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Off-line Signature Recognition Using Weightless Neural Network and Feature Extraction

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Abstract *: The problem of automatic signature recognition and verification has been extensively investigated due to the vitality of this field of research. Handwritten signatures are broadly used in daily life as a secure way for personal identification. In this paper a novel approach is proposed for handwritten signature recognition in an off-line environment based on Weightless Neural Network (WNN) and feature extraction. This type of neural networks (NN) is characterized by its simplicity in design and implementation. Whereas no weights, transfer functions and multipliers are required. Implementing the WNN needs only Random Access Memory (RAM) slices. Moreover, the whole process of training can be accomplished with few numbers of training samples and by presenting them once to the neural network. Employing the proposed approach in signature recognition area yields promising results with rates of 99.67% and 99.55% for recognition of signatures that the network has trained on and rejection of signatures that the network .has not trained on, respectively*

***Index Terms*—Feature extraction, off-line signature recognition, RAM-based neural network, weightless neural network (WNN)**

I. Introduction

The signature is a conventional biometric way for authentication and authorization purposes in financial and legal transactions. Handling bank accounts, employee attendance and other such situations require systems for automatic signature recognition. Identifying the owner of a signature using an automatic recognition system involves comparing the provided signature with those stored in a database. While the verification process tests the provided signature and gives an output of either accepting it as a genuine signature or rejecting it as a forged signature [1]. Hence, due to its lively role in our daily life, the field of signature recognition and verification has been widely investigated.

Two methods for automatic signature recognition are available, namely the on-line and off-line methods. The former method also called the dynamic method utilizes time, stroke, speed, and pressure of writing. So, signatures which are recognized using this method are captured using digitizing tablets or pressure sensitive pens. The latter method also called the static method utilizes scanned or photographed images of signatures for recognition. Off-line recognition is cheaper than the on-line one [2], while it is more complex because of the lack of available information about the signature [3].

In this paper, a novel use of the weightless neural network (WNN) and feature extraction is presented. The WNN is flexible, easy to design and implement, and capable of training with few samples. Besides these characteristics, the proposed feature vector is easy to compute, has relatively reasonable size and differentiates among samples excellently. Therefore, the proposed system is considered as a new way for handwritten signature recognition in an off-line manner and can be generalized for solving a variety of problems.

The rest of this paper is organized as follows: Section II introduces some previous works, Section III explains briefly the weightless neural network, Section IV describes the overall proposed system, Section V gives an explanation about the used data set and the designed weightless neural network, Section VI presents the obtained results and a comparison with other studies, and Section VII concludes this paper.

II. Literature Review

Vast number of researches considered the problem of signature recognition using different techniques. Some of those studies are presented here.

Porwik and Para used in [2] feature extraction for off-line signature recognition. They have formed the feature vector for signature images from Hough transformation, center of gravity and horizontal and vertical histograms.

Darwish and Auda used in [4] fast back propagation neural network as a classifier. Moment and topological features have been adopted for constructing a vector with 210 features in order to setup an off-line signature recognition.

Pansare and Bhatia have also used in [5] feature extraction for off-line signature recognition. The used features for composing their feature vector are: maximum horizontal and vertical histogram, center of mass, normalized area of signature, aspect ratio, tri surface feature, six fold surface feature and transition feature. The classifier they have used is the back propagation neural network.

Ubul et. al. presented in [6] an off-line signature recognition system using three classifiers and also feature extraction. The used classifiers are the Euclidean distance (ED) classifier, the K-nearest neighbor (K-NN) classifier and the Bayes classifier. Grid features were used for constructing the feature vector.

III. WEIGHTLESS NEURAL NETWORK

Also known as n-tuple classifier or RAM-based neural network. WNN deals with binary inputs/outputs and no weights on the connectors among its artificial neurons. The neurons can be imagined as look-up tables and input patterns are mapped in i.e. learning the WNN involves changing the contents of those look-up tables rather than correcting the weights as it is the case of conventional artificial neural networks (ANNs). Thereby, RAMs all what is required for building up WNN, and hence this neural network is very fast to learn [7]. Learning to recognize an image using WNN necessitates building a number of logic functions in order to describe the problem. In the testing stage, these functions assess true in case of an image belongs to the class that the function represents and false for all other classes [8].

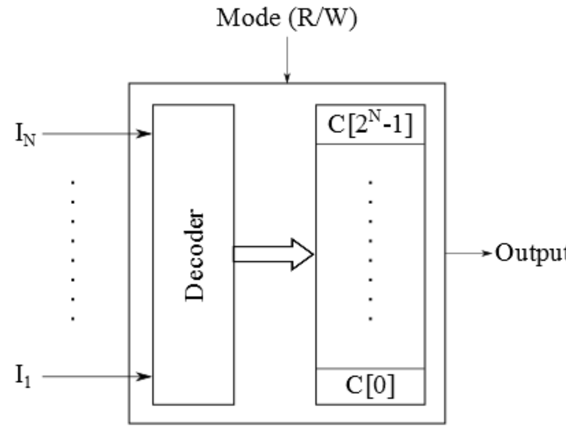

Fig. 1. 1-Bit RAM Node. The lines $I_1 - I_N$ for addressing the memory locations $C[0] - C[2^N - 1]$. The mode line is for toggling between the write and read modes.

Fig. 1 shows the 1-bit word RAM node that is used for assembling the WNN. The N-address lines, called a tuple of size N, are connected to a logical decoder for addressing only one memory location from 2^N available locations. Furthermore, the RAM node has a control input for toggling the RAM mode between "Write" and "Read" in the training phase and testing phase, respectively.

A discriminator that consists of M RAMs which are connected to an adder is shown in Fig. 2. This device performs generalization i.e. delivering the correct output during the testing phase for unseen patterns in the training phase. Each of the RAMs' address lines is connected in a random manner to only one bit from the input binary pattern. Therefore, the result of multiplying the number of RAMs by the tuple size $(M \times N)$ must be equal to the number of bits composing the input binary pattern. Each discriminator is trained on one input pattern, so the number of discriminators composing the WNN must be equal to the number of available input patterns.

All memory locations are set to '0' before starting to train the network. During the training phase ("Write" mode), one of the input patterns is presented to one of the discriminators and '1's are stored in the memory locations which are addressed by the N address lines of the RAMs in the discriminator. Then another different input pattern is presented to another discriminator for training it, and so on. Therefore, it is necessary to provide a number of discriminators as much as the number of

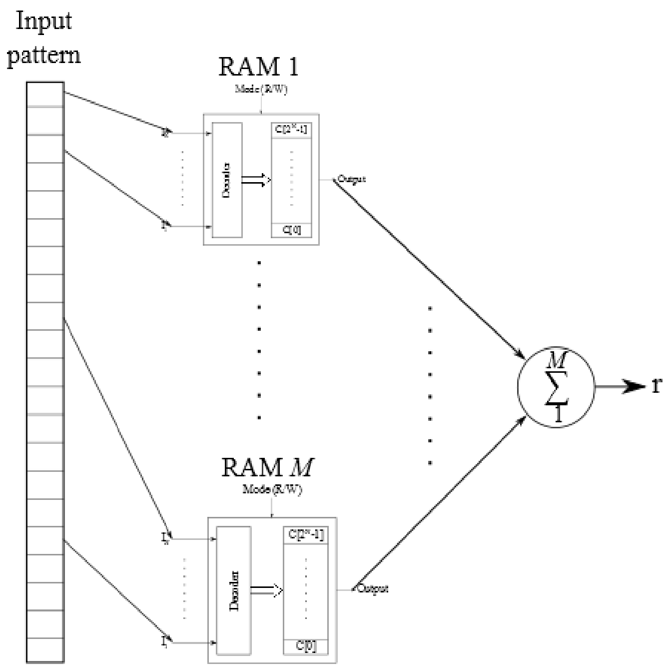

Fig. 2. A discriminator. It consists of M RAMs each has N input address lines which are randomly connected to the elements of the input vector. The response (r) of the discriminator represents a counter for those RAMs with output of '1'.

pattern classes. For example in the applications of handwritten digits recognition, 10 discriminators are composing the WNN as there are 10 digits (0-9).

During the testing phase ("Read" mode), the neural network uses the information that has been stored in the RAMs of discriminators during the training phase; in fact this information are '0's or '1's. The testing process begins by presenting an unseen (new) input pattern to the WNN that is composed of k discriminators, like the one shown in Fig. 3. Also, k represents the number of different patterns. The presented pattern will address same memory locations in all discriminators, the addressed locations depend on the available '1's in the pattern. The contents of those locations are read and summed individually within each discriminator. The result of summation represents the response (r) of the corresponding discriminator. The value of r $(0 \leq r \leq M)$ gives an indication about the amount of likeness between the input test pattern and the

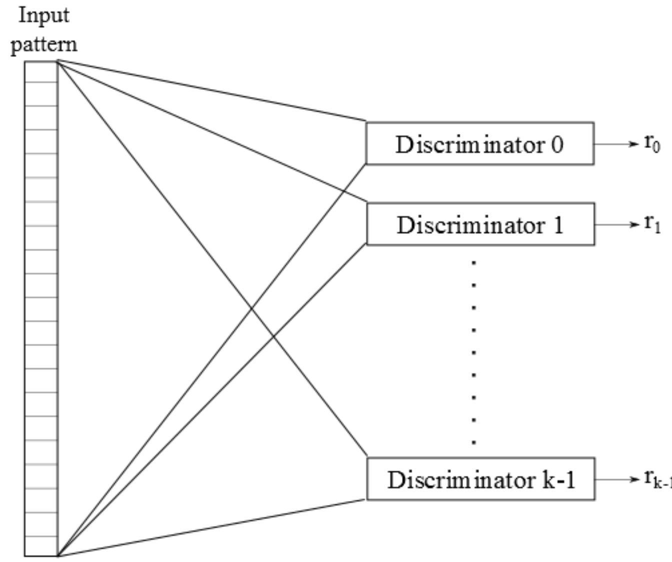

Fig. 3. A WNN that consists of k discriminators. Each discriminator is trained for recognizing one class of patterns. Hence, this WNN is able to recognize k classes of patterns.

pattern that is used for training the corresponding discriminator. Hence, the input test pattern is put into the class of discriminator which have the maximum value of r.

Consequently, it is clear that WNN is easy to design and implement because it requires memory slices and counters only [8]. While the conventional ANNs are more complex as they require a large number of adders and multipliers in order to handle the weights on the connectors and the sum-and-threshold artificial neurons [9]. Furthermore, the training process is much simpler in the case of WNN than in ANN. Where it is sufficient to present the training samples once to the WNN, while training the ANN demands presenting the training samples in a repetitive manner in order to correct the weights [8].

IV. The Overall Proposed System

The proposed automatic off-line signature recognition system is composed of three major steps namely: preprocessing, feature extraction, and recognition.

A. Preprocessing

Dealing with signatures as captured images may need some preprocessing as images may contain some noise, or have different sizes, etc. Moreover, the way that people sign is not precisely systematic, for example seating position or hand placement has an effect on the angle of signature. After applying preprocessing, the images will be standard and ready for feature extraction. Three types of preprocessing are applied in this study; these are: binarization, image resizing, and thinning.

1) Binarization

The WNN deals with binary data only, also we are trying to make the process of feature extraction simpler; therefore, it is necessary to change the gray scale image into binary format (black “0” and white “255”). For this a threshold filter is used (1), where each of the original pixels $I(i,j)$ are converted to the binary format $b(i,j)$ using a specific threshold (Th). Fig. 4 shows an original signature image and its binary image.

$$b(i,j) = \begin{cases} 255 \text{ if } I(i,j) \geq \text{Th} \\ 0 \text{ if } I(i,j) < \text{Th} \end{cases} \quad (1)$$

2) Image Resizing

The sizes of available signature images are different, therefore, resizing of images is required in order to bring them to a standard size. Following the nature of the used database, the sizes of all images are shrank to 128×32.

3) Thinning

Sometimes the type of pen/paper or amount of writing pressure could affect the attributes of the obtained signature images. Thinning is a process that can obliterate all those unwanted effects by getting objects or shapes to single pixel wide instead of multi pixels wide. Hence, the advantage

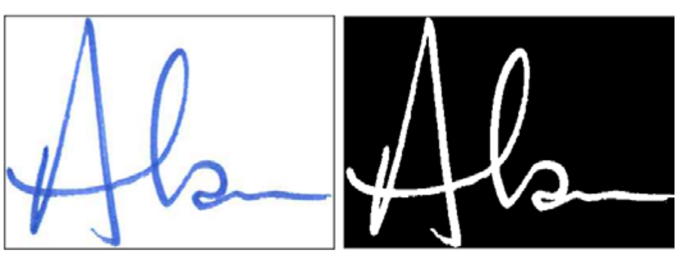

Fig. 4. Two images for the same signature. On the left: the original signature image. On the right: the binary format of the image.

Fig. 5. Thinned signature image. The signature line is one pixel wide instead of multi pixels wide which is shown in Fig. 4.

of thinning is that feature extraction becomes invariant to image attributes. Fig. 5 shows the thinned signature image which is resulted from applying thinning process on the binary format image (Fig. 4).

B. Feature Extraction

Extracting features is the process of decoding the input pattern in numeric values, it is necessary to decrease the amount of data which will be presented to the classifier. Developing a feature vector is a crucial step in designing signature recognition systems as the selected features represent the unique information about the signatures. Therefore, an optimum feature vector has to be formed for solving this complex problem. An optimum feature vector is easy to compute, has a small size and capable of classifying the samples accurately.

Numerous types of features have been used in the researches such as: the proportion factor which describes the relation between the width and height of the signature, the vertical and horizontal histogram which represents the projection of vertical and horizontal signature pixels, the center of gravity which is represented by a point where two orthogonal lines cross through it and the number of signature pixels (black pixels) within the resulting quarters are the same [2, 5], the normalized area of a bounded signature which is the ratio of the signature area (the number of pixels encompassing the signature) to the area of the bounding box [5] and the grid features in which the signature is divided into rectangles then the area for each small rectangle is calculated [6].

Due to their simplicity in computation thus the grid features have been intensively used in the studies of off-line signature recognition. All the features which are used in this study are from the type of grid features. They can be classified into two main types: the first one is the horizontal and vertical grids and the second one is the rectangular grids (Fig. 6).

1) Horizontal and Vertical Grids

For the horizontal grid, the signature image is horizontally divided into 4 segments; refer to Fig. 6

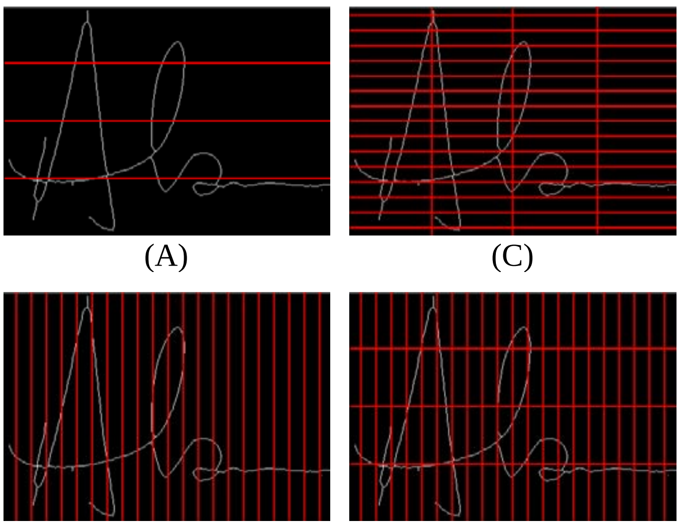

Fig. 6. Feature extraction from signature images using four different grids. A: image is divided into horizontal segments. B: image is divided into vertical segments. C: image is divided into horizontally rectangular segments. D: image is divided into vertically rectangular segments.

(A), the segmentation lines are the red lines. Then the area of each part of the signature is computed, this area is computed throughout counting the number of white pixels inside each segment. Hence the number of obtained features from the horizontal grids is 4.

Likewise, for the vertical grid, the signature image is vertically divided into 64 segments; refer to Fig. 6 (B), the segmentation lines are the red lines. Then the area of each part of the signature is computed. The number of obtained features from the vertical grids is 64.

2) Rectangular Grids

Horizontal and vertical small rectangular grids are extracted from the signature images.

For the horizontal rectangular grid, the signature image is divided into small horizontal rectangles, refer to Fig. 6 (C). The same number of segments which have been used for vertical and horizontal grids are used for the rectangular grids i.e. the number of resulting rectangles is 256. Thus the number of obtained features from the horizontal rectangular grid is also 256.

Likewise, for the vertical rectangular grid, the signature image is divided into small vertical rectangles, refer to Fig. 6 (D). The number of obtained features from the vertical rectangular grid is 256.

Extracted features are normalized individually in order to put them in the range of 0 to 1. Then a threshold has been used for rounding the normalized values to 0 or 1, this is an essential step because as it has been mentioned earlier that the used neural network accepts binary inputs only. After that the binary features are assembled in a vector of the length 580 elements (4+64+256+256).

C. Recognition Algorithms

Once the signature recognition system has gotten trained using the feature vector that has been extracted from the training signature images, it will be ready for classifying the unseen samples.

So in the recognition stage, the test signature image is preprocessed then feature extraction is performed to get back the feature vector which is converted to binary values as described above then afterwards it is fed to the trained neural network which will classify it to one of the classes or reject it as not an included class.

The two algorithms for training and testing the automatic signature recognition system are given below:

A. Training Algorithm

1. Set all memory locations to ‘0’.
2. Read a training signature image.
3. Preprocess the image (binarization, image resizing, thinning).
4. Extract features (horizontal grid, vertical grid, horizontal rectangular grid, vertical rectangular grid).

5. Normalize the obtained features to put them in the range of ‘0’ to ‘1’.
6. Round the normalized values to ‘0’ or ‘1’.
7. Construct the feature vector from the resulting binary features.
8. Train the WNN (RAMs on “write” mode):
    8.1. Select a discriminator to be trained on a specific class of signatures.
    8.2. Randomly distribute the elements of the binary feature vector on the available tuples in the discriminator.
    8.3. For each RAM in the discriminator, store ‘1’ in one location that is addressed by the corresponding tuple.
9. Repeat steps 1-8 until all training signature images are presented to the neural network.
10. End.

B. *Testing Algorithm*

1. Read a testing signature image.
2. Preprocess the image (binarization, image resizing, thinning).
3. Extract features (horizontal grid, vertical grid, horizontal rectangular grid, vertical rectangular grid).
4. Normalize the obtained features to put them in the range of ‘0’ to ‘1’.
5. Round the normalized values to ‘0’ or ‘1’.
6. Construct the feature vector from the resulting binary features.
7. Test the WNN (RAMs on “read” mode):
    7.1. Randomly distribute the elements of the binary feature vector on the available tuples in the discriminator.
    7.2. Repeat step 7.1 to connect the feature vector to all of the available discriminators.
    7.3. Sum the outputs of RAMs within each discriminator to obtain the responses of the discriminators.
    7.4. If the highest response is less than the threshold then reject the image, else assign the image to the class of that discriminator with the highest response.
8. Repeat steps 1-7 until all testing signature images are classified.
9. End.

V. EXPERIMENTAL SETUP

The used signatures are taken from the data set of “ICDAR 2011 Signature Verification Competition (SigComp2011)” [10], it is freely available on http://www.iapr-tc11.org/mediawiki/index.php/ ICDAR_2011_Signature_Verification_Competition _(SigComp2011). The data set contains off-line and on-line signature samples. In this study, we used only the off-line signatures which are constituted of PNG images. The total number of used signature images is 1240, they are for 62 different signatories i.e. 20 signatures for each signatory. Signatures for 40 signatories (800 signatures) are used to train and test our proposed system. For each signatory only 5 signatures are used for the training, while the other 15 signatures are used for the testing. The remaining 440 signatures of the other 22 signatories are used to test the ability of the network to reject signatures not included in its classes.

Since 40 classes of signatures are need to be classified, the designed WNN consists of 40 discriminators. Now the number of RAMs which are contained within each discriminator and the number of their address lines (tuple size) have a relevance to the size of feature vector. It has been mentioned that the elements of the feature vector are randomly distributed on the address lines of the RAMs within a discriminator (one element to one address line). Consequently, the number of RAMs multiplied by the tuple size must be equal to the size of feature vector. Hence, the designed neural network contains 290 RAMs within each discriminator, and each of them has 2 address lines.

We had pointed earlier that the possible response of a discriminator is $(0 \leq r \leq M)$, where M is the number of RAMs. Hence, in our designed system the maximum value of r will be 290. A threshold is set in order to decide whether to classify a test image to one of the available classes or to reject it as not an included class. We have decided to set the threshold to 270, it means if the maximum response is less than 270 then the image will be rejected; otherwise the image will be assigned to the discriminator with the maximum response.

TABLE I
A comparison between the proposed signature recognition system and other systems

Author & reference	Classifier	No. of training samples	No. of testing samples	Recognition rate (%)
Porwik and Para [2]	Combined method with Hough transformation	Not indicated	Not indicated	94.60
Darwish and Auda [4]	Fast back propagation NN	8	8	98.60
Pansare and Bhatia [5]	Back propagation NN	19	24	82.60
Ubul et. al. [6]	Euclidean distance (ED)	10	10	86.45
	K-nearest neighbor (K-NN)	10	10	93.53
	Bayes	10	10	89.26
The proposed system	Weightless neural network (WNN)	5	15	99.67

VI. Results

The recognition rate that is obtained using the proposed system is 99.67%, and the rejection rate for those untrained on signatures is 99.55%.

Table I summarizes a comparison between the obtained results using the proposed signature recognition system with other systems. It is clear from the table that the proposed system has achieved the best recognition rate. Moreover, the ratio of the number of training samples to the number of testing samples is extremely low for the proposed system, it means that the number of required signatures for training the neural network in order to obtain this recognition rate is very low in comparison to other studies. One has to keep in mind the simplicity of the proposed system and its training process which needs presenting the training samples once only i.e. there is no update for the weights.

VII. Conclusion

A weightless neural network has been designed and used with feature extraction for solving the problem of handwritten signature recognition. The whole process that is carried out by the proposed system can be summarized by three main steps: preprocessing the signature images, feature extraction, and recognition. The input to the system is a signature image, and the output form the system is assigning the signature to one of the classes or reject it as not included class. The proposed system is simple to design and implement as hardware, and it has achieved very good results.

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