Arabic Handwritten Signature Identification

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ABSTRACT

This paper proposes a new intelligent off-line Arabic handwritten signature identification and verification system based on texture analysis. The system uses the texture as feature and back propagation neural network as classifier. The signature image is preprocessed by several operations (Noise removal, Conversion of the signature image to binary image, Finding outer rectangle, Thinning and Size normalization) then the fractal number and co-occurrence matrix are computed to estimate texture features. In this work, two off-line Arabic handwritten signature identification systems are constructed. The first one uses the nearest Euclidean distance, while the other uses back propagation neural network. The paper analyzes and compares the results obtained from the two proposed systems to show the robustness level of the proposed intelligence system. Furthermore, the proposed system was tested by using **Genuine** signatures and has achieved a CCR (Correct Classification Rate) of 100% in best cases, while it was tested by using **Forged** signatures it has achieved a CRR approximated to 96.3% in best cases. The experimental results showed that the proposed system is efficient and competent with other state-of-the-art texture-based off-line signature identification systems.

Keywords: Texture analysis, Back propagation artificial neural network, Offline signature identification and verification.

التعرف على التوقيع اليدوي العربي

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الملخص

يقترح البحث نظاما ذكائيا جديدا للتعريف والتحقق من التواقيع الرقمية اليدوية الغير حية بالاعتماد على تحليل النسيج . يستخدم النظام النسيج كميزات (صفات) و الشبكة العصبية ذات الانتشار العكسي كمصنف. ومن اجل تهيئة صورة التوقيع نحتاج الى عدة عمليات يطلق عليها المعالجة الاولية وتشمل (إزالة الضوضاء، تحويل صورة التوقيع إلى صورة ثنائية، العثور على المستطيل الخارجي، التنحيف، وتطبيع الحجم) ثم احتساب العدد الكسوري والمصفوفة الظاهرة لتخمين ميزات النسيج. تم خلال هذا البحث بناء نظامين للتعريف والتحقق من التواقيع العربية اليدوية الغير حية. استخدم النظام الاول اقصر مسافة الاقليدية بينما استخدم الاخر الشبكة العصبية ذات الانتشارالعكسي. لقد تمت تحليل ومقارنة النتائج المستحصلة من النظامين المقترحين لاظهار مستوى قوة النظام الذكائي المقترح. كما اختبر النظام المقترح باستخدام تواقيع حقيقية وحققت CCR (نسبة التصنيف الصحيحة) 100٪ في أفضل الحالات، في حين انه تم اختباره باستخدام تواقيع المزورة وحقق CRR (الصحيح قيم مرفوض) يقترب إلى 96.3٪ في أفضل الحالات. أظهرت النتائج التجريبية أن النظام المقترح كفوء وحقق تعريف التواقيع الغير حية والمعتمدة على صفة النسيج.

الكلمات المفتاحية: تحليل النسيج، الشبكة العصبية الاصطناعية ذات الانتشار العكسي، التعرف والتحقق من التوقيع دون الاتصال بالإنترنت.

1. Introduction

The off line signature identification is one of the reliable and oldest identification methods, which is in use over a century all over the world. However, the advent of Automatic Signature Identification System has made the handwritten signature identification to be more reliable, inexpensive and less time consuming. The wide and frequent use of signature as a means of biometric identification emphasizes the need for automatic identification systems, where a correct assessment of identification is a crucial point. It is one of the authentic approaches, which is broadly used in documents such as bank checks, credit cards, and many other documents of greater importance. Signature Identification system is the process of recognizing an individual's handwritten signatures [1]. This system is capable of efficiently addressing two individual, but strongly related tasks: (a) identifying the signature of the owner and (b) deciding whether the signature is genuine or forged [2]. The signature identification and verification could be classified into two types based on the format of input information: online signature identification and verification [3,4,5,6,7,8 and 9] and offline signature identification and verification [10,11,12 and 13].

Features of signature identification and verification systems could be roughly divided into two types: (i) global features which are extracted from the whole signature, including block codes, Wavelet and Fourier series, etc. and (ii) local features which are calculated to describe the geometrical and topological characteristics of local segments, such as position, tangent direction, and curvature [15 and 14].

Various off-line techniques have been proposed in the literature for the signature identification and verification problem. This is a long-established pattern classification problem [16], since signature is one of the most widely used authentic methods due to its acceptance in government, legal, financial and commercial transactions [17]. It is considered as a challenging research area [18]. Table (1) summarizes the most widely used signature identification and verification systems.

The main contribution of this paper is the proposal of an intelligent off-line Arabic handwritten signature identification system, based on texture analysis by using scanned images of signatures. In the system, the texture is used as features and back propagation neural network and nearest Euclidean distance as classifiers. The fractal number and co-occurrence matrix are computed to estimate texture features. The results from two signature identification methods are analyzed and compared to show the robustness level of the proposed intelligence system with texture features. The rest of the paper is organized as follows: The description of the proposed system is presented in section 2, the data set collection details is explained in section 3, pre-processing of signature images are discussed in Section 4. Sections 5 and 6, describe the texture analysis and features extraction and the classification machines respectively. The experimental results are presented and discussed in sections 7 and 8, while section 9 concludes the work and presents suggestions as future work.

Table (1) Publication Samples of Signature Identification and Verification Systems

Authors/ Year	Paper Title	Features & Methods
Deng et al [19] 1999	"Wavelet-based off-line handwritten signature verification"	The curvature data of the traced closed contours are decomposed into multi resolutional signals using wavelet transforms & optimal threshold value.
Fang et al [20] 1999	A Smoothness Index Based Approach for Off-line Signature Verification	Smoothness Features are combined with global shape features & minimum distance classifier.
Baltzakis&	A new signature verification	global and texture features & Neural

Papamarkos [2] 2001	technique based on a two-stage neural network classifier	network.
Ueda l [21] 2003	Investigation of Off-Line Japanese Signature Verification Using a Pattern Matching	modified pattern matching method, which is independent of signature stroke width.
Özgündüz et al. [12] 2005	Verification and recognition by support off-line signature vector machine (SVM)	global, directional and grid features of signatures & SVM.
Shanker, & Rajagopalan [13] 2007	Off-line signature verification using DTW	The vertical projection feature is extracted from signature images & elastic matching.
Liu & Tang [14] 2007	Offline signature verification using online handwriting registration	Shape descriptor , which combines the duration and amplitude variances of handwriting & nearest neighbor classifier.
Vargas et al. [15] 2008	Off-line Signature Verification Based on High Pressure Polar Distribution	High Pressure Polar Distribution & K-Nearest Neighbor and Probabilistic Neural Network.
Bansal etal. [1] 2009	Offline signature verification using critical region matching	Matching Critical points extracted from the signature shape & optimal distance threshold.
Bertolini et al [22] 2010	Reducing forgeries in writer-independent off-line signature verification through ensemble of classifiers	Signature Shape and genetic algorithm.
Ismail et al [23] 2011	An efficient off-line signature identification method based on Fourier descriptor and chain codes	Fourier descriptor and chain codes & designed a multilayer feed forward artificial neural network.
Shirdhonkar1 and Kokare [24] 2011	Off-Line Handwritten Signature Identification Using Rotated Complex Wavelet Filters	Complex wavelet filters & Canberra distance measure.
Zhou et al [25] 2011	Handwritten Signature Recognition based on the SDAPCI-MS Imaging Technique	analyzing the characteristic of the handwritten signature’s appearance and stroke based on SDAPCI-MS Imaging Technique & improved inadequacies of the similarity algorithm.

2.The Proposed System

The aim of this work is to propose an Arabic handwritten identifier and verifier based on texture features (box counting algorithm and co-occurrence matrix) by using supervised feed-forward neural network with back propagation training algorithm for identifying and verifying Arabic handwritten signatures. The proposed system consists of three stages: (1) **Pre-processing stage**, (2**) Feature Extraction stage** and (3) **Classification stage**. The block diagram of the proposed system is shown in Figure (1).

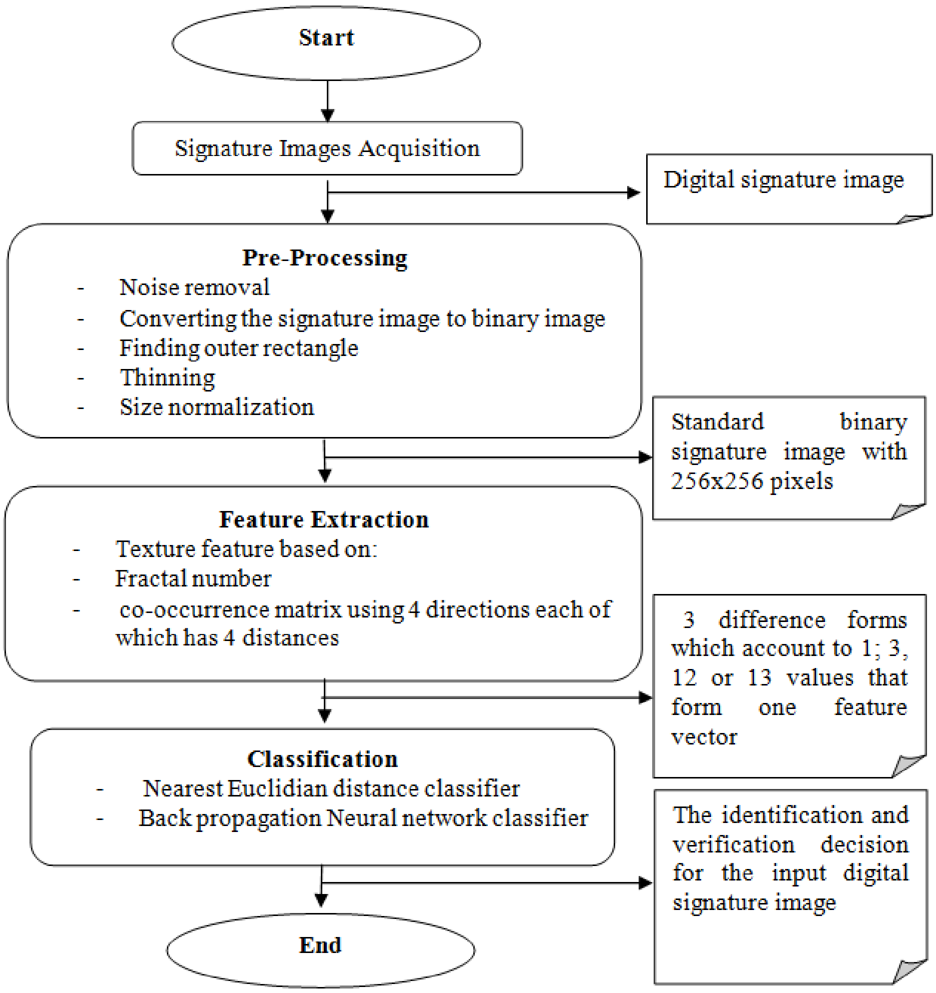


Figure (1) Block Diagram of the Proposed Arabic Handwritten Signature Identification and Verification

3. Data Set

The signatures to be processed by the proposed system should be in the digital image format. Scanning the signatures from the document is called the acquisition step which converts a number of paper sheets to a set of digital images, each of them containing one or more signatures. The data set of signatures (database) comprised of 200 Arabic handwritten signatures were collected by the authors from 20 people (10 signatures per person) in different times and pens. One hundred (100) signatures are used in the training phase of the proposed system. The set of signatures is referred to as "Signature training set". While, one hundred (100) genuine signatures and thirty (30) forged signatures are used to test the proposed system. This set is referred to as "Signature testing set. All of the signatures were signed by black pen on A4 (297 x 210 mm) white paper and scanned by Epson ScanMarker 3630 at 300 DPI (Dots per inch) resolutions.

4. Preprocessing

1- The preprocessing step is applied in both training and testing phases. The aim of this step is to make signatures standard and ready for feature extraction. The preprocessing steps include the following processes:
2- Noise removal: in the off-line signature identification and verification preprocessing, it is usually necessary to eliminate the noise introduced during the acquisition process by using mean filter [26]. The noise attached to a scanned

signature image has to be removed to avoid errors in the further processing steps. It is achieved by using an 3*3 median filter to generate the cleaned image [27].

3- Signature image binarization: the signature images are converted to binary images (image binarization) by using Otsu's thresholding method which is used to the reduction of a graylevel image to a binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal [33 and 28].The value of threshold is between (0-1) and it is depending on signature itself, so it is impossible to fix it for all signatures.

4- Finding the signature outer surface: it is very important as it involves in finding the outer surface [28 and 29] of the signature, which is a rectangle with the least size that all pixels of signature are in it. The outer rectangle can be found by using horizontal and vertical projection of the signature image which is determined by applying a threshold on the horizontal and vertical projections of the signature image [29].

5- Thinning signature image: the purpose of the thinning step is to reduce the image components to their essential information so that further analysis and recognition are facilitated; it gives a good abstraction of the original signature, with a low noise level. The thinning algorithm used in this paper is inspired from [30 and 31].

6- Size normalization: the final process is normalizing each signature image by size normalization by using Bilinear interpolation algorithm [28 and 29]; all signature images are aligned to a fixed dimension of 256X 256 i.e. each of them has 65536 pixels. The normalization is the most important preprocessing step that affects identification rate directly [32].

5. Feature Extraction

Feature extraction is an important stage in establishing a handwriting identification and verification system, which transforms a data space into a feature space. In this research, a set of features that are uniquely characterized as a candidate signature is used. These features are categorized as global features that treat signature image as a whole [34] and Statistical features are derived from the distribution of pixels of a signature image [35 and 36] based on fractal number and co-occurrence matrix respectively. All these features are arranged in three difference forms which account to 1; 3, 12 or 13 values that form one feature vector. The feature vector is passed on to the classifier for classification. The quality of the features determines how well the proposed system works [37].

5.1 Box Counting to Estimate the Fractal Dimension

Fractal shapes occur universally in the natural world [38]. Fractals have been used with varying success in a wide range of scientific fields [39]. The concept of the fractal was first introduced by Mandelbrot [40], who used it as an indicator of surface roughness. The fractal dimension has been used in image classification to measure surface roughness to recognize different natural scenes such as mountains, clouds, trees, and deserts [40,41].

The surface roughness feature has been used in coastlines, lungs, landscapes, turbulent water flow, and even in the chaotic fluctuation of prices on the Chicago commodity exchange [38]. Fractal was introduced to analyze texture in [41]. It measures geometric complexity, which could be used to describe many spatial patterns of textures [42]. Later Keller et al [43] applied it in textured image segmentation.

There are several different types of dimensions (Self-similarity, box counting, topological dimension, Hausdorff dimension, and Euclidean dimension) [44 and 45]. One of the variety dimension methods for estimating the fractal dimension is the box-counting method [46 and 47]. It can be computed automatically and be applied to patterns with or without self-similarity [37]. The box-counting dimension is calculated for the signature images as follows: [47 and 37]

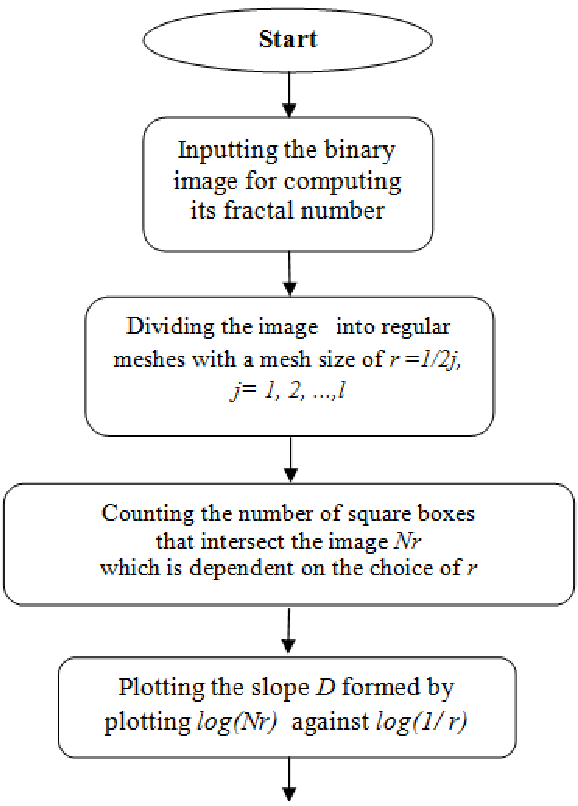
The signature image is treated as two dimensional array and the coordinates are defined as (x, y). Then, the (x, y) coordinates is partitioned into grids which measure s x s. If the minimum and maximum binary image levels in the $(i,j)^{th}$ grid fall into the k^{th} and the l^{th} boxes respectively , the coordinate of n_r in the $(i,j)^{th}$, grid is defined as:

$$n_r(i, j) = l - k + 1 \qquad \dots(1)$$

While, N_r is defined as the summation of the contributions from all the grids that are located in a window of the image.

$$N_r = \sum_{i,j} n_r(i, j) \qquad \dots(2)$$

If $r\, N_r$ is computed for different values of r, then the fractal dimension can be estimated as the slope of the line that best fits points $(\log(1/r), \log N_r)$. This paper computes the fractal number for a signature image and produces one feature that is added to feature vector. The block diagram of computing the fractal dimension [48,49 and 50] is shown in Figure (2.)



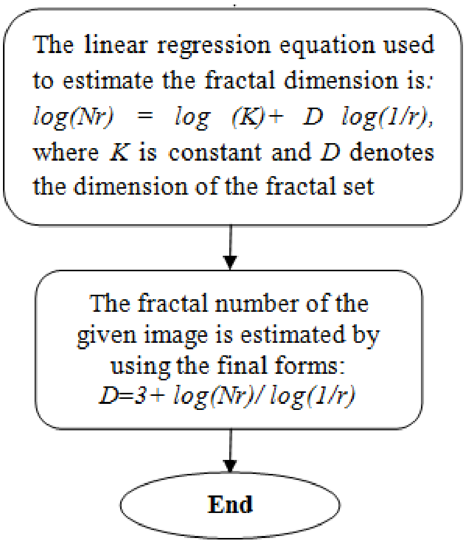


Figure (2) Block Diagram for the Fractal Number Estimation Using Box Counting Algorithm

5.2 The Co-Occurrence Matrix

The co-occurrence matrices of the signature image are used to extract another texture feature group. In a gray-level image, the co-occurrence matrix $P_d[i,j]$ is defined by first specifying a displacement vector $d=(dx,dy)$ and counting all pairs of pixels separated by d and having gray level values i and j. In this work the signature image is binary and therefore the co-occurrence matrix is a 2x2 matrix describing the transition of black and white pixels [51 and 52]. Therefore, the co-occurrence matrix $P_d[i,j]$ is defined as:

$$P_d[i,j] = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \quad \ldots(3)$$

where p_{00} represents the number of times that two white pixels appear, separated by d. p_{01} that represents the number of times that a combination of a white and a black pixel occurs, separated by d. p_{10} is the same as p_{01}. The p_{11} represents the number of times that two black pixels appear, separated by d.

In this work, the co-occurrence matrix is computed for a signature image in four orientations (directions 0˚, 45˚, 90˚ and 135˚) and four distances (1,2,3 and 4) for each direction. This procedure produces 16 matrices then only $P_{(0,0)}$, $P_{(1,1)}$ *and* , $P_{(0,1)}$ values are used as texture features of a signature image. This means that 48 texture features are estimated (3 features are estimated for one direction and one distance).

6. Classification

The final stage of the proposed Arabic handwritten identification and verification system is the classification. The classification algorithm is chosen to be used in an Arabic handwritten identification and verification is highly dependent on the properties and the format of the features that represent the signature image. The main goal of identification process is recognizing true class of an unknown input signature. In other word, a classifier must determine the class of an input sample. In this case, the input of the proposed system is a handwritten Arabic signature and the output is a class number that determines the class of input signature. On the other hand, in the verification, classifier must examine an input signature to determine whether it is genuine or forged. Thorough out this paper two classifiers are used to identify and verify an Arabic Handwritten signature. The first one is nearest distance classifier which is based on Euclidian distance [53] ,while, the second classifier is based on ANN using Backpropagation algorithm. The backpropagation algorithm [54 and 55] is one of the most popular and widely used network-learning algorithms. It has been derived from the generalized Delta Learning rule that aims to minimize error in subsequent iterations during the training phase.

6.1 Nearest Distance Classifier

In the proposed signature identification system, a classifier calculates a distance of the input signature from all sample signatures in the training set. If the minimum distance is less than a predefined threshold value then the class of the input signature is the same as the class of the nearest distance to the signature in the training set. Euclidean Distance is a famous method that calculates the distance points which is used to find the distance between two signatures [29].

Assuming that p = (p_1, p_2,..., p_n) and q = (q_1, q_2,..., q_n) are two signature feature vectors , then the distance from p to q, or from q to p is given by the following equation : [53] .

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + ... + (p_i - q_i)^2 + ... + (p_n - q_n)^2} \quad \text{...(4)}$$

6.2 Neural Network Classifier

In this work, a back-propagation neural network is used to classify signatures. The network consists of three layers; the first layer consists of neurons that are responsible for input feature vectors into the neural network. The number of neurons equals (which are arranged in three different forms that account to 1; 3, 12 or 13 neurons depending on the form one feature vector). The second layer is a hidden layer which allows neural network to perform the error reduction that is necessary to obtain the desired output. The final layer is the output layer that is determined by the size of the desired output set. There is one output node that represents the index of the signature classes. The transfer function used between the input layer and hidden layer is hyperbolic tangent sigmoid transfer function whereas, the output layer neuron is estimated by using the linear transfer function. Figure (3) shows the topology of the used artificial neural network classifier (back propagation) by using thirteen neurons for input, twenty neurons for hidden layer and one neuron for output.

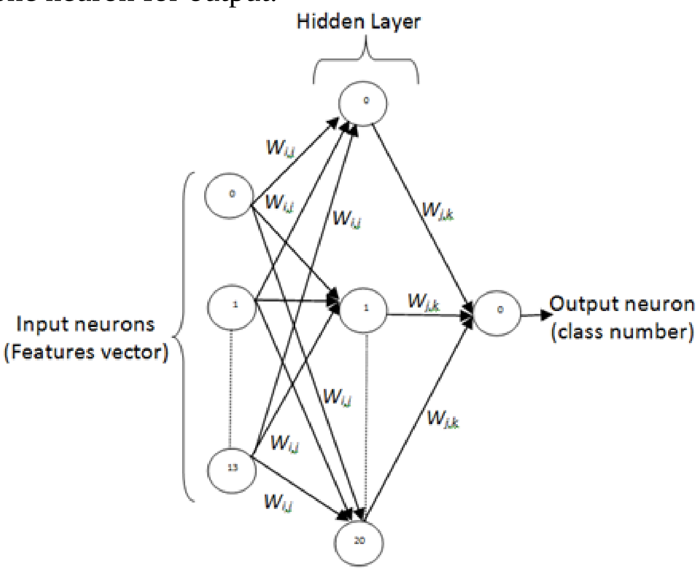


Figure (3) topology of the used artificial neural network classifier (back propagation)

6.1.1 Training Phase

The ANN is trained to classify Arabic handwritten signature features. In the training phase of the ANN, the weight values between the input, the hidden and the output layers are initialized with random values. After repeatedly presenting features of the input samples and desired targets, the output with the desired outcome are compared and it is used to measure the error then adjusting the weight. This process is repeated until the error rate of the output node reaches a minimum value. The training algorithm used is Gradient descent with momentum back propagation. All the training signature images were divided into 10 classes (each class represents one person). The description of the training set has already been explained in section 3.

6.1.2 Testing Phase

In this phase, the features are extracted based on the same approach as in the training phase. In signature identification, the input is an unknown signature and system must identify the owner of that. But, the goal of signature verification is examination of an input signature to determine whether it is genuine or forged. The summary of testing set had been provided in section 3. Figure (4) illustrates the training and testing phases of the proposed Arabic handwritten signature identification and verification system.

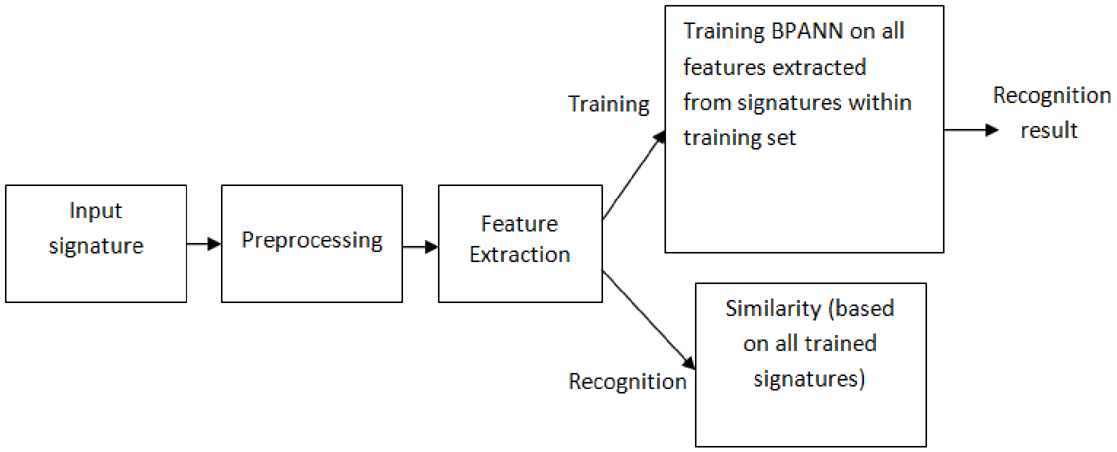


Figure (4) Training and using the proposed Arabic handwritten signature identification and verification

7. Results

The experimental results are presented to show the effectiveness of the proposed offline Arabic handwritten signature identification, which estimates the texture features by using the fractal number and co-occurrence matrix. The proposed system was carried out on a 3.00 GHz Intel (R) Core TM 2Duo processor with 8 GB RAM on Windows Vista platform by using MATLAB R2009a. Figure (5) shows samples of signature images while the results of the pre-processing stage are illustrated in Figure (6).

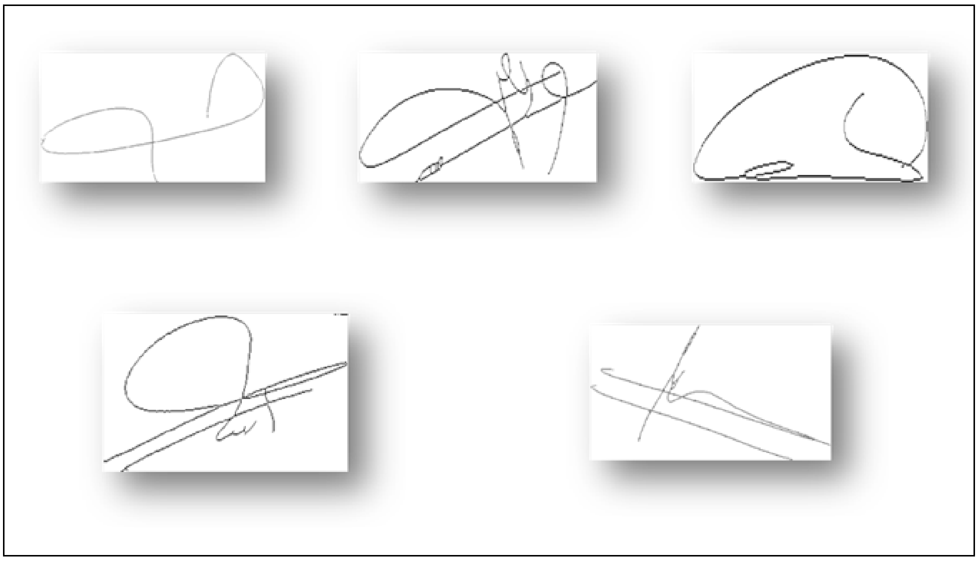
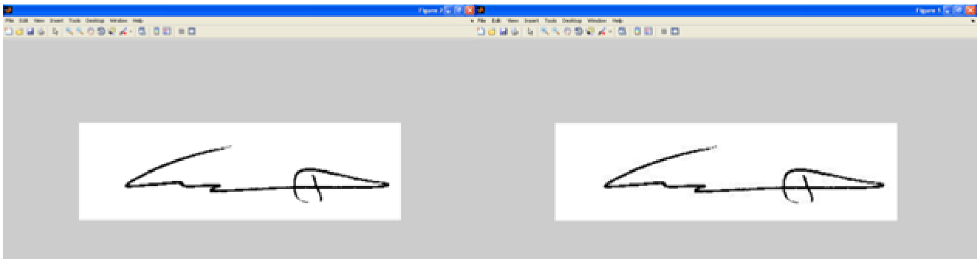
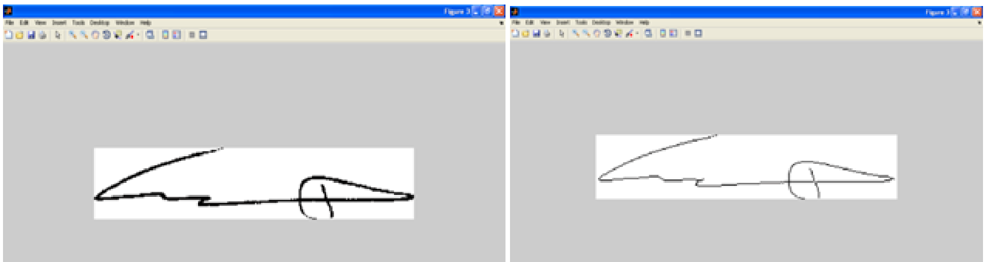


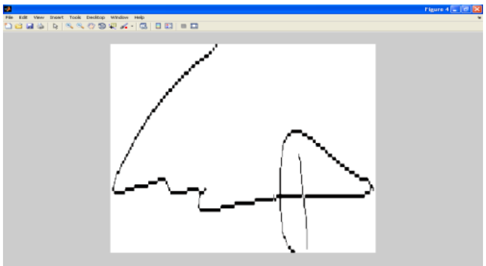
Figure (5) Signature Image Samples



a - Noise removal (mean filter) **b- Signature image (Binary image)**



c- Finding outer rectangle **d- Thinning**



e- Size normalizing and converting to binary image

Figure (6) The Results of a Preprocessing Stage

Two different classifiers were tested and evaluated to find out the more reliable off-line Arabic handwritten identifier and verifier. The first classifier used the nearest distance based on Euclidean distance in identification system while the second one used BPANN in both identification and verification processes. The proposed off-line Arabic handwritten identification and verification system was tested by using the signature database collected by the authors as illustrated in section 3.

The proposed system was tested based on texture features estimated by co-occurrence matrix and combination of a fractal number feature with the texture features estimated by using co-occurrence matrix. The evaluation has been divided into two groups; the first group used genuine signatures while the second group used forged signatures.

7.1 Evaluation Using Genuine Signatures

In the proposed off-line Arabic Handwritten signature identification and verification system, the evaluation of the system identification (recognition) is determined by the (CCR) [2 and 28] which represents the accuracy of a system. While the evaluation of system verification is determined by False Rejection Rate (FRR) and False Acceptation Rate (FAR) [2 and 12]. Pourshahabi *et al* [28] have defined another evaluation term called as Equal Error Rate (EER) which is usually considered as the optimum state of the verification system [28].

The evaluation results of testing the first classifier by using nearest Euclidean distance and the second classifier by using BPANN (based on either fractal number feature or based on 3 features estimated from co-occurrence matrix in 4 orientations (directions 0˚ , 45˚,90˚ and 135˚)) and 4 distances (as explained in section 4.2) are illustrated in tables 2 and 3 respectively.

Table (2) CCR for the first classifier used the nearest neighbor

Or \ Ds	D=1	D=2	D=3	D=4
Orientation =0˚	81.25%	87.5%	83.75%	81.25%
Orientation =45˚	85.00%	87.5%	85%	81.25%
Orientation =90˚	80%	82.5%	85%	71.25%
Orientation =135˚	78.75%	88.75%	85%	90%
Fractal feature	90%			

Table (3) CCR for the second classifier used the BPANN

Or \ Ds	D=1	D=2	D=3	D=4
Orientation =0˚	90%	90%	90%	90%
Orientation =45˚	90%	80%	90%	100%
Orientation =90˚	90%	90%	90%	90%
Orientation =135˚	90%	90%	100%	100%
Fractal feature	100%			

A simple comparison between the evaluation of the results of the first classifier and the second classifier shows that the evaluation of the second one which is based on BPANN is more **accurate** than the first one. This led to make more evaluations to the BPANN classifier. The evaluation results based on the combination of all estimated from co-occurrence matrix (all distances for each orientation) are illustrated in table (4).

Table (4) CCR system 2 all distances

Features	CCR
Features estimated when orientation = 0˚.	80%
Features estimated when orientation = 45˚.	90%
Features estimated when orientation = 90˚.	90%
Features estimated when orientation =135˚.	90%

The evaluated results of identifying the classifier by using BPANN based on the features estimated from co-occurrence matrix in 4 orientations (directions 0˚ , 45˚,90˚ and 135˚) and 4 distances (as explained in section 4.2) combined with the fractal number features are illustrated in tables 5.

Table (5) CCR of the classifier used the BPANN

Or \ Ds	D=1	D=2	D=3	D=4	All distances

Orientation =0˚	80%	100%	100%	100%	90%
Orientation =45˚	80%	100%	100%	100%	80%
Orientation =90˚	90%	90%	90%	90%	90%
Orientation =135˚	100%	90%	90%	90%	90%

The evaluated results of verifying the classifier by using BPANN (based on either fractal number feature or based on the features estimated from co-occurrence matrix in 4 orientations (directions 0˚ , 45˚,90˚ and 135˚) and 4 distances (as explained in section 4.2) are illustrated in tables 6 and 7 respectively.

Table (6) FAR of the classifier used the BPANN

Or \ Ds	D=1	D=2	D=3	D=4	All distances
Orientation =0˚	6%	3%	5%	5%	14%
Orientation =45˚	7%	12%	5%	0	2%
Orientation =90˚	7%	9%	4%	5%	5%
Orientation =135˚	8%	5%	0	0	4%
Fractal feature	0				

Table (7) FRR of the classifier used the BPANN

Or \ Ds	D=1	D=2	D=3	D=4	All distances
Orientation =0˚	4%	7%	5%	5%	6%
Orientation =45˚	3%	8%	5%	0	8%
Orientation =90˚	3%	1%	6%	5%	5%
Orientation =135˚	2%	5%	0	0	6%
Fractal feature	0				

The evaluated results of verifying the classifier by using BPANN (based on fractal number feature combine with the features estimated from co-occurrence matrix in 4 orientations (directions 0˚ , 45˚,90˚ and 135˚) and 4 distances as explained in section 4.2) are illustrated in tables 8 and 9 respectively.

Table (8) FAR of the classifier used the BPANN

Or \ Ds	D=1	D=2	D=3	D=4	All distances
Orientation =0˚	16%	0	0	0	4%
Orientation =45˚	8%	0	0	0	12%
Orientation =90˚	6%	4%	2%	5%	5%
Orientation =135˚	0	6%	4%	4%	3%

Table (9) FRR of the classifier used the BPANN

Or \ Ds	D=1	D=2	D=3	D=4	All distances
Orientation =0˚	4%	0	0	0	6%
Orientation =45˚	12%	0	0	0	8%
Orientation =90˚	4%	6%	8%	5%	5%
Orientation =135˚	0	4%	6%	6%	7%

The ERR of the best results (the shadow fields in the tables 3 and 5) equal 0.

7.2 Evaluation Using Forged Signatures

The evaluation of the proposed off-line Arabic handwritten signature verification system is determined by the (CRR) and the False Accept Rate (FAE) [2].The CRR is found when the system is tested by using forged signatures and correctly gives a negative response, whereas the FAE is found when the system is tested by using forged signatures and wrongly gives a positive response. The verification evaluation of the proposed system based BPANN was done by using signature set which has 30 forged signatures. This evaluation has been estimated for verifying the proposed system that has a high CCR only which are mentioned as shadow fields in tables 3 and 5. The evaluated results are shown in Figure (7), by using 10 variety feature groups. The first three groups (group1, group2 and group3) have been estimated by using co-occurrence matrix features with specific orientation and distance while the last seven groups (group4,…,group10) combine the fractal number feature with the features estimated by using co-occurrence matrix with specific orientation and distance.

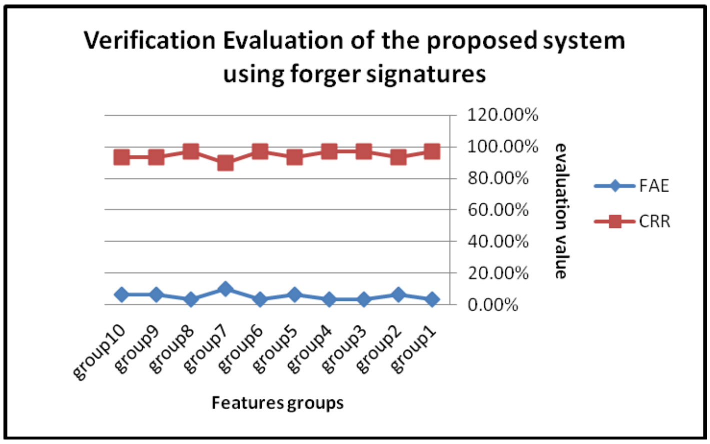


Figure (7) Verification Evaluation of the Proposed System using Forger Signatures

8. Discussion

It was experimentally observed that the combination of a fractal number feature with the texture features estimated by using co-occurrence matrix had increased the accuracy of the proposed system. Three groups of texture features that were estimated from co-occurrence matrix have 100 % CCR (shadow fields in table 3), while ten groups of features that combined a fractal number feature with the texture features estimated by using co-occurrence matrix have 100% CCR (shadow fields in table 5).

After conducting several experiments for the proposed system based on different feature combinations, it was experimentally observed that the combination of a fractal number feature with the texture features that were estimated by using co-occurrence matrix had increased the accuracy of the proposed system. Three groups of texture features that were estimated from co-occurrence matrix have 100 % CCR (shadow fields in table 3), while seven groups of features that combined a fractal number feature with the texture features that were estimated by using co-occurrence matrix have 100% CCR (shadow fields in table 5). The CCR of these evaluations equal 100%. On the other hand, the testing results of the proposed system regarding to forged signatures showed that the best evaluation performance has been obtained based on features groups 1,3,4,6 and 8 only. The CRR of these evaluations was 96.7%. Although, the authors were unable find any papers which have used the same test sets especially for Arabic handwritten signatures, it may be useful to validate the experimental results with other published results that have employed different identification and verification systems. Hence, the performance of the proposed system is compared with the performance of other identification and verification systems. The Ueda's proposed system [21] which deals with an off-line Japanese signature verification by using a pattern matching method reported FAR and FRR equal 9.1. Whereas, the FAR and FRR of the system described by Vargas et al [15] equal 14.66 and 10.01 respectively. The error rates of the suggested system by Qiao et al [14] equal 7.3 and 7.4 for two used data sets. The Iranian (Persian) signature verification system proposed by Sigari et al [29] had FAR and FRR values equal 15 and 15 respectively while they equal 14.5 and 12.5 for Iranian (Persian) signature verification system proposed by Pourshabi et al [28]. It is possible to get full evaluation performance (CCR equal 100% and FAR and FRR equal 0%) when testing the system by using genuine signatures, but it is impossible to get full evaluation performance (100% CRR) when testing the system by using forged signatures. However, the best performance evaluations of the proposed intelligent off-line Arabic handwritten signature identification and verification system equals 100 % CCR, and equals 0% for FAR and FRR. On the other hand, the performance evaluation of the proposed system against forged signatures reported CRR value equals 96.7%. These values indicate that the proposed system outperforms or close to all signature identification and verification system mentioned above.

9. Conclusion and Future Work

This paper had proposed an intelligent off-line Arabic handwritten signature identification and verification system. The proposed system extract the features based on texture analysis of the signature image. Fractal number feature and co-occurrence matrix are computed to estimate texture features. In order to evaluate the performance of the proposed system, two signature tests were used that comprised genuine and forged signatures. The experimental results showed that the proposed system had yielded good results in identification and verification processes because FAR = 0%, FRR= 0% ,CCR =100% and CRR = 96.3%. Only ten cases of the experimental results had demonstrated that the proposed system had achieved high performance as shown in Figure 5. A necessary future direction is to validate the proposed algorithms by using a standard handwritten Arabic signatures database. Such a method will enable us to compare our performance evaluation results with those presented by other authors for the same test signatures. Another improvement, suggested is the adaptation of our approach to Fuzzy logic technique in other features domains.

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REFERENCES

[1] Bansal A., Gupta B., Khandelwal G. and Chakraverty S, (2009),"Offline Signature Verification Using Critical Region Matching", International Journal of Signal Processing, Image Processing and Pattern, Vol. 2, No.1, March.

[2] Baltzakis H. and Papamarkos N., (2001), "A new signature verification technique based on a two-stage neural network classifier" , Engineering Applications of Artificial Intelligence, vol. 14, pp. 95–103.

[3] Hastie T., Kishon E., Clark M., and Fan J., (1991),"A model for signature verification", in Proceedings of the IEEE Conference on Systems, Man, and Cybernetics, 1, pp. 191–196. Technical report (Feb. 1992): http://stat.stanford.edu/~trevor/Papers/signature.

[4] Lee L. L., Berger T., Aviczer E., (1996),"Reliable on-line human signature verification systems", IEEE Trans. on Pattern Anal. and Machine Intell, Vol. 18, No. 6, pp. 643–647.

[5] Kashi R. S., Hu J., Nelson W.L. and Turin W., (1998),"A Hidden Markov Model approach to online handwritten signature verification", IJDAR, Vol. 1,No. 2, pp. 102–109.

[6] Jain A. K., Griess F. D., and Connell S. D., (2002), "On-line signature verification", Pattern Recognition, Vol. 35, No. 12, pp. 2963–2972.

[7] Guru D. S. and Prakash H. N.,(2009), "Online Signature Verification and Recognition: An Approach Based on Symbolic Representation", IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 31, No. 6, pp. 1059-1073.

[8] Guru D. S., Prakash H. N. and Manjunath S., (2009), "On-line Signature Verification: An Approach Based on Cluster Representations of Global Features", Seventh International Conference on Advances in Pattern Recognition. Kolkata, India.

[9] Even S., Goldreich O. and Micali S., (1996), "On-Line/Off Line Digital Signatures", Journal of Cryptol-ogy, Springer-Verlag, Vol. 9 pp. 35-67.

[10] Coetzer J., Herbst B.M. and Preez J.A., (2004), "Offline Signature Verification Using the Discrete Radon Transform and a Hidden Markov Model". EURASIP Journal on Applied Signal Processing,Vol. 4, pp. 559–571.

[11] Hou W., Ye X. and Wang K.,(2004), "A Survey of Off-line Signature Verification", Proceedings of the 2004 International Conference on intelligent Mechatronics and Automation. Chengdu, China, August.

[12] Ozgunduz E., Senturk T. and Karsligil E., (2005), "Off-line signature verification and recognition by support vector machine", in thirteen European Signal Processing Conference, Antalya, Turkey, 4-8 September.

[13] Shanker A. P. and Rajagopalan A. N., (2007), "Off-line signature verification using DTW", Pattern Recognition Letters, Vol. 28, No.12, pp. 1407-1414.

[14] Qiao Y., Liu J., and Tang X., (2007), "Offline signature verification using online handwriting registration" in CVPR, IEEE Conf. on, Minneapolis, Minnesota, USA , pp. 1–8, 18-23 June.

[15] Vargas J., Ferrer M., Travieso C., and Alonso J., (2008), "Off-line signature verification based on high pressure polar distribution", In ICFHR08, Montereal, August.

[16] Hastie T., Kishon E., Clark M., and Fan J., (1991), "A model for signature verification", Proc. IEEE Int. Conf. on Systems, Man Cybern., October, Vol. 1, pp. 191-196.

[17] Nalwa V., (1997), "Automatic on-line signature verification", Proceedings of the IEEE, Vol .85,No. 2, pp. 215–239.

[18] Han, C. ,Chang,P. C. ,Hsu C., and Jeng B. S.,(1999), "An on-line signature verification system using multi-template matching approaches", Security Technology, Proceedings. IEEE 33rd Annual International Carnahan Conference on ISBN: 07803524,pp. 477-480

[19] Deng P. S., Liao H. M., Ho C. W. and Tyan H. R.,(1999), "Wavelet-based off-line handwritten signature verification", Computer vision and image understanding , Vol.76, Issue 3, pp. 173-190, December.

[20] Fang B., Wang Y. Y. , Leung C.H., Tang Y.Y., Kwok P.C.K., Tse K.W. and Wong Y.K (1999), "A Smoothness Index Based Approach for Off-line Signature Verification", Document Analysis and Recognition, ICDAR '99, Proceedings of the Fifth International Conference on ISBN: 07695031, pp. 785-787.

[21] Ueda K.,(2003), "Investigation of Off-Line Japanese Signature Verification Using a Pattern Matching", Proc. Of the 7th ICDAR, Edinburgh, Scotland, UK.

[22] Bertolini D., Oliveira L. S., Justino E., and Sabourin R.,(2010), "Reducing forgeries in writer independent off-line signature verification through ensemble of classifiers", Pattern Recognition, Vol. 43, pp. 387–396.

[23] Ismail A. I., Ramadan M. A., El-Danaf T. S., Samak A. H., (2011),"An efficient offline signature identification method based on Fourier Descriptor and chain codes", International Journal of Biomedical Engineering and Technology (IJBET), Volume 5 , No. 1.

[24] Shirdhonkar M.S., Kokare M., (2011), "Off-line Handwritten Signature Identification Using Rotated Complex Wavelets Filter", International Journal of Computer Science Issues, Vol.8, No.1, pp. 478-482.

[25] Zhou S., WU J., Tang B., Sun Y., (2011), "Handwritten Signature Recognition based on the SDAPCI-MS Imaging Technique", IJACT, International Journal of Advancements in Computing Technology, Vol. 3, No. 7, pp. 148-153.

[26] Kovari B.,Albert I., and Charaf H.,(2008), "A general approach to off-line signature verification", WSEAS Transactions on Computers, Vol. 7, No. 10, pp. 1648-1657.

[27] Guler I. and Meghdadi M., (2008), "A different approach to off-line handwritten signature verification using the optimal dynamic time warping algorithm", Digital Signal Processing Vol. 18 No. 6, pp. 940-950.

[28] Pourshahabi M. R., Sigari M. H., Pourreza H. R.,(2009), "Offline Handwritten Signature Identification and Verification Using Contourlet Transform", International Conference of Soft Computing and Pattern Recognition, Malacca, Malaysia, pp. 670-673, December.

[29] Sigari M. H, Pourshahabi M. R., Pourreza H. R, (2011),"Offline Handwritten Signature Identification and Verification using Multi-Resolution Gabor Wavelet" , International Journal of Biometrics and Bioinformatics (IJBB), Vol. 5, No. 4 .

[30] Kasturi R. Govindaraje V., (2002), "Document image analysis: A primer", Sadhana Vol. 27, No. 1, pp. 3–22.

[31] Amin, A. (1998), "Off-line Arabic character recognition-the state of the art", Pattern Recognition, Vol. 31, No.5, pp. 517-530.

[32] Cavalcanti G. D. D. C. Doria R. C., Filho E C. B. C., (2002), "Feature Selection for Off-line Recognition of Different Size Signatures", Proceedings of the 12th IEEE Workshop on Neural Networks for Signal Processing, pp. 355- 364.

[33] Otsu, N., (1979), "A Threshold Selection Method from Gray-Level Histograms", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 9, No. 1, 1979, pp. 62-66.

[34] Nguyen, V., Blumenstein M. and Leedham G., (2009), "Global features for the off-line signature verification problem", In: Proceedings of 10th ICDAR, pp. 1300–1304

[35] Ammar M., Fukumura T., (1986),"A new effective approach for offline verification of signatures by using pressure features", in Proc. 8th Int. Conf. Pattern Recognition ICPR, Paris, France, pp. 566-569.

[36] Nagel R. N. and Rosenfeld A., (1977),"Computer detection of freehand forgeries", IEEE Transactions on Computers, Vol. C-26,No.9 , pp. 895-905.

[37] Yu L., Zhang D., Wang K., and Yang W., (2005),"Coarse iris classification using box-counting to estimate fractal dimensions", Pattern Recognit., Vol. 38,No. 11, pp. 1791–1798.

[38] Alligood K.T., Sauer T. D., and Yorke J. A., (1996), "Chaos: An Introduction to Dynamical Systems", Springer.

[39] Mandelbrot B. B, (1983), "The fractal geometry of nature", W. H. Freeman and Co., New-York.

[40] Mandelbrot B. B., Ness , J. V., (1968), "Fractional Brownian motions, fractional noises and applications", SIAM Rev. Vol. 10,No. 4, pp. 422–437.

[41] Pentland A. P., (1984),"Fractal Based Description of Natural Scenes", IEEE transaction on Pattern Analysis and Machine Intelligence, Vol. PAMI-6 , No. 6, pp.661-674.

[42] Vinoy K.J., Abraham J. K., and Varadan V. K., (2003), "Fractal Dimension and Frequency Response of Fractal Shaped Antennas", IEEE Antennas and Propagation Society International Sympo-sium, Vol. 4, pp. 222-225.

[43] Keller J. M., Chen S. , and Crownover R. M., (1989), "Texture description and segmentation through fractal geometry", Comput. Vision Graph Image Process. 45, pp. 150–166.

[44] Chaudhuri B.B. and Sarkar N., (1995), "Texture Segmentation using fractal dimension", IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 17, No. 1, pp. 72–77.

[45] Crownover R. M., (1995), "Introduction to fractals and chaos", Jones & Bartlett Publication.

[46] Li J.,Du Q. and Sun C., (2009), "An improved box-counting method for image fractal dimension estimation", Pattern Recognition 42 , pp. 2460- 2469

[47] Peitgen H.O., Jurgens H. and Saupe D., (1992),"Chaos and Fractals: New Frontiers of Science", Springer, Berlin, pp. 202–213

[48] Hastings H. M. and Sugihara G., (1993), "Fractals, A user's guide for the national Sciences", Oxford University Press, Oxford, England.

[49] Feng Z and Zhou H. (2001),"Computing method of fractal dimension of image and its application", Journal of Jiangsu University of Science and Technology, No. 6, pp. 92-95.

[50] Jayalalitha G. and Uthayakumar R. ,(2007), "Estimating the Skin Cancer using Fractal", International Conference on Computational Intelligence and Multimedia Applications (ICCIMA), Proceedings of a meeting held 13-15 December, Sivakasi, Tamil Nadu, India. Vol. 2 pp. 306-311.

[51] Zhang Y. J.,(1996), "A Survey On Evaluation Methods For Image Segmentation", Pattern Recognition 29, pp. 1335 - 1346.

[52] Jain R., Kasturi R. and Schunck B., (1995), "Machine Vision", McGraw-Hill, New York.

[53] Deza M. M. and Deza E., (2009) "Encyclopedia of Distances", Springer, Berlin–Heidelberg.

[54] Schalkoff R. (1999), "Artificial Neural Networks", McGraw-Hill.

[55] Taysi N, (2010), "Application of Neural Network models on analysis of prismatic structures", Sci. Res. Essays, Vol. 5, No. 9, pp. 978-989.