

Handwritten Arabic Characters Recognition Based on Wavelet Entropy and Neural Network

Abstract

In this work, a wavelet packet and Shannon entropy (SEWP) technique for handwritten Arabic characters recognition system is proposed. Entropy has been applied in many applications, however, the combination of Shannon entropy with wavelet transform (WT) is proposed in this study for handwritten Arabic characters recognition. The investigation procedure is based on feature extraction and classification. In the stage of feature extraction, the distinguished features of handwritten Arabic characters were extracted using the SEWP technique. In the phase of classification, probabilistic neural network (PNN) was applied because of its rapid response and ease in implementation. In practical investigation, performances of different wavelet transforms in conjunction with Shannon entropy were compared with one another. In addition, the capability analysis on the proposed system was examined by comparing with other systems proposed in latest literatures. Referring to our experimental results, the PNN classifier could achieve a better recognition rate with SEWP as a feature extraction method.

Keywords: Arabic characters; Shannon entropy; Wavelet; Probabilistic neural network.

1. Introduction

For the past four decades there has been increasing interest amongst researchers in problems related to machine simulation of the human reading process. Intensive research has been carried out in this area as is testified by an enormous number of technical papers and reports in the literature devoted to character recognition. This subject has attracted immense research interest not only because of the very challenging nature of the system but also because it provides the means for automatic processing of large volumes of data in postal code reading, office automation and other business and scientific applications. Optical character recognition (OCR) deals with the recognition of optically processed characters rather than magnetically processed ones. In a typical OCR structure, input characters are read and digitized by an optical scanner. Each character is then positioned and segmented and the resulting matrix is fed into a preprocessor stage for smoothing, noise elimination, and size normalization. Off-line recognition can be considered the most general case: no special device is required for writing and signal interpretation is independent of signal generation, as in human recognition (Srihari et. al, 2005; Abdulla, 1988; Mahmoud, 1991; Hussain & Cowel, 2000; Hussain & Zalik, 2000).

Many investigators have been working on cursive script recognition for more than three decades (Shridhar, 1997). Nevertheless, the field remains one of the most challenging problems in pattern recognition and all the existing systems are still limited to restricted applications. The process by which people recognize handwritten characters, words and documents has been the subject of intense interest and study by researchers from diverse fields (Liu, 1997). A good interpretation of the mechanism of human recognition of handwritten documents will have a significant impact on the development of machines capable of recognition and understanding of handwritten documents. However, the human recognition process is quite complex and it combines information extracted at different levels: characters, whole words, key words, and contextual processing (Liu, 1997; Bulacu, 2010). The efficiency of human recognition of handwriting can be attributed to the effective integration of multiple cues and exploitation of redundancies contained in most documents. However, if the goal of this study is to develop machines that are capable of automatic transcription of handwritten documents, then one must recognize the immense difficulty of adopting the human recognition process. A document on

practical approaches to handwriting recognition will include characters, words, phrases, sentences, and whole paragraphs.

Handwriting recognition, in its most general structure, is the transcription of a handwritten document into machine written text. The process starts at the document level and goes through the following steps: extraction of lines from the document, extraction of words from the line, holistic or character based recognition of words, including punctuation marks such as periods, commas, colons, semicolons, apostrophes, etc. and finally, a post processing step for integration of contextual and a priori knowledge to develop and enhance the recognition process. There are two main approaches to handwriting recognition: (a) techniques based on holistic approaches whereby an entire word or a character string is recognized as a unit and (b) techniques based on extraction and recognition of characters (also referred to as segmentation-recognition approach) contained in a word or a string (Liu, 1997; Shridhar, 1997).

Many papers have been concerned with the recognition of Latin, Chinese and Japanese characters. However, although Arabic characters are used in several widespread languages, little research has been conducted toward the automatic recognition of Arabic characters because of the strong cursive nature of its writing rules. Several good literature review papers were published on Arabic character recognition (Jambi, 1991; Ahmed, 1994; Amin, 1997; Bulacu, 2010). A recent comprehensive one is given by (Ahmed, 2000). Classical optical off-line recognition of handwriting is composed of a pre-processing stage, character segmentation, feature extraction and a classification stage (Casey, 1996; Srihari et. al, 2005). Preprocessing consists of several operations like thresholding, noise removal, page orientation, skewing of lines removal, line segmentation, word segmentation, and pictures and figures removal. There is little difference in these processes between Arabic language and Latin-alphabet-based languages (Abdulla, 1988; Mahmoud, 1991; Hussain & Cowel, 2000; Hussain & Zalik, 2000).

Work on isolated printed Arabic characters and numerals took a lot of forms. Overall vertical level of the character compared with the baseline was studied (Talba, 1987). The chain code describing the sequence of character strokes using the 8-direction strokes was followed by the mainstream of researchers (Alshebeli, 1997). Nevertheless, hexagonal sampled procedure was also found (Khellah, 1994). Different methods for matching the unknown character with the standard characters were followed.

Segmentation of characters is an important step in character recognition for cursive writing whether hand written or printed. There are three strategies for segmentation: the classical approach in which segments identification is based on "character-like" properties, the recognition-based segmentation strategy, in which the system searches the image for components that match classes in its alphabets, and the third strategy is the holistic method, in which the system seeks to recognize words as a whole, thus avoiding the need to segment into characters (Casey, 1996). Different algorithms were followed to apply one of the above methods or the other, like hierarchical syntactic procedure (Haj-Hassan, 1990), quadratic discriminating functions (Udpa, 1992), the method of moment invariant algorithm (El-Khaly, 1990), accumulative invariant moment was used as an identifier in character recognition (El-Dabi, 1990), and even segmentation of printed Arabic characters was tried without the thinning process (El-Sheikh, 1988). Use of clustering technique was chosen for classification (El-Desouky, 1992) or tree representation for the description of various characters (Al-Waily, 1989; Saleh, 1994; Saleh, 1996). Use of tree representation and fuzzy constrained graph models which tolerate large varieties in writing styles were also reported (Abuharba, 1994).

Recognition of different fonts of Arabic printed text was tried using pre-processing and structural feature extraction (Kavianifar, 1998). (Pham, 2007) proposed SIFT method for Arabic font recognition. Parallel Arabic OCR systems were also proposed (Alherbish, 1997). Hidden Markov models which proved to be very successful in the area of automatic speech recognition was tried in the area of open-vocabulary Arabic OCR system (Bazzi, 1999). Work on limited hand-written Arabic text database was tried. A system based on four types of basic features, namely, the end points, corners, the strokes and the branch points gave reasonable results (Jambi, 1991). Recognition of typewritten Arabic characters gave good results using external features such as character area ratio, n-th quadrant ratio, vertical line ratio, horizontal line ratio, number of upper edges, and other similar features (Al-Ohali, 1995). Online character recognition uses the feature extraction process results in a sequential manner which is called the chain code. Treatment of secondary characters (mainly the points above and below the characters) is definitely an integral part of the recognition process (El-Gwad, 1990).

Neural Network was used in some literatures as a powerful classifier (Said, 1998; Al-Kadi, 1995; Altuwaijri, 1995; Al- Sharaidah, 2000). (Said et al., 2000) proposed a text-independent approach and derived writer-specific texture features using multichannel Gabor filtering and (SGLD). The method requires uniform blocks of text that are generated by word de-skewing, setting a predefined distance between text lines/words and text padding. Two sets of 20 writers, 25 samples per writer were used in the evaluation. Nearest-centroid classification using weighted Euclidean distance and Gabor features achieved 96% writer identification rate. Eglin et al. applied the SGLD to extract several features to characterize the writing style of ancient Latin and Arabic manuscripts of the middle-ages. They proposed that The SGLD is identical on different text areas of the same document and is robust to noise and does not require any image segmentation or layout analysis. They reduced the features dimensionality by using Haralick descriptors. From these mixtures of features, they defined a ‘‘style similarity’’ measure and formed a large database of images samples of writings with a paleographic description to develop a reliable image retrieval system for medieval writings styles. (Srihari et al., 2005) proposed a large number of features divided into two categories-- Macro-features operating at document / paragraph / word level and Micro-features operating at word/ character level. Text dependent statistical evaluations are performed on a dataset containing 1000 writers who copied 3 times a fixed text of 156 words. The results have shown that micro-features are better than macro-features in identification tests with a performance exceeding 80%. (Bulacu, 2010) proposed an automation process of writer identification using scanned images of handwriting and thereby provided a computer analysis of handwriting individuality. The relationship of handwriting styles between any two samples is computed by using proper distance measures between their corresponding feature vectors. The features and writer classification operate in the general framework of statistical pattern recognition. Joining texture-level and allograph-level features yields very high writer identification and verification performance, with usable rates for datasets containing 103 writers.

In this study wavelet entropy and probabilistic neural network combination is proposed for Arabic handwritten character recognition. The features are extracted by means of entropy calculated for WP coefficients, which are added to probabilistic neural network for classification.

Neural Network was used in some literatures as powerful classifier (Said, 1998; Al-Kadi, 1995; Altuwaijri, 1995; Al- Sharaidah, 2000). Said (Said et al., 2000) propose a text-independent approach and derive writer-specific texture features using multichannel Gabor filtering and (SGLD). The method requires uniform blocks of text that are generated by word de-skewing, setting a predefined distance between text lines/words and text padding. Two sets of 20 writers, 25 samples per writer are used in the evaluation. Nearest-centroid classification using weighted Euclidean distance and Gabor features achieved 96% writer identification rate. Eglin et al. applied the SGLD to extract several features to characterize the writing style of ancient Latin and Arabic manuscripts of the middle-ages. They propose that The SGLD is identical on different text areas of the same document and is robust to noise and does not require any image segmentation or layout analysis. They reduced the features dimensionality by using Haralick descriptors. From these mixtures of features, they defined a ‘‘style similarity’’ measure and formed a large database of images samples of writings with a paleographic description to develop a reliable image retrieval system for medieval writings styles. (Srihari et al., 2005) proposed a large number of features divided into two categories. Macro-features operating at document / paragraph / word level and Micro-features operating at word/ character level. Text dependent statistical evaluations are performed on a dataset containing 1000 writers who copied 3 times a fixed text of 156 words. The results have shown that micro-features are better than macro-features in identification tests with a performance exceeding 80%. (Bulacu, 2010) proposed an automation process of writer identification using scanned images of handwriting and thereby to provide a computer analysis of handwriting individuality. The relationship in handwriting style between any two samples is computed by using proper distance measures between their corresponding feature vectors. The features and writer classification operate in the general framework of statistical pattern recognition. Joining texture-level and allograph-level features yields very high writer identification and verification performance, with usable rates for datasets containing 103 writers.

In this study wavelet entropy and probabilistic neural network combination is proposed for Arabic handwritten character recognition. The features are extracted by means of entropy calculated for WP coefficients, which are added to probabilistic neural network for classification.

1. Main characteristics of Arabic Writing

Emphasis is a distinguishing feature of Semitic languages such as Arabic language. The term ‘emphasis’ refers to consonants generated with a secondary constriction in the subsequent vocal tract and a primary constriction typically in the dental/alveolar region (Zitouni and Sarikaya, 2009). Arabic text is written from right to left and is always cursive. The figure of an Arabic character alternates consistent with its location in the word. An Arabic character has up to four different shapes; the shape of a character depends on the type of character to its right and its position within the word. Table 1 shows the Arabic character set in the four different shapes. The Arabic character set is composed of 28 basic characters. Fifteen of them have dots and 13 are without dots. Dots above and below the characters play a major role in distinction some characters that differ only by the number or location of dots. Take the example the letters: ب ت ث ي ن . In their middle form, all these five letters are written the same way. They differ only by the number or the locations of the dots. There are four characters which may take another character “Hamzah ”. Those are “Alif ”, “Waw ”, “Yaa ” and “Kaf ”. There are also some other secondary forms used above and below the characters to indicate vowels but we shall eliminate them now from our discussions. Arabic characters do not normally have fixed width or fixed size, even in printed form.

Table 1: The basic forms of Arabic alphabets

Stand alone	Initial connected with ا	Middle connected with ا and س	Final connected with س	Other form
ا	ا	سا	سا	ا Or اى
ب	با	سبا	سب	
ت	تا	ستا	ست	
ث	ثا	سثا	سث	
ج	جا	سجا	سج	
ح	حا	سحا	سح	
خ	خا	سخا	سخ	
د	دا	سدا	سد	
ر	را	سرا	سر	
ز	زا	سزا	سز	
س	سا	سسا	سس	
ش	شا	سشا	سش	
ص	صا	سصا	سص	
ض	ضا	سضا	سض	
ط	طا	سطا	سط	
ظ	ظا	سظا	سظ	
ع	عا	سعا	سع	
غ	غا	سغا	سغ	
ف	فا	سفا	سف	
ق	قا	سقا	سق	
ك	كا	سكا	سك	
ل	لا	سلا	سل	
م	ما	سما	سم	
ن	نا	سنا	سن	
ه	ها	سها	سه	
و	وا	سوا	سو	
ي	يا	سيا	سي	

3. Wavelet Transform using in Feature Extraction

3.1 Wavelet Packet Transform Feature Extraction Method

To decompose the data into wavelet packet transform (WPT), we start from the common form of the equivalent low pass of discrete time signal

$$u(t) = \sum_m X_m p(t - mT), \quad (1)$$

where X_m is a sequence of discrete speech signal values, which are obtained by data acquisition stage; the signal $p(t)$ is a pulse, whose figure represents an important signal design problem when there is a bandwidth restriction on the channel; and T is the sampling time. Considering that $\phi(t - mT)$ is a scaling function of a wavelet packet, i.e., $\phi \in W_{2^N}^0$, then a finite set of orthogonal subspaces can be constructed as (Daubechies, 1988; Lei et al., 2005)

$$W_{2^N}^0 = \bigoplus_{(l,n) \in \rho N} W_{2^l}^0, \quad (2)$$

where $W_{2^N}^0 \subset L^2(R)$, $\rho N = \{(l, n)\}$ is a dyadic interval that forms a disjoint covering of $[0, 2^N]$, $W_{2^l}^n$ denotes the closed linear span of process $\sqrt{2^l} \psi_n(2^l t - m)$, $m \in Z$, and $\{\psi_n(t)\}_{n \in N}$ is called the wavelet packet, considered by the scaling function ϕ . Therefore, the speech signal model in (1) is customized as

$$u(t) = \sum_m \sum_{(l,n) \in \rho N} X_m \sqrt{2^l} \psi_n(2^l t - m). \quad (3)$$

The speech signal model in (3) is the basic form of wavelet packet transform, which is used in signal decomposition. The signal is carried by orthogonal functions, which shape a wavelet packet composition in $W_{2^N}^0$ space. We may use the discrete wavelet packet transforms (DWPT) procedure as

$$\phi_{l+1}^{2n}(i) = \sum_{k \in Z} h(k - 2i) \phi_l^n(k) \quad (4)$$

$$\phi_{l+1}^{2n+1}(i) = \sum_{k \in Z} g(k - 2i) \phi_l^n(k), \quad (5)$$

where $\phi_{l+1}^n \in W_{2^{l+1}}^n$ and $\phi_l^n \in W_{2^l}^n$. These two processes can be carried out recursively during the binary tree structure, with $O(N \log N)$ computational complexity. Using (3), (4), and (5), the coefficients of the linear combination may be shown to be the reversed versions of the decomposition sequences $h[k]$ and $g[k]$ (with zero padding), respectively. Continuously, we can reconstruct $\phi_0^1(i)$ via the terminal functions of an arbitrary tree-structured decomposition

$$\phi_0^1(i) = \sum_{l \in L, n \in C_l} \sum_{k \in Z} f_{ln}(i - 2^l k) \phi_l^n(k), \quad (6)$$

where L is the set of levels having the terminals of a given tree; C_l is the set of indices of the terminals at the l th level; and $f_{ln}[i]$ is the equivalent sequence generated from the combination of $h[k]$, $g[k]$ and decimation operation, which leads from the root to the (l, n) th terminal, i.e.,

$$\phi_l^n(i) = \sum_{k \in Z} f_{ln}(k - 2^l i) \phi_0^1(k). \quad (7)$$

For a certain tree structure, the function ϕ_l^n in (7) is called the constituent terminal function of ϕ_0^1 . In this work, the tree consists of two stages, and therefore has three high pass nodes and three low pass nodes.

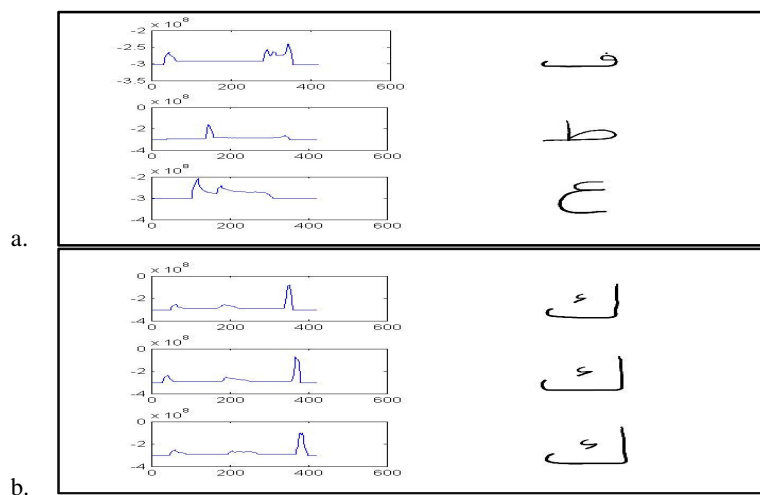
The wavelet packet is used to extract additional features to guarantee higher recognition rate. In this study, WPT is applied at the stage of feature extraction, but these data are not proper for classifier due to a great amount of data length (for example, a speech signal of 35582 number of samples will reach 71166 after WPT decomposition at level two). Thus, we have to seek for a better representation for the speech features. Avci, Hanbay and Varol (2006) proposed a method to calculate the entropy value of the wavelet norm in digital modulation recognition. In the biomedical field, Behroozmand and Almasganj (2007) presented a combination of genetic algorithm and wavelet packet transform used in the pathological evaluation, and the energy features are determined from a group of wavelet packet coefficients. Kotnik, Kacic and Horvat (2003) proposed a robust speech recognition scheme in a noisy environment by using wavelet-based energy as a threshold for denoising estimation. Sasi, 1997 proposed a Handwritten Character Recognition using Fuzzy, Neuro-fuzzy and Wavelet Transform method. Wavelet-based features for texture classification and segmentation was presented by (Charalampidis and T. Kasparis, 2002; Unser, 1995). Very few works are reported on script identification particularly using wavelet transform based features (Hiremath & Shivashankar, 2008). In this paper, we use Shannon entropy obtained from WP tree nodes for feature vector constructing to be used for handwritten character recognition.

3.2 Wavelet Packet Entropy

For a given orthogonal wavelet function, a library of wavelet packet bases is generated. Each of these bases offers a particular way of coding signals, preserving global energy and reconstructing exact features. The wavelet packet is used to extract additional features to guarantee higher recognition rate. In this study, WPT is applied at the stage of feature extraction, but these data are not proper for classifier due to a great amount of data length. Thus, we have to seek for a better representation for the speech features. Previous studies showed that the use of entropy of WP as features in recognition tasks is efficient (Avci, Hanbay and Varol, 2006). As seen above, the entropy of the specific sub-band signal may be employed as features for recognition tasks. In this paper, the Shannon entropy obtained from the WP will be employed for handwritten Arabic character recognition. The Shannon wavelet packet features extraction method can be summarized as follows:

- Decomposing the each column of the grey form image by wavelet packet transform at depth 4 (level 4), with Daubechies type (db1).
- Calculating the wavelet Shannon entropy for each column of all nodes of wavelet packet at depth 4 for wavelet packet using the equation (look Fig.1):

$$El(s) = -\sum_i s_i^2 \log(s_i^2) \quad (6)$$



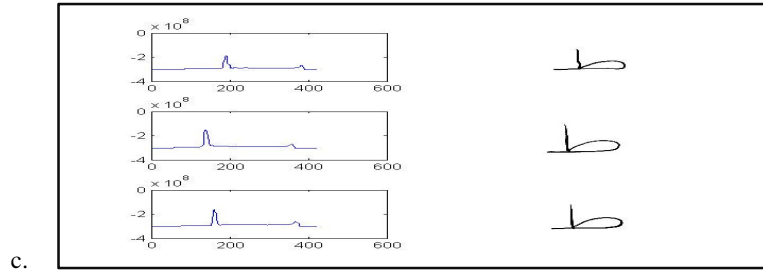


Figure 1: The entropy features for a. Different character features, b. Similar character (ك sounds K) features. c. Similar character (ط sounds T) features.

Where s is the signal and s_i are the WPT coefficients. Entropy is a common concept in many fields, mainly in signal processing (Turkoglu et al., 2003). Classical entropy-based criterion describes information-related properties for a precise representation of a given signal. Entropy is commonly used in image processing; it possesses information about the concentration of the image. On the other hand, a method for measuring the entropy appears as a supreme tool for quantifying the ordering of non-stationary signals. Fig.1a shows Shannon entropy calculated for WP at depth 4 for three different handwritten Arabic characters. Fig.1b and c show the features for similar handwritten Arabic characters. We can notice that the feature vector extracted by Shannon entropy is appropriate for handwritten Arabic characters recognition. This conclusion has been obtained by interpretation the following criterion: the feature vector extracted should possess the following properties (Farooq & Datta, 2003): 1) Vary widely from class to class. 2) Stable over a long period of time. 3) Should not have correlation with other features.

4. Proposed Probabilistic Neural Networks Algorithm

Although there exist numerous enhanced versions of the original PNN, which are either more economical, or exhibit an appreciably better performance, for simplicity of exposition (Ganchev et al., 2007), we adopt the original PNN for classification task (Fig.2). The proposed algorithm denoted by PNN depends on the following construction:

$$Net = PNN(X, P, SP),$$

where X is matrix of 24 input Arabic Handwritten character feature vectors (pattern) of 440 entropy values taken from WP sub signals for net training:

P is the target class vector

$$P = [1, 2, 3, \dots, 24], \quad (7)$$

The SP parameter is a spread of radial basis functions. We use a SP value of one because that is a typical distance between the input vectors. If SP approaches zero, the network will act as a nearest neighbor classifier. As SP becomes larger, the designed network will take into account several nearby design vectors. We create a two layer network. The first layer has radial basis transfer function (RB) neurons (as shown in Fig.3):

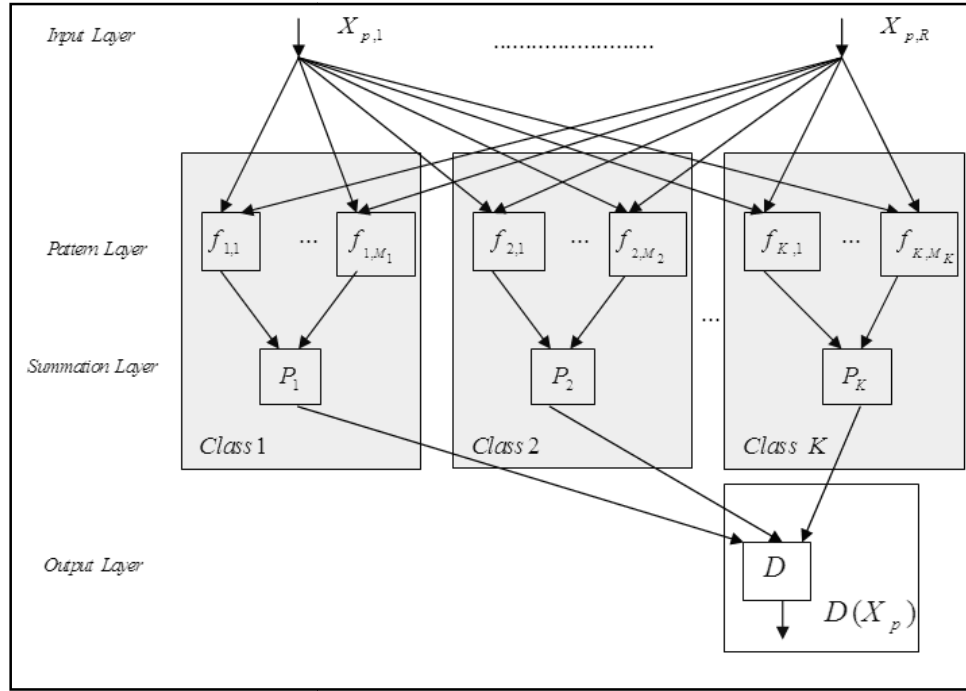


Fig. 2 Structure of the original probabilistic neural network

$$RB(n) = \exp(-n^2), \quad (8)$$

and calculates its weighted inputs with Euclidean distance (ED);

$$ED = \sum \sqrt{((x - y)^2)}, \quad (9)$$

and its net input with net product functions, which calculate a layer's net input by combining its weighted inputs and biases. The second layer has competitive transfer function (see Fig.4) neurons, and calculates its weighted input with dot product weight function. It is Weight function applies weights to an input to get weighted inputs. The proposed net calculates its net input functions (called NETSUM) that calculate a layer's net input by combining its weighted inputs and biases. Only the first layer has biases. PNN sets the first layer weights to X' , and the first layer biases are all set to $0.8326/SP$ resulting in radial basis functions that cross 0.5 at weighted inputs of $\pm SP$. The second layer weights are set to P (Wasserman et al., 1993).

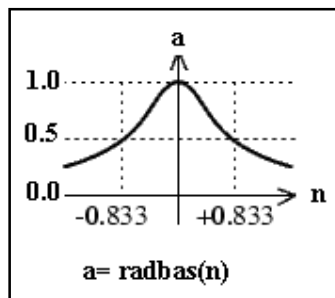


Fig. 3 Radial basis transfer function

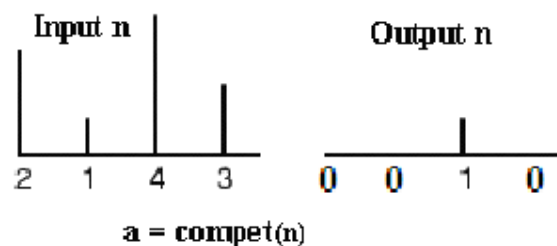


Fig. 4 Competitive transfer function

Now, we test the network on new feature vectors (testing) with our network to be classified. This process is called simulation.

5. Results and Discussion

In the proposed work, testing Arabic handwritten characters as separated images and separated words were recorded via a scanner device. The Arabic handwritten characters and words were recorded by four Arab males. The recording process was provided in normal conditions. Our investigation of Arabic handwritten classifier system performance is performed via several experiments depending on different classification types.

Even though the methods proposed for Arabic handwritten characters by means of several approaches, they are still inadequate in terms of accuracy. In the approach we present in this paper, we propose research study of the Arabic handwritten characters classification in its two forms; separated letters and separated words that leads to the relatively comprehensive list of the characters that are used in any Arabic text. In other words, the presented study may be considered as an investigation work aiming to build a system that identifies the handwritten Arabic text. We solve the problem by using conventional character recognition method (feature extraction and then classification). This helps greatly to find out sharp reference difference between these Arabic handwritten characters to stand as a main step for automatic Arabic handwritten text recognition. This approach is based on a combination between entropy and WT to accomplish feature extraction obtained for each character from binary image form. The obtained feature extraction vector is added to PNN to be classified as seen in the flow chart presented in figure 5.

Table 2: Recognition rate using PNN for separated characters

Character	No. of testing	Recognized	Not recognized	Recognition Rate (RR)
أ	12	12	0	100%
س	12	8	4	66.66%
ج	12	9	3	75%
ب	12	12	0	100%
و	12	10	2	83%

ض	12	12	0	100%
ر	12	9	3	75%
ك	12	6	6	50%
م	12	9	3	75%
ع	12	11	1	91.66%
ف	12	12	0	100%
ط	12	12	0	100%

Table 3: The recognition rate results of separated character for comparison

Number of Character	RR of SEDWT [%]	RR of SEWP [%]	RR of LEDWT [%]	RR of LEWP [%]
1108	83.1	81.96	64.11	72.64

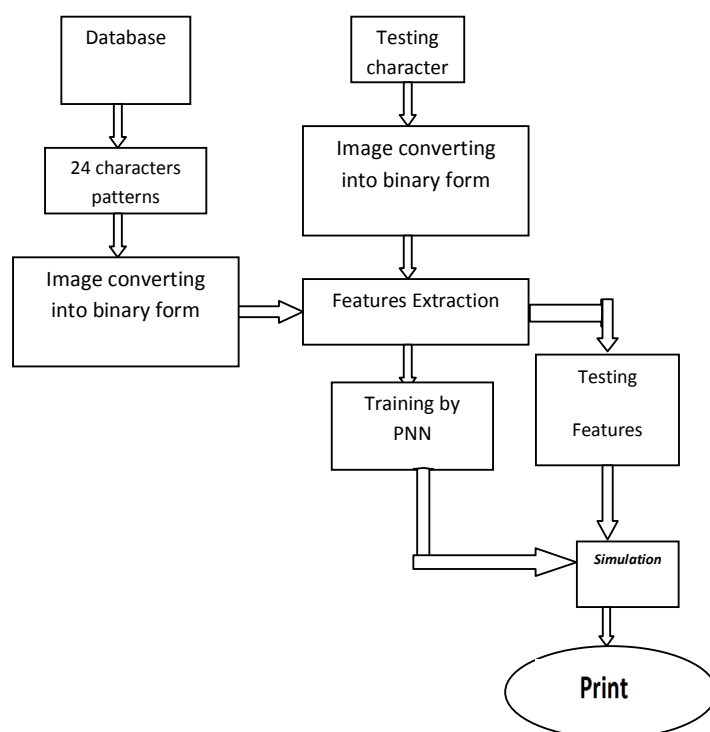


Fig. 5: Flow chart for proposed system

Table 2 tabulates the results of proposed method for separated Arabic handwritten characters. The recognition rate (RR) reached 84.69%. In the next experiment, several feature extraction methods with PNN classifier were analyzed to expose the usefulness of proposed system in Arabic handwritten character recognition. The following experiment investigates the proposed method in term of recognition rate. This can be concluded after interpretation of the results in Tab. 2, where the results of DWT at level five with Shannon entropy denoted before by (SEDWT), WP at level five with Shannon entropy denoted by (SEWP), DWT at level five with log energy entropy (LEDWT) and WP at level five with log energy entropy (LEWP) are tabulated. It was found that the recognition rates of WP methods

are superior (83.1, 72.64) compared with DWT methods (81.96&64.11). In other hand, methods of Shannon entropy are superior (83.1, &81.96) compared with the log energy methods (72.64&64.11).

Table 4: Results of proposed method for segmentation method

Character	No. of testing	Recognized	Not recognized	Recognition rate (RR)
ع	100	90	10	90%
ب	100	72	28	72%
ا	100	66	34	66%
ر	100	75	25	75%
Mean RR				75.75%

Table 5: Results of proposed method for separated word method

Character	No. of testing	Recognized	Not recognized	Recognition rate
ع	100	90	10	90%
ب	100	72	28	72%
ا	100	91	9	91%
ر	100	82	18	82%
Mean RR				83.75

A comparative study of the proposed feature extraction method with other methods was performed. The proposed feature extraction method with segmentation the word into characters (table 4) and the proposed feature extraction method with separated word recognition method (table 5) are investigated. For all these methods PNN classifier is utilized. The results were conducted for four words as tabulated in table 4 and table 5. The best recognition rate selection obtained was 83.75 for separated word methods.

6. Conclusion

In the presented research paper, handwritten Arabic character recognition system based Shannon entropy and wavelet packet is studied. The benefit of such method is its capability to reduce the huge data into a less values, and the computing speed is also accomplished. In the beginning of feature extraction, WT is applied for handwritten Arabic character image (column by column). Then Shannon entropy are extracted from wavelet coefficients and used as a representative feature vector. For classification PNN is applied. The recognition performance of this method was demonstrated on an Arabic character database of total 27 individual writer. 1108 different images were used in the experiments. Experimental results showed both DWT and WP linked with Shannon entropy are suitable for feature extraction method. However, WP produced better performance in term of recognition rate. The results of WP were improved by increasing the number of levels unlike DWT, which has no clear improvement, occurs by feature vector length extension.

7. References

- Abdulla W.H., A.O.M. Saleh and A.H.Morad, (1988). A Preprocessing Algorithm for Hand-Written Character Recognition. Pattern Recognition Letters. 7 , 13-18.
- Abuharba I.S.I., S.A. Mahmoud and R.J. Green, (1994). Recognition of Handwritten Cursive Arabic Characters. HLL Transaction of Pattern Analysis and Machine Intelligence.16:6. 664-672.

- Ahmed P. and Y. Al-Ohali, (2000). Arabic Character Recognition: Progress and Challenges. Journal of King Saud University. 12, Comp. & Inf. Sci. 85-116.
- Alherbish J. and R.A. Ammar, 1997. Arabic Character Recognition in a Multi-processing Environment. Al-Kadi Z. and S. Serhan, (1994). The Use of Learning Networks in Recognition of Arabic Numeral. Dirasat Jordan University. 22B:4. 933-949.
- Al-Ohali Y.A.M, (1995). Development and Evaluation Environment for Typewritten Arabic Character
- Al-Waily R.S.A., (1989). A Study on Preprocessing and Syntactic Recognition of Hand-Written Arabic
- Amin A., 1997. Handbook of Character Recognition and Document Image Analysis," Chapter 15 orld Scientific Pub. Co. 397-420.
- Avci, D. (2009), An expert system for speaker identification using adaptive wavelet sure entropy, *Expert Systems with Applications*, 36, 6295–6300.
- Avci, E. (2007), A new optimum feature extraction and classification method for speaker recognition: GWPNN, *Expert Systems with Applications* 32, 485–498.
- Bazzi I., R. Schwartz and J. Makhoul, (1999). An Ominfont Open-Vocabulary OCR System for English and Arabic. IEEE Transaction on Pattern Analysis and Machine Intelligence. 21: 6. 495-504.
- Behroozmand R., Almasganj F., "Optimal selection of wavelet packet-based features using genetic algorithm in pathological assessment of patients' speech signal with unilateral vocal fold paralysis", *Computers in Biology and Medicine* 37 (2007) 474 –485.
- Bulacu M (2010). Statistical pattern recognition for automatic writer identification and verification, <<http://dissertations.ub.rug.nl/faculties/ppsw/2007/m.l.bulacu/>>, last visited date 12/4/2010.
- Casey R.G. and E. Lecolinet, (1996). A Survey of Methods and Strategies in Character Segmentation. IEEE Transaction on Pattern Analysis And Machine Intelligence. 18:7.
- Characters. M.Sc. Thesis, Basrah University, Iraq.
- Charalampidis D. and Kasparis T.(2002), "Wavelet-based rotational invariant roughness features for texture classification and segmentation," *IEEE Trans. Image Process.*, vol. 11, no. 8, pp. 825–837, Aug. 2002.
- Cognition, 19, 174–188.
- Avci, E., Hanbay, D., & Varol, A. (2006). An expert discrete wavelet adaptive network based fuzzy inference system for digital modulation recognition. *Expert System with Applications*, 33, 582–589.
- Conference on Information Visualization. 51-56.
- Daubechies I.(1988), Orthonormal bases of compactly supported wavelets, *Comm. Pure Appl. Math.*,41, 909–996.
- El-Khaly F. and M.A. Sid-Ahmed, (1990). Machine Recognition of Optically Captured Machine Printed
- El-Sheikh T.S. and R.M. Guindi, (1988). Computer Recognition of Arabic Cursive Script. Pattern Recognition. 21:4. 293-302.
- Farooq, O. & Datta, S. (2003), Phoneme recognition using wavelet based features, *Information Sciences* 150, 5–15
- Ganchev T., Tasoulis D., Vrahatis M., Fakotakis D. (2007), Generalized locally recurrent probabilistic neural networks with application to text-independent speaker verification, *Neurocomputing* 70, 1424–1438.
- Hiremath P S and S Shivashankar: Wavelet Based Co-occurrence Histogram Features for Texture Classification with an Application to Script Identification in a Document Image, *Pattern Recognition Letters* 29, 2008, pp 1182-1189.
- Hussain F. and J. Cowell, 2000. Character Recognition of Arabic and Latin Scripts. Proceedings of the Hussain F., B. Zalik and S. Kolmanic, 2000. Intelligent Digitisation of Arabic Characters. Proceedings of the Conference on Information Visualization. 337-342.
- Hussain F. and J. Cowell, 2000. Character Recognition.
- Jambi K. M., 1991. Arabic Character Recognition: Many Approaches and One Decade. The Arabian Journal for Science and Engineering. 16: 4B. 499-508.

- Kotnik B., Kacic Z., Horvat B.: Noise robust speech parameterization based on joint wavelet packet decomposition and autoregressive modeling. [INTERSPEECH 2003](#)
- Lei Z., Jiandong L., Jing L., and Guanghui Z (2005). A Nove Wavelet Packet Division Multiplexing Based on Maximum Likelihood Algorithm and Optimum Pilot Symbol Assisted Modulation for Rayleigh Fading Channels, *CIRCUITS SYSTEMS SIGNAL PROCESSING*, VOL. 24, NO. 3, PP. 287–302.
- Liu K., Suen C. Y., Cheriet M., Said J. N., Nadal C, TangY.Y., “Automatic Extraction of Baselines and Data from Check Images”, *Int. Journal of Pattern Recognition and Artificial Intelligence* 11 (1997), 675–697.
- M. Okada, M. Shridhar, “Extraction of User Entered Components from a Personal Bankcheck Using Morphological Subtraction”, *Int. Journal of Pattern Recognition and Artificial Intelligence* 11 (1997), 699–715.
- M. Unser, “Texture classification and segmentation using wavelet frames,” *IEEE Trans. Image Process.*, vol. 4, no. 11, pp. 1549–1560, Nov. 1995.
- Mahmoud S. A., I. AbuHaiba and R.J. Green, 1991, Skeltonization of Arabic Characters Using Clustering Based Skeltonization Algorithm. *Pattern Recognition*. 24: 5. 453-464.
- Pham V., Miyaki T, Yamasaki T., Aizawa K. (2007), Geometrically invariant object-based watermarking using SIFT feature, *Proceedings of IEEE International Conference on Image Processing*, VOL. 5, 2007, pp. 473-476.
- Proceedings of the 2nd IEEE Symposium on Computers and Communications.
- Recognition. M.Sc. Thesis, King Saud University. Riyadh. Al-Sharaidah, M. A., 2000. Recognition of Handwritten Arabic Characters via Neural Networks M.Sc. Thesis, Jordan University.
- Said H, Tan TN, Baker KD. Personal identification based on handwriting. *J Pattern Recog Soc* 2000;33:149–60.
- Sasi S (1997), *Handwritten Character Recognition using Fuzzy, Neuro-fuzzy and Wavelet Transform*
- Shridhar M. (1997), Gilles F. Houle, Fumitaka Kimura: Handwritten Word Recognition Using Lexicon Free and Lexicon Directed Word. *ICDAR -97*: 861-865
- Srihari S (2005), Beal M, Bandi K, Shah V, Krishnamurthy P. A statistical model for writer verification. In: 8th International conference on document analysis and recognition, vol. II, 2005. p. 1105–9.
- Turkoglu, I., Arslan, A., & Ilkay, E. (2003). An Intelligent system for diagnosis of the heart valve diseases with wavelet packet natural Networks. *Computer in Biology and Medicine*, 33, 319–331.
- Wasserman, E. A., Elek, S. M., Chatlosh, D. L., & Baker, A. G. (1993). Rating causal relations: Role of probability in judgments of response-outcome contingency. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19, 174–188.
- Zitouni I. and Sarikaya R. (2009), Arabic diacritic restoration approach based on maximum entropy models *Computer Speech and Language*, 23, 257–276.