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Offline Signature Verification with ANN using Shape Properties a Feasibility Report

K. Srivastava[1], Subhash Chandra[2] and Sushila V. Maheshkar[3]

[1,2,3]Department of Computer Science and Engineering, Indian School of Mines, DHANBAD
E-mail: [1]kk.ism07@gmail.com, [2]subhash08mit @gmail.com, [3]sushila_maheshkar@yahoo.com

Abstract—*We propose a novel signature matching approach using image properties as the basic input feature set. The authentication procedure involves the training of neural network using proposed extracted property features. The extracted features of the uploaded image are compared with the features stored in the database. The key advantage of using this approach is that it provides a more efficient and adaptable matching paradigm. From the survey it is observed that efficiency lies in the range (91-97) % is obtained using the proposed approach which is higher than the contemporary offline signature verification algorithms.*

Keywords: *Offline signature, neural network, feature extraction, Support Vector Machine(SVM), True Acceptance Rate(TAR),False Acceptance Rate(FAR),False Reject Rate(FRR).*

1. INTRODUCTION

The traditional biometrics used in authentication and establishing identities are basically of two types:

behavioral and

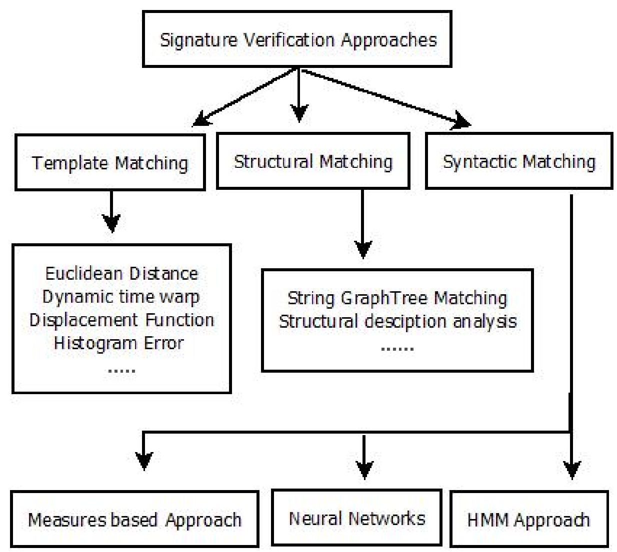
physiological

Handwriting, speech etc are categorized as behavioral biometrics while Iris pattern, Signature, Fingerprint etc are clubbed as physiological biometrics.

There are several approaches to verifying a physiological biometric such as signature, the most naïve of them being template matching approach. In addition there are several other techniques of signature verification like hidden Markov model approach (HMM), Statistical approach, Structural or syntactic approach and neural network based approach[12].

Some of these approaches are enumerated alongside. The most naïve of them is the template matching approach. More efficient matching can be achieved by the statistical and structural approaches [7,10]. Both these approaches can be implemented using a variety of techniques, some of which are mentioned in the figure given.

Here we are concerned with studying and implementing the neural network based backpropagation learning classifier for signature verification [1,5]. It is our objective to discuss the theoretical background and the implementation details regarding the aforementioned technique.



The main merits of using artificial neural networks in the signature verification scheme can be enumerated as under [3]:

1)**Expressiveness:** neural networks are an attribute based representation and are well suited for pattern recognition problems.

2)**Self-Organization:** An ANN can create its own organization or representation of the information it receives during learning time.

3)**Execution speed:** The training phase in neural networks is quite a time taking procedure. However this is a one time cost and is compensated in the long run.

4) ***Fault Tolerance via Redundant***

Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

We have studied and implemented the neural network approach to signature verification using backpropagation learning . The preprocessed signatures are extracted and are used as inputs to our given neural network. They behave as the basic features which are used to distinguish between a genuine signature and a forgery.

2. PRELIMINARIES

Offline Signature Verification

In this technique we scan the signed document and extract the feature set of the scanned image. Verification decision is made on the basis of local and global extracted feature sets. Offline signature verification is relatively unexplored research topic; this apathy is due to the inherent limitation of static features extracted to uniquely identify any image.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks closely simulate the working of human neural system [9]. They model themselves on the human brain and follow a learning procedure using several approaches including supervised, unsupervised and reinforcement.

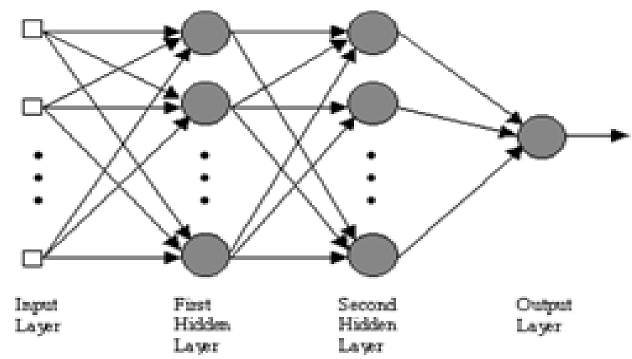
Shape properties: The various shape properties[2,6] we have used to classify the signatures are enumerated briefly:

1) **Area:** The covered area of the signature
2) **Centroid:** The geometrical centre of the image region concerned
3) **Eccentricity:** The ratio of the distance between the foci of the ellipse containing the image and its major axis.
4) **Euler number:** Scalar that specifies the number of objects minus the number of holes in an image.
5) **Entropy:** Scalar value measuring the randomness of the image.
6) **Mean:** Computes the mean of pixel values in the image.
7) **Global signature angle:** Represents the overall direction of line strokes in the skeleton image, in degrees.
8) **Number of closed loops:** Loops are connected regions in the image which are fully enclosed by signature pixels.

These properties will serve as the input tuple to the backpropagation network [8].

4. BACKPROPAGATION LEARNING

The backpropagation learning algorithm is implemented through a multi layer perceptron [4]. The MLP is organized as a collection of several layers, each of which acts as the input to the next layer. We have a single input layer, one output layer and one or more hidden layers.



5. METHODOLOGY

The proposed approach uses several stages to verify a given signature image. The steps involved and their functions are described below:

1) **Signature acquisition:** *for this purpose we use an A4 paper template that collects several signature specimens using a good grade scanner(200 dpi resolution).*
2) **Preprocessing:** *To complete the verification procedure, an image must undergo several processing steps. They are:*
   - *Image binarization*
   - *Image cropping and resizing*
   - *Image thinning*
3) **Feature extraction:** *We extract several image features during this phase. These features play an important role in authentication of input signatures. Here we have used several features such as eccentricity, skewness, kurtosis, entropy, euler number, hough space etc. These are elementary features used for unique identification of images.*
4) **Signature verification:** *the extracted features are fed to a multi layer perceptron and the images are compared using backpropagation learning.*

6. PROPOSED ALGORITHM

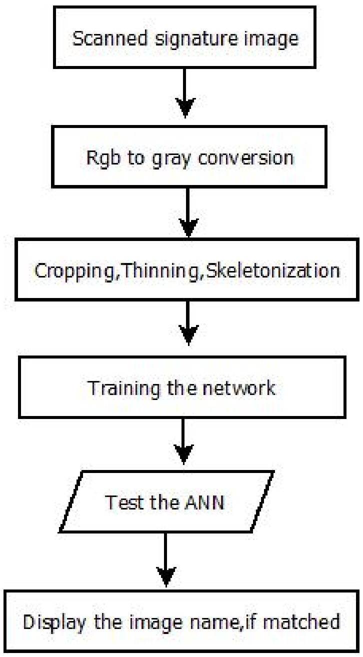
- The signature image is scanned using a good quality scanner (preferably 200dpi or higher).
- The input image undergoes some preprocessing to enable the future computations to proceed smoothly. The preprocessing steps include conversion of rgb image to

grayscale, image binarization, cropping, thinning, skeletonization etc.

- The input properties are extracted and organized as an input array to the backpropagation network.

The selected feature vectors are directed as inputs to the neural network. The network is trained using several input patterns.

- The trained neural network is used to classify the signature images as either genuine or forged. If the image is a match then display the image name.



The step by step working of the algorithm is described.

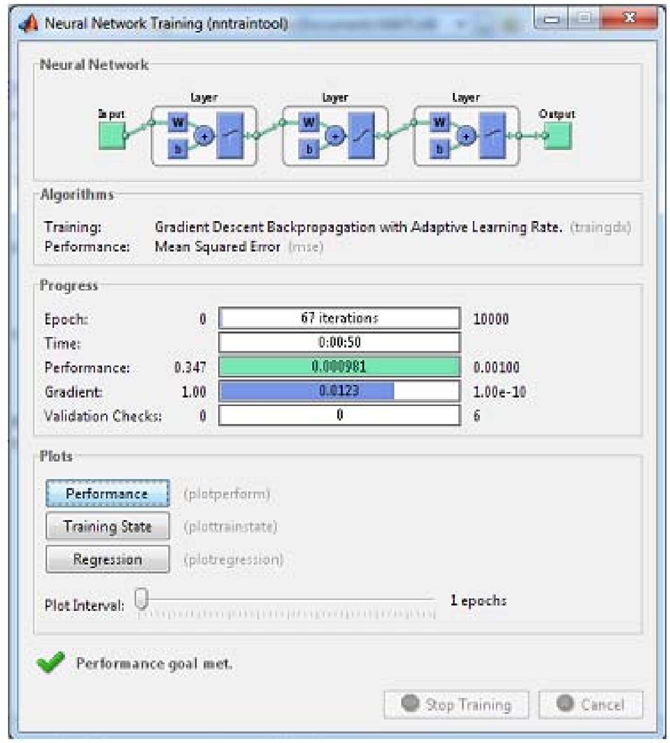
Training the ANN

The network weights and biases are initialized. The system behaves as a neural network classifier using the **nnet** command in Matlab.

The training process requires a set of examples of proper network behavior -- network inputs p and target outputs t. The training proceeds in Matlab using the **nntool** command.During training the weights and biases of the network are iteratively adjusted to minimize the network performance function net.perform. The default performance function for feed forward networks is mean square error mse -- the average squared error between the networks outputs a and the target outputs t.

Now we need to train the network in order to obtain the correct weights such that the network behaves as an efficient classifier.

The training parameters can be measured using several graphical features such as training performance plots, confusion matrix, Receiver operating Characteristic etc.



Training the given Network

Testing the NN

The MATLAB Instrument Driver Testing Tool is used to test the neural network. The MATLAB Instrument Driver Testing Tool (midtest) provides a graphical environment for creating a test to verify the functionality of a MATLAB instrument driver.

The midtest provides a way to [11, 13]:

1) Verify property behavior.
2) Verify function behavior.
3) Save the test as a MATLAB code.
4) Export the test results to MATLAB workspace, figure window, MAT-file, or the MATLAB Variable Editor.
5) Save test results as an HTML page.

7. PERFORMANCE EVALUATION

Performance Analysis of the system includes an evaluation of all possible errors – False Acceptance and False Rejection give a fairly good idea of the efficiency for verification .The True Acceptance Rate (TAR) and the True Rejection Rate (TRR) are the correct-classification rates. False Acceptance Rate (FAR) and False Rejection Rate (FRR) are the negative complements. The system is evaluated based on these parameters.

Ismail et al. [23] developed an off-line signature verification method. A data base of 2400 signature images is considered. Chain code feature extraction is used to represent a boundary by a connected sequence of straight-line segments of specified length and direction. Seven different types of distance measure were used based on feature vectors derived from eigen-signatures. The highest accuracy of 96.2% is obtained with the Manhattan distance measure.

Justino et al. [24] proposed an off-line signature identification system based on Hidden Markov Models (HMMs) to detect random, casual, and skilled forgeries. Three features: a pixel density feature, a pixel distribution feature and an axial slant feature are extracted from a grid segmentation scheme. A database of 1600 genuine signatures is used to determine the optimal codebook size for detecting random forgeries. Signatures of 60 writers with 40 training signatures, 10 genuine test signatures, 10 casual forgeries, and 10 skilled forgeries per writer is used in another data set for experimentation. A False Acceptance rate of 2.83% is obtained and a False Rejection rate of 1.44%, 2.50%, and 22.67% are obtained for random, casual, and skilled forgeries, respectively. Some techniques involving off-line signature verification based on HMM are described in [25-32]

Armand et al. [27] presented a system based on the Modified Direction Feature. The feature extraction technique employs a hybrid of two other feature extraction techniques: Direction Feature (DF) and Transition Feature (TF). DF extracts the direction transitions based on the replacement of foreground pixels by their direction values. TF records the locations of the transitions between 1s and 0s in a binary image. A centroid feature and a trisurface feature are also used for enhancing the accuracy of the result. Two Neural Network classifiers are used to classify the signatures. A database totalling 2106 signatures is used and the highest accuracy obtained was 91.12%. Senol and Yildirim [28] presented an off-line signature verification system based on Neural Network. C. Oz [29] introduced an off-line signature verification system based on Artificial Neural Network. Techniques regarding off-line signature verification based on Neural Network are described in [30-32]

Oliveira et al. [39] developed an off-line signature verification system based on the Writer-Independent approach. Receiver Operating Characteristic (ROC) curves is used to improve the performance of the system. ROC graphs are two dimensional graphs in which true positive rate (TPR) and false positive rate (FPR) are plotted on the Y and X axis respectively. They used a two-fold technique. At first, different fusion strategies are analysed based on the ROC. Next, the result of the first stage is further improved by combining the classifiers without the need of joint training. They used two sets of data (160 genuine signatures, 40 forgery signatures and 1200 genuine, 300 forgery signatures). Support Vector Machine is used as a classifier and they obtained 91.80% as the highest recognition rate.

The parameter readings for our system in various cases are depicted in the following lines.

Comparison Table

METHOD	**NO OF SAMPLES**	**FAR**	**FRR**	**TAR**	**TRR**	**EFFICIENCY**
Kshitij Isoidea et al. [15]	240	4.1667	7.2917	92.7083	95.8333	94.2708
H. Baltzakisa et al. [16]	2000	9.8105	3.0000	97.0000	90.0192	94.1229
Ismail et al. [17]	2400	1.7100	2.8800	-	-	96.2000
Justino et al. [18]	1600	22.0000	10.0000	-	-	91.1200
Armand et al. [27]	2106	8.2000	6.3000	-	-	91.8000
Oliveira et al. [33]	1700	5.3000	4.8300	-	-	91.9000

The average efficiency of our system can be inferred by taking the mean of the above mentioned values:

Mean Efficiency (Ɲ) = (Ɲ 1+ Ɲ 2+ Ɲ 3+ Ɲ 4+ Ɲ 5)/5

= 93.0446%

8. CONCLUSION

This paper discusses a method for verifying handwritten signatures using error backpropagation of artificial neural networks. Our studies seek to establish the relative advantages of handwritten signature verification using neural networks vis-à-vis the traditional methods of offline signature verification. The given method of pattern classification reduces the high error rates encountered with the template based matching approaches [15, 19]. The aforementioned NN classifier using multi layer perceptron gives fairly accurate readings. A major reason for the widespread usage of NN classifier is its power and ease of use. [17, 18]. We have used the backpropagation algorithm to proceed with our operations, simply because of its effectiveness and the ease of deployment [14, 16]. The overall efficiency obtained is between 94% and 95%,much above the commonly used template matching methods. The resulting classifier produces some very promising results and hence is a viable alternative to offline signature verification using traditional template based approaches.

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