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Off-Line Signature Recognition Based On Angle Features and GRNN Neural Networks

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***Abstract*—**This research presents a handwritten signature recognition based on angle feature vector using Artificial Neural Network (ANN). Each signature image will be represented by an Angle vector. The feature vector will constitute the input to the ANN. The collection of signature images will be divided into two sets. One set will be used for training the ANN in a supervised fashion. The other set which is never seen by the ANN will be used for testing. After training, the ANN will be tested for recognition of the signature. When the signature is classified correctly, it is considered correct recognition otherwise it is a failure.

***Keywords*—**Signature Recognition, Artificial Neural Network, Angle Features.

I. Introduction

THE signature is defined as: the name of a person written with his or her own hand or the act of signing one's name for the purpose of authenticating writing in a permanent form [1]. A recognition system is often categorized into two major classes: on-line signature recognition system and off-line recognition system. The difference between on-line and off-line signature recognition lies on how data are obtained.

In an online system, a signature data can be obtained from an electronic tablet. In this case, dynamic information about writing activity such as speed of writing, pressure applied, pen movements are available. In off-line systems, signatures are written on papers as they are done traditionally and converted to electronic forms with the help of a camera or a scanner and obviously, dynamic information is not available. In general, the dynamic information represents the main written style of a person [2], [3].

This paper presents an off-line signature recognition system which is based on an angle feature algorithm to extract features of signatures (saved in database) using Generalized Regression Neural Network (GRNN) which is often used for function approximation. It has a radial basis layer and a special linear layer. The neural network is used by dividing the database of signatures into two groups: one for training the GRNN neural network and the other group for testing.

II. Proposed System

The previous researches used an algorithm of angle feature extraction with Takagi- Sugeno (TS model) [3], [4]. However, this research proposed to use angle feature extraction with ANN algorithm.

The system algorithm is described in the following steps:

1) Collecting a database of handwritten signatures with format (.tif) that will be used for angle feature extraction algorithm, and the database consists of 300 signatures: 10 signatures for 30 persons.
2) Dividing the database into two sets, each set consists of 150 signatures: one for the training phase and the other set for the testing phase.
3) Implementing pre-processing steps on all signatures to be ready to extract features, these steps are: binarization, noise removal, normalization, and thinning.
4) Implementing an angle feature algorithm on all signatures. This algorithm divides the image (signature) into parts, and calculates the summation of the angles of all points in each part with respect to the bottom left corner of the part and each summation represents the feature for each part.
5) Training the Generalized Regression Neural Network (GRNN) on the training set of the signatures.
6) Testing the GRNN using the testing set, and the resulting score of this phase represents the recognition rate.

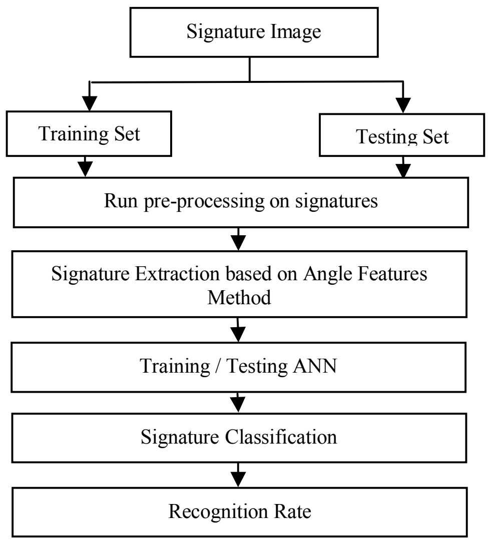

Fig. 1 General Flow Chart of the Proposed Method

III. Implemented System

This section explains the implemented system that was used to perform the aim of this research.

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A. Pre-Processing Image

In this phase the proposed system executes four steps to format the image before it extracts the features. These steps are, as shown in Fig. 2:

1) **Binarization:** this process converts the image into binary image.
2) **Noise removal:** to remove the noise from image.
3) **Normalization:** before finding the signature features, the original image can be normalized in a canonical form so that different images of the same signature can be normalized similarly. In this step, the signatures are scaled to size 80 pixels × 160 pixels.
4) **Thinning:** In this step we use morphological operations on binary images to eliminate the effect of different line thicknesses resulting from the use of different writing pens.

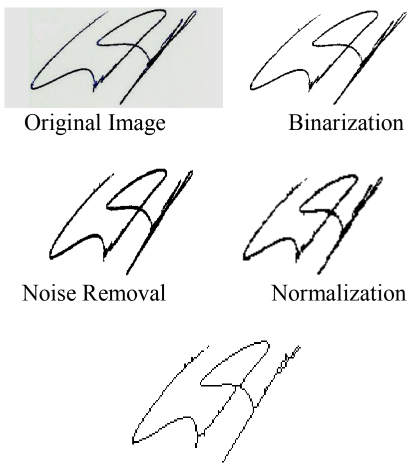

Fig. 2 Pre-processing Image

B. Extract Features

After executing pre-processing, the image is ready to extract features by angle features algorithm. The features are extracted as follows:

1) Partitioning the image into blocks of different sizes (with block size 8×8, 4×4, and 2×2pixels) as shown in Fig. 3.
2) In each block, take the angles of all black points with respect to the bottom left corner and calculate the summation and normalize it by dividing with the number of black points in the box.

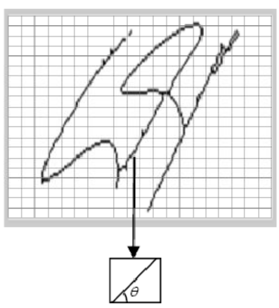

Fig. 3 Partitioning Image into Blocks

C. Artificial Neural Networks

The type of neural network that was used in this system is Generalized Regression Neural Network (GRNN). A Generalized Regression Neural Network (GRNN) is often used for function approximation. As shown in Fig. 4, it has a radial basis layer and a special linear layer [5].

A GRNN is a variation of the radial basis neural networks. A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function [4].

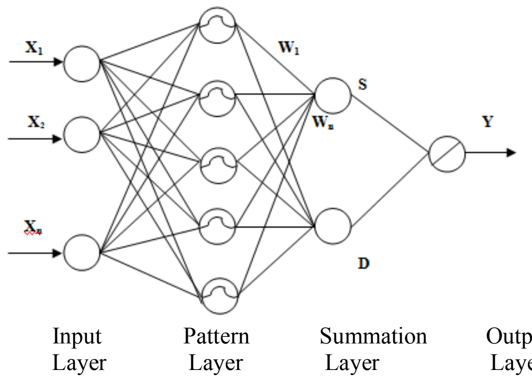

Fig. 4 GRNN Architecture

A GRNN consists of four layers: input layer, pattern layer, summation layer and output layer as shown in Fig. 4.

1) The first layer is input layer that is connected to the pattern layer and in this layer each neuron presents a training pattern and its output.
2) The pattern layer is connected to the summation layer.
3) The summation layer has two different types of summation, which are a single division unit and summation units. Where the summation and output layer together perform a normalization of output set. In training of network, radial basis and linear activation functions are used in hidden and output layers.

Each pattern layer unit is connected to the two neurons in the summation layer, S and D summation neurons. S summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, D summation neuron is used to calculate unweighted outputs of pattern neurons.

4) The output layer merely divides the output of each S summation neuron by that of each D-summation neuron, yielding the predicted value Y to an unknown input vector x [4].

$$Y = \frac{\sum_{i=1}^{n} w_i \exp - D_i}{\sum_{i=1}^{n} \exp - D_i} \tag{1}$$

where:

$$D_i = \sum_{k=1}^{m} \left(\frac{x_i - x_{ik}}{\sigma}\right)^2 \quad (2)$$

$$\sigma = \frac{d_{\max}}{\sqrt{m}} \quad (3)$$

where w_i is the weight connection between the i^{th} neuron in the pattern layer and the S-summation neuron, n is the number of the training patterns, D_i is the Euclidean distance with Gaussian Function. This function calculates the distance between an input (x_i) and the mean (x_{ik}) of those inputs, d_{max} is the maximum distance between the chosen centers, m is the number of elements of an input vector.

And this network has certain characteristics:

1) Fast learning.
2) Good convergence with a large number of training examples.
3) Handling of sparse data well [5].

IV. Results Analysis and Comparison

Experimental case studies were applied on a database of the collected images as mentioned earlier. This database contained 300 images from 30 persons, and each person signed 10 signatures. We divided this database into two sets: 150 signatures as training set and 150 signatures as testing set, and each set contained from images. The details of these case studies are described below:

A. Case Study 1: Comparison between Different Sizes of Blocks

This experiment has been carried out to assess the effect of the difference in the size of blocks when partitioning the image in features extraction phase on the results of recognition. The recognition rate values to select the best size for block according to the highest recognition rate that has been achieved. It has been found that when the block is smaller, the results of the recognition rate are higher. The following figures and tables display different recognition rates because the block sizes are different.

TABLE I
Recognition Rate with Blocks Size: (8×8)

Number of Images	Recognition Rate	Time (mins)
300	63.33%	7
200	70%	5
100	84%	3
50	92%	1
The number of features is 200		

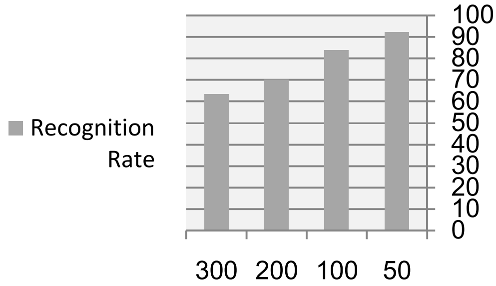

Fig. 5 Recognition Rate with Blocks Size: (8×8)

From this experiment, we noticed from Table I and Fig. 5, when the block size is (8×8) the recognition rate with 50 images was 92% in one minute. And by increasing number of images, the recognition rate is decreasing with longer time. Where, the recognition rate with the total number of images (300) was 63.33% in 7 minutes.

TABLE II
Recognition Rate with Blocks Size: (4×4)

Number of Images	Recognition Rate	Time (mins)
300	85%	15
200	88%	8
100	96%	5
50	100%	2
The number of features is 800		

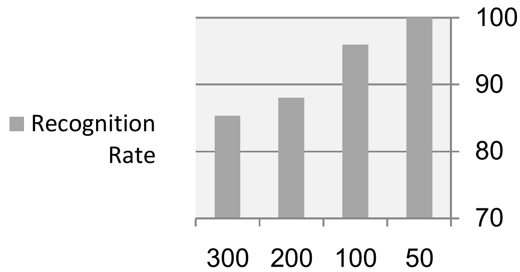

Fig. 6 Recognition Rate with Blocks Size: (4×4)

From Table II and Fig. 6, we noticed that when the block size is (4×4) the recognition rate with 50 images was 100% in 2 minutes. And by increasing number of images, the recognition rate is decreasing with longer time. Where, the recognition rate with the total number of images (300) was 85.33% in 15 minutes.

TABLE III
Recognition Rate with Blocks Size: (2×2)

Number of Images	Recognition Rate	Time (mins)
300	94.67%	31
200	95%	22
100	98%	9
50	100%	5
The number of features is 3200		

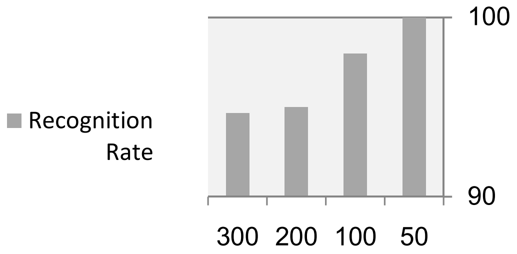

Fig. 7 Recognition Rate with Blocks Size:(2×2)

From Table III and Fig. 7, we noticed that when the block size is smaller (2×2) the recognition rate with 50 images was 100% in 5 minutes. By increasing the number of images, the recognition rate is decreasing with longer time. Where, the recognition rate with the total number of images (300) was 94.67% in 31 minutes.

We concluded from these experiments the best block size is (2×2) where the recognition rate is highest.

B. Case Study 2: Comparison of Angle and DCT Feature Extraction Algorithms

This experiment has been carried out to assess the effect of the difference between feature extraction algorithms. For the safe of comparison in this work of this system, we executed another algorithm to extract features. This algorithm is Discrete Cosine Transform (DCT). Recognition rate values were varied between this algorithm and the proposed algorithm (Angle feature algorithm) and we noticed the difference in the time. The following table displays the results of this experiment.

TABLE IV
COMPARISON OF ANGLE FEATURE AND DCT FEATURE EXTRACTION ALGORITHMS

Number of Images	Recognition Rate with Angle Feature	Time (mins)	Recognition Rate with DCT	Time (mins)
300	94.67%	31	64%	40
200	95%	22	82%	30
100	98%	9	96%	18
50	100%	5	100%	11

C. Case Study 3: Comparison of Algorithms using Two Databases

This experiment has been carried out to assess the effect of different databases of signatures. In order to perform this experiment, we used a database from another signature verification system [4].

The following table illustrates different recognition rates between two databases. Each database was extracted features using angle feature algorithm and classified with GRNN algorithm, as shown in the results in Table V.

TABLE V
COMPARISON BETWEEN TWO DATABASES USING OUR ALGORITHM

Number of Images	The system's Database	Other system's Database
300	94.67%	96.66%
200	95%	96%
100	98%	98%
50	100%	100%

V. CONCLUSION

This study has presented a hybrid method for the recognition of signatures. The technique of feature extraction using the algorithm of angles, calculation to extract angle features has been used, followed by Generalized Regression Neural Network (GRNN) for classification which has been implemented as well.

From this research it has been proven that, different techniques for signatures recognition where each one has its own approach for recognizing the signature. The recognition rate depends on the method that is used to extract the features of a signature and the technique that used as a classifier. Generalized Regression Neural Network (GRNN) is used as a classifier and extracted features with the Angle Features Algorithm gave 94.7% recognition rate.

The change in size of blocks that resulted from partitioning of image using the proposed algorithm produced different results. That means, when the block was small, the angle features was finer and this affected on the recognition rate where the recognition was higher as follows:

1) With block size (8×8) of angle features, the recognition rate was 63.33% in 7 minutes time.
2) With block size (4×4) of angle features, the recognition rate was 85.33% in 15 minutes time.

With block size (2×2) of angle features, the recognition rate was 94.67% in 31minutes time. Therefore, this size (2×2) produced better recognition rate in relatively longer time.

By comparing the angle feature algorithm of this system with Discrete Cosine Transform (DCT) algorithm, the algorithm of this system (Angle Features) is the finest in shortest time, where it gave recognition rate 94.7% in 31 minutes, and the (DCT) algorithm gave recognition rate 64% in 43 minutes at the same block size of features for both algorithms.

The proposed algorithm was tested using two different databases (this system database's and other system database's [2]). The recognition rate with this system's database was 94.67%, and the recognition rate with the other system's database was 96.66%. The other database was used by [2] and proposed a recognition rate of 90.21%, whereas our algorithm resulted in 96.66% which is higher for the same database.

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