin{cases} w_{l(t)} + \eta(t)(i - w_l(t) & if\ l \in N_j(t) \\ w_l(t), & if\ l \notin N_j(t). \end{cases} \quad (4)$$

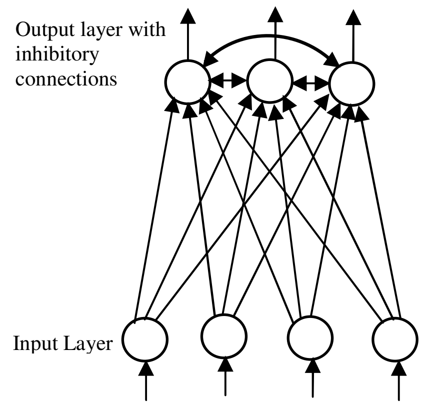

Figure-7
Simple Competitive Learning Network

Initially, the weights and learning rate are set. The input vectors are given, based on the initial weights, the the winner unit is calculated either by Euclidean distance method or sum of the product method. An epoch (iteration) is said to be completed once all the input vectors are presented to the network. By updating the learning rate, several epochs of training may be performed.

Architecture of MLP's: The MLP's neural networks are attractive for classification problems because they are capable to learn from noisy data and to generalize. The first neural network model (perceptron) was developed by Rosenblatt in the late 1950's. These models differ in their architecture and in the way they learn and behave, so they are suitable for different types of problems.

Figure 8 a simple MLP consists of three layers: an input layer, a hidden layer and an output layer. The input layer contains a number of elements, which pass weighted inputs to the neurons of the hidden layer, according to the connection weights[12]. Inputs to the neurons are input features of the signature. for this purpose, asset of data is given as input to the network, and the weights of the neuron connections are adjusted in a way that the output of the network approximates the desired output to set the weights, the mean square error (MSE) is computed. The MSE is the sum of the squared differences between the desired output and the actual output of the output neurons averaged overall training exemplars[13,14].

The training algorithm of the back propagation involves four stages initialization of weights, feed forward, back propagation of errors and updating of the weights and biases.

In figure 9 only the feed forward phase of operation is shown. But during the back propagation phase of learning, the signals are sent in the reverse direction.

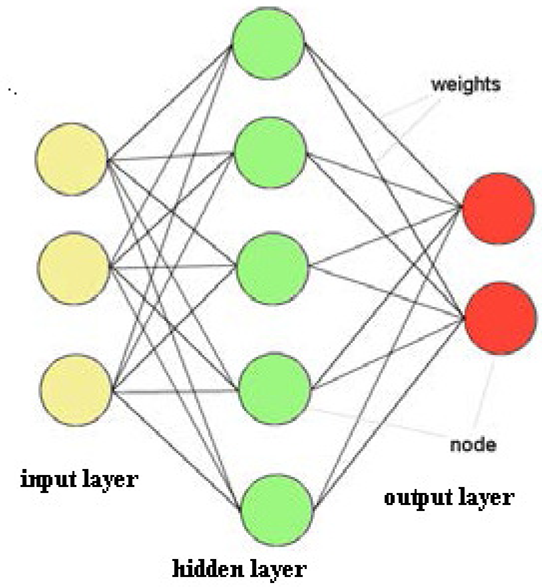

Figure-8
Architecture of MLP's neural network

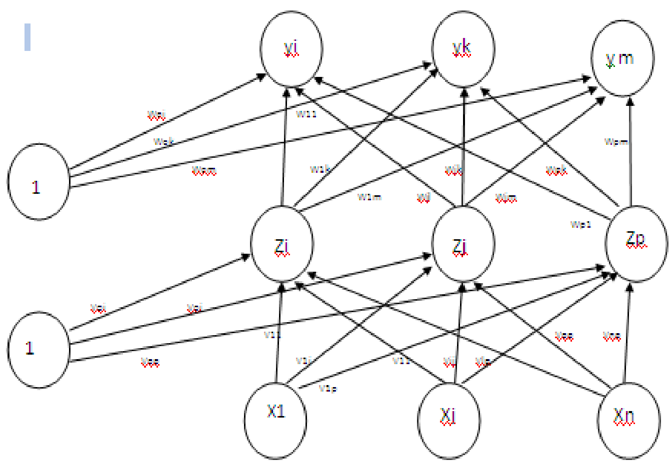

Figure-9
Architecture of Back Propagation Network

Initially, the weights and learning rate are set. The bias acts like weights on connection from units whose output is always 1[15]. During first stage which is initialization of weights, some random values are assigned. In feed forward stage each input unit (X_i) receives an input signal and transmits this to each of the hidden units $z_1 \ldots z_p$. Each hidden unit then calculates the activation function to form the response of the net for the given input pattern. We have use 70% or 42 sample of our input data for training, 15% or 9 samples for testing, 15% or 9 sample for validation.

Results and Discussion

As a result of the application of SOM training algorithm, nodes eventually become "ordered". To evaluate a signature recognition verification system, there are two types of error rates that are usually defined: False Rejection Rate(FRR) or Error Type I, the percentage of rejection of genuine signatures and False Acceptance Rate (FAR) or Error Type II, the percentage of acceptance of forgeries and Total Error Rate (TER), sum of the FRR and FAR. These errors for the SOM NN based HSV is calculated during training using different epochs are shown in table 1 and 2.

Table -1

S. No.	No. Of iteration	FAR %	FRR %	TER %
1.	100	15%	12%	27%
2.	102	12.5%	15%	27.5%
3.	103	12.5%	10%	22.5%
4.	104	14.5%	12%	26.5%
5.	105	17.5%	15%	32.5%

The result in table-2 shows output of two layer feed forward MLP network with sigmoid hidden neuron and linear output neurons trained by back propagation algorithm.

Table-2

S. No.	No. of iteration	FAR %	FRR %	TER %
1.	100	15%	15%	29%
2.	102	16.5%	15%	31.5%
3.	103	8.5%	11%	18.5%
4.	104	16%	12%	28%
5.	105	15%	12%	27%

The result in table-1, table-2 gives the performance of our algorithm for signature verification using SOM, MLP neural network in different iteration (Epoch) values. Total error rate TER minimum value is finding in 103 iteration.

Conclusion

This paper presents a method for recognition and verification of hand written signature by using a SOM, MLP neural network. The FAR and FRR can be reduced further by increasing the reference sample size and/or also the number of features. In the SOM trained by unsupervised, all the units in the neighbourhood that receive positive feedback from the winning unit participate in the learning process. The MLP's networks trained by supervised pose one or more layers of nodes between input and output layer. The learning capabilities of MLP are better because it has multilayer network. This is advantageous over single layer net in the sense that, it can be used to solve more complicated problem. Our next step is to evaluate the robustness of the system by using a large database and to overcome the problem of signature verification. Future work entails creating a NN-Markov Model hybrid system for HSV.

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