A Haar Wavelet-Based Zoning For Offline Arabic Handwritten Character Recognition

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Abstract

Due to the nature of handwriting with high degree of variability and imprecision, obtaining features that represent characters is a difficult task. In this research, a features extraction method for handwritten Arabic Character recognition is investigated. Its major goal is to maximize the recognition rate with the least amount of elements. This method compute the 1 level Haar Wavelet Transform for Binary character image, then divide the Wavelet space into 8 Zones, for each Zone, three features have been extracted: mean, standard division, and skewness. The Recognition have been done using Mahalanobis distance. The proposed method provides good recognition accuracy of 73% for handwritten characters even with fewer train samples.

Keyword: Haar Wavelet, Zoning, Mahalanobis Distance, Skewness.

الخلاصة

نظراً للطبيعة الغير دقيقة والمتغيرة للنصوص المكتوبة بخط اليد فأن مهمة الحصول على الخواص التي تمثل الحروف ستكون جداً صعبة، لذا في هذا البحث، سيتم بحث طريقة لاستخلاص الصفات المعتمدة لتمييز الحروف العربية المكتوبة باليد، الهدف الرئيسي لهذه الطريقة هو تعظيم نســبة التمييز مع أقل عدد من الصفات. هذه الطريقة أولاً تحسب تحويل هار الموجي ذو المستوى الواحد لصورة الحرف الثنائية ، من ثم يتم تقسيم منطقة التحويل الموجي الى 8 مناطق، لكل منطقة يتم استخلاص 3 صفات: المعدل، الانحراف المعياري والميلان. أما مرحلة التمييز فتم حسابها باستخدام مسافة مهنلوبس. الطريقة المقترحة اعطت نسبة تمييز 73% مع عدد قليل من صور الحروف المدربة .

الكلمات المفتاحية: هار الموجي، المناطق المقسمة، مسافة مهنلوبس، الميلان.

1. Introduction

Handwriting character recognition has been one of the most fascinating and challenging research areas in field of image processing and pattern recognition in the recent years. It contributes immensely to the advancement of an automation process and can improve the interface between man and machine in numerous applications. In generally, Character recognition is a process of converting an image of a handwritten or printed text in to a computer editable format [Lorigo2006]. Handwritten character recognition is of two types:

- Online handwritten character recognition.
- Offline handwritten character recognition.

In online handwritten character recognition, the character is recognized as soon as it has been written. On the other hand, in offline handwritten, the character has been written first, and the recognition has been performed later on [Ali,2004]. In this paper the offline character recognition has been performed for **Arabic characters**. Arabic language is universal and it is a formal language for 25 countries, of population over than 300 million. Additionally, many Arabic characters are used in different languages such as Ardu, Farsi, Jawi, Kardi [AL-Shantnawi,2008]. Arabic Handwriting character recognition still lacks a good recognition rate since it depends much on the writer and because we do not always write the same word in exactly the same way. Because of the huge variability of the Arabic handwriting style and the noise affecting the data, it is almost impossible to directly recognize handwritten character from its bitmap representation. Thus, the need of features extraction method that allows extracting a feature set from the character image is obvious for classification. In fact, features extraction is a preprocessing step that aims at reducing the dimension of the data while extracting relevant

information. In this step, each character is represented as a feature vector, which becomes its identity. These features, as mentioned by [Goraine,1992], must be reliable, independent, small in number, and reduce redundancy in the character image.
Features extraction methods are based on two types of features: statistical and structural. Major statistical features, used for character representation, are derived from distribution of points: zoning, projections and profiles, crossing and distances. characters can be represented by structural features with high tolerance to distortions and style variations. This type of representation may also encode some knowledge about character structure or may provide some knowledge as to what sort of components make up that character. This paper describes a features extraction method based on structural features and Haar Wavelet Transform. The outline of the paper is as follows. In section II, we explore a number of features extraction methods in use in the field of Arabic handwriting recognition. In section III, we describe the used lexicon. In section IV, we propose a features extraction method that captures characteristics such as loops, legs, stems and diacritics in the script. In section V, we give an overview of the obtained results. We, finally draw, in section VI, a conclusion with some outlooks.

2. Related Work

Many researchers have proposed several techniques for handwritten as well as printed character recognition. Vikas J Dongre *et al.* [Vikas,2010] has given a review of various techniques used for feature extraction and classification of Devnagari character recognition, The various feature extraction techniques like Fourier transforms, wavelets, zoning, projections etc has been discussed in [Vikas,2010]. Abdul Rahiman M et al. [Abdul,2009] has also proposed a Malayalam OCR system. The proposed system has used Daubechies wavelet (db4) for feature extraction and neural networks for recognition. The system has been given an accuracy of 92%. Li Z.C and et al. [Li,1995] proposed method for feature extraction called zoning which based on partition the character into several blocks, to evaluate the recognition rates of the distinct blocks of characters. Gheith A. Abandah, and Khaled S. Younis [Gheith,2008] used principal component analysis technique to select best subset of features out of a large number of extracted features. And they used parametric and non-parametric classifiers and found out that a subset of 25 features is needed to get 84% recognition accuracy using a linear discriminant classifier, and using more features does not substantially improve this accuracy. In [Wunsch,1995] a discrete, one-dimensional orthogonal wavelet is applied to the character contour and a descriptor is constructed with the approximation bands of the transform; here the aim is to prevent variations of writing style from affecting the classification. Chen G. Y. and *et al*. [Chen,2003] introduce a descriptor that applies orthonormal wavelets on the normalized contour of each digit, up to third detail level, so as to obtain a smoothed pattern representation.

3. Arabic Character Characteristics

The Arabic alphabet contains basically 28 letters are written from write to left. Each letter can take from two to five different shapes, thus, roughly the alphabet set can expand to 84 different shapes according to the position of the letter (beginning, middle, end or isolated) (see table(1)) as well as according to the style of writing (Nasekh, Roqa'a, Farisi and few others) [Khorsheed,2002]. This is one reason makes Arabic recognition complex. The second reason is the similarities among the different letters and the differences among the same latter. For example, letters Baa (باء), Taa(تاء), and Thaa(ثاء) (number 2,3 and 4 respectively in Arabic Alphabet) are three different letters, but they have similar body shape, they only differ in number and position of dots (one, two or three dots below or above the body of the character). Also Jeem(جيم), Hhaa(حاء) and Khaa(خاء) (number 5, 6, & 7 respectively in Arabic Alphabet) differ only in one dot. On the other hand the differences among the same letter, for example, letter Haa(هاء) (number 26 in the Arabic Alphabet) has three completely different shapes through its positions. Officially, there is a set of rules to write Arabic letters, but few follow. These rules may help character recognition to extract features or segment text, such as so called base-line rule. This rule states that there are three lines. Each letter or group of letters has their lines where they should be lie [Plamondon,2000].

4. The Proposed Recognition System

In this section, the proposed recognition system is described. This system is consists of Data collection, preprocessing, feature extraction, and classification or recognition stages. The detailed diagram of the proposed recognition system is shown in Fig. 4

4.1 Data Collection

First of all, the data of Arabic characters is collected in the written form on blank papers by people of different age groups. These characters are written by different blue/black ball point pen. The collected samples of handwritten characters are scanned by scanner and converted into BMP format on 300 dpi. Then all the characters are separated and resized into 64 by 64 pixel images. The example of the samples of handwritten characters is given below**:**

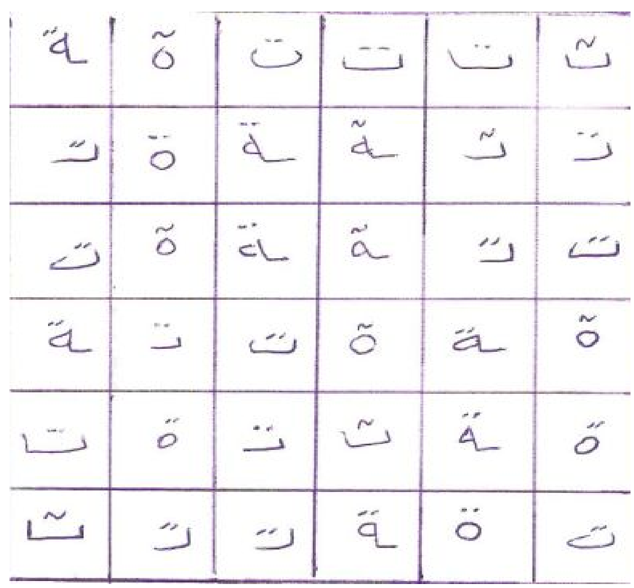


Figure (1) The Samples of Arabic Handwritten Characters

4.2 Pre-Processing

The pre-processing is a series of operations performed on the scanned input image, in order to reduce the noise coefficients and to increase the readability of the input image by the processing system.

The pre-processing stage is the most important stage of the recognition system because it directly affects the reliability and efficiency in the feature extraction and classification stages [Prewitt ,1970]. The pre-processing stage consists of the following operations:

4.2.1 Reduce The Noise

It is inevitable that all images taken from a camera or from scanner will contain some amount of noise [Rice ,1945]. To prevent that noise is mistaken for the next stages, the noise must be reduced. Therefore the image is first smoothed by applying a Gaussian filter, where The formula for a d-dimensional Gaussian probability distribution is:

$$p(x_1, x_2) = \frac{1}{2\pi\sigma^2} \exp(-\frac{x_1^2 + x_2^2}{2\sigma^2}) \qquad (1)$$

where x is a d-element column vector of variables along each dimension, σ is the standard deviation [Rosenfeld 1971].

4.2.2 Detect The Edges

A large change in image brightness over a short spatial distance indicates the presence of an edge [Canny,1986]. The edges can be founding by determining gradients of the image. Gradients at each pixel in the smoothed image are computing by applying what is known as the Sobel-operator. First step is to approximate the gradient in the x- and y-direction respectively by applying the kernels shown in fig. (2). The gradient magnitudes (also known as the edge strengths) can then be determined as an Euclidean distance measure by applying the law of Pythagoras as shown in Equation (2). The gradient magnitudes often indicate the edges quite clearly. However, the edges are typically broad and thus do not indicate exactly where the edges are. To make it possible to determine this, the direction of the edges must be determined and stored as shown in Equation (3) [Mitra,2002] .

$$\text{Edge Magnitude} = \sqrt{s_1^2 - s_2^2} \qquad (2)$$

$$\text{Edge Direction} = \tan^{-1}\left[\frac{s_1}{s_2}\right] \qquad (3)$$

The edge direction is perpendicular to the edge itself because the direction specified is the direction of the gradient, along which the gray levels are changing [Mitra2002].

-1	-2	-1
0	0	0
1	2	1

G_x

-1	0	1
-2	0	2
-1	0	1

G_y

Figure (2) Sobal masks in horizontal and vertical directions

4.2.3 Thinning The Edges

The purpose of this step is to convert the “blurred” edges in the image of the gradient magnitudes to “sharp” edges. Basically this is done by preserving all local maxima in the gradient image, and deleting everything else. This can be doing by using the following steps for each pixel in the gradient image [Canny1986]:

1. Round the gradient direction to nearest 45◦, corresponding to the use of an 8-connected neighborhood.
2. Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. i.e. if the gradient direction is north (theta =90◦), compare with the pixels to the north and south.
3. If the edge strength of the current pixel is largest; preserve the value of the edge strength. If not, suppress (i.e. remove) the value.

4.2.4 Binarization

It a process of convert a gray scale image to bi-level image taking into consideration a threshold pixel value for comparison. The threshold pixel value can be computed based on the following equation:

$$T = \frac{1}{w \times h} \sum_{i=1}^{w} x_i \sum_{j=1}^{h} y_j \quad \text{...(4)}$$

Where w and h are the dimension of the image [Goraine1992].

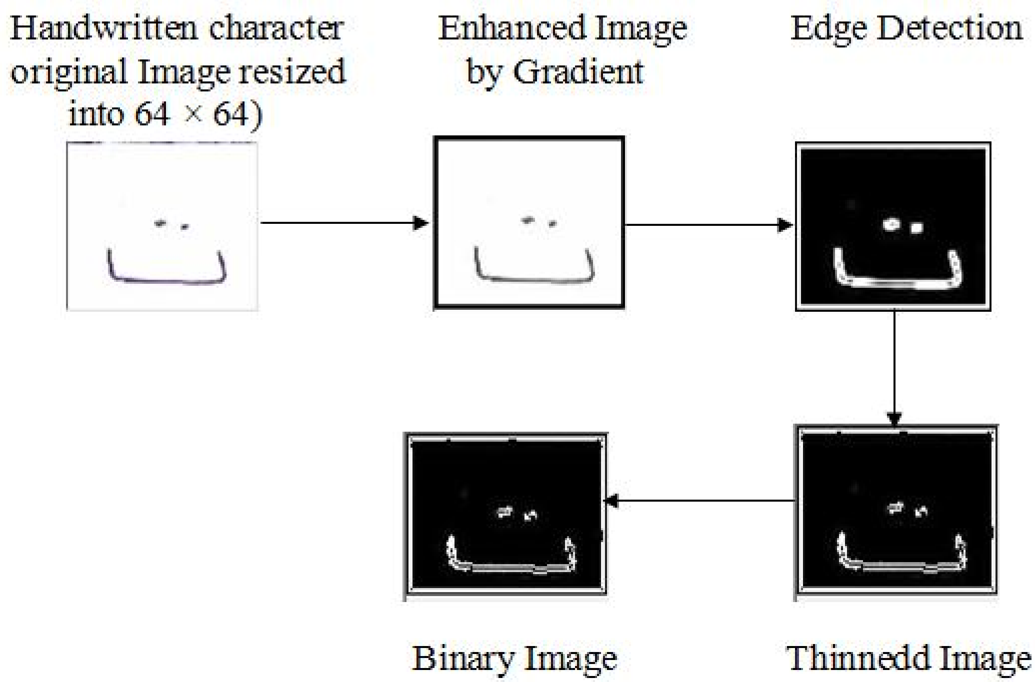


Figure (3) The Results of Preprocessing operations

4.3 Feature Extraction

in this stage, the features of the characters that are crucial for classifying them at recognition stage are extracted. This is an important stage as its effective functioning improves the recognition rate and reduces the misclassification. The Algorithm and the methods that have been used in proposed approach will be briefly described:

4.3.1 Haar Wavelet Transform: The Haar Transform (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation [Mallat1999]. A precise formula for the values of first average subsignal, $a^1=(a_1, a_2, \ldots, a_{N/2})$, at one level for a signal of length N i.e. $f=(f_1, f_2, \ldots\ldots, f_N)$ is

$$a_n = \frac{f_{2n-1} + f_{2n}}{\sqrt{2}}, n = 1,2,3,\ldots, N/2 \quad \text{..................(5)}$$

and the first detail subsignal, $d^1=(d_1, d_2, \ldots, d_{N/2})$ at the same level is given as:

$$d_n = \frac{f_{2n-1} - f_{2n}}{\sqrt{2}}, n = 1,2,3,\dots,N/2 \dots\dots\dots\dots\dots\dots(6)$$

In order to give an idea of its implementation in image analysis, the procedure of its application may be explained with the help of a simple example as shown below. Apply 2D HT to the following finite 2D signal. Example 1:

$$I = \begin{pmatrix} 1 & 2 & 3 & 4 \\ 4 & 3 & 7 & 8 \\ 6 & 2 & 1 & 8 \\ 2 & 5 & 4 & 7 \end{pmatrix}$$

using 1D HT along first row, the approximation coefficients are:

$$\frac{1}{\sqrt{2}}(1+2) \;\; and \;\; \frac{1}{\sqrt{2}}(3+4)$$

and the detail coefficient are:

$$\frac{1}{\sqrt{2}}(1-2) \;\; and \;\; \frac{1}{\sqrt{2}}(3-4)$$

The same transform is applied to the other rows of *I.* By arranging the approximation parts of each row transform in the first two columns and the corresponding detail parts in the last two columns we get the following
results:

$$\begin{pmatrix} 1 & 2 & 3 & 4 \\ 4 & 3 & 7 & 8 \\ 6 & 2 & 1 & 8 \\ 2 & 5 & 4 & 7 \end{pmatrix} \xrightarrow{1D\ HT\ on\ row} \frac{1}{\sqrt{2}} \begin{pmatrix} 2 & 7 & :-1 & -1 \\ 7 & 15 & :1 & -1 \\ 8 & 9 & :4 & -7 \\ 7 & 11 & :-3 & -3 \end{pmatrix}$$

in which approximation and detail parts are separated by dots in each row. By applying the following step of 1D HT to the columns of the resultant matrix, we find that the resultant matrix at first level is:

$$\frac{1}{\sqrt{2}} \begin{pmatrix} 2 & 7 & :-1 & -1 \\ 7 & 15 & :1 & -1 \\ 8 & 9 & :4 & -7 \\ 7 & 11 & :-3 & -3 \end{pmatrix} \xrightarrow{1D\ HT\ on\ columns} \frac{1}{\sqrt{2}} \begin{pmatrix} 10 & 22 & :0 & -2 \\ 15 & 20 & :1 & -10 \\ \dots & \dots & \dots & \dots \\ -4 & -8 & :-2 & 0 \\ 1 & -2 & :7 & -4 \end{pmatrix}$$

Thus we have

$$A = \begin{pmatrix} 10 & 22 \\ 15 & 20 \end{pmatrix} \quad H = \begin{pmatrix} 0 & -2 \\ 1 & -10 \end{pmatrix} \quad V = \begin{pmatrix} -4 & -8 \\ 1 & -2 \end{pmatrix} \quad D = \begin{pmatrix} -2 & 0 \\ 7 & -4 \end{pmatrix}$$

Each piece shown in example 1 has a dimension (number of rows/2)×(number of columns/2) and is called *A*, *H*, *V* and *D* respectively. *A* (approximation area) includes information about the global properties of analyzed image, Removal of spectral coefficients from this area leads to the biggest distortion in original image. *H* (horizontal area) includes information about the vertical lines hidden in image, Removal of spectral coefficients from this area excludes horizontal details from original image. *V* (vertical area) contains information about the horizontal lines hidden in image, Removal of spectral coefficients from this area eliminates vertical details from original image. *D* (diagonal area) embraces information about the diagonal details hidden in image, Removal of spectral coefficients from this area leads to minimum distortions in original image. To get the value at next level, again HT is applied row and column wise on the piece A, obtained earlier as in example 1. Thus the HT is suitable for application when the image matrix has number of rows and columns as a multiple of 2 [Romero2009].

4.3.2 Zoning Mechanism

In this method, the character image is divided into number of partition called Zone, this number of partition should not be big number nor small because the big and small affect the recognition rate [Lorigo2006].

4.3.3 Skewness

Skewness is often used to show the symmetry of the data about the mean, using this formula:

$$skewness = \frac{1}{\sigma^3} \sum_{i=1}^{n} (x_i - mean)^3 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Where mean is the average of the image, and sigma is:

$$sigma = \sigma = \left(\sum_{i=1}^{n} (x_i - mean)^2 \Big/ n \right)^{1/2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

From the formula, one can see that skewness is either zero(symmetric), or negative (shifted to the left), or positive (shifted to the right) [Vikas2010].

4. 3.4 Algorithm for Feature Extraction

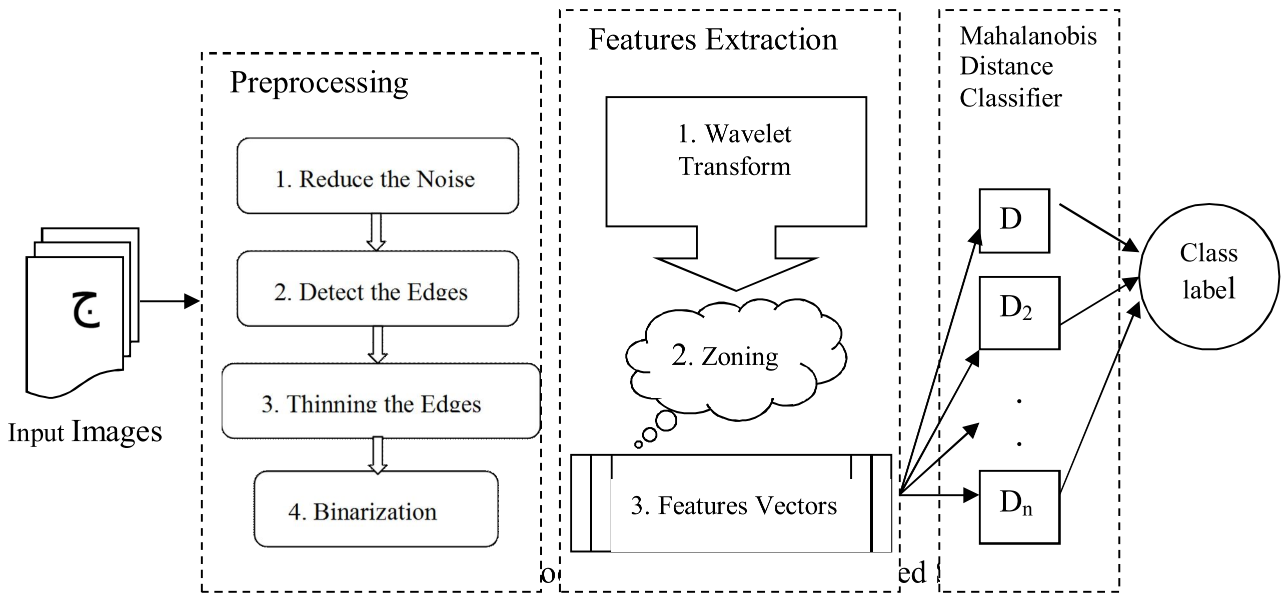
1. The 1D Haar Wavelet transform applies on each row of the binarized image, the size of this image is 64×64.
2. The 1D Haar Wavelet transform applies on each column of the resulted image from the step 1.
3. divide the resulted image from the step 2 into 8 zone, the size of each zone is 8×8.
4. compute mean, standard division and skewness for each zone, then store the computed features values to form a 24 sized vector.
5. repeat the steps from 1 to 4 for each train and test image.

4.4 Recognition Using Mahalanobis Distance

The mahalanobis distance has been used for recognition of the Arabic character, The Mahalanobis distance is used to identify and gauge *similarity* of an unknown sample set to a known one. It differs from Euclidean distance in that it takes into account the correlations of the data set and is scale-invariant. In other words, it has a multivariate effect size. In order to use the Mahalanobis distance to recognize a test point as belonging to one of N classes, one first estimates the covariance matrix of each class, usually based on samples known to belong to each class. Then, given a test sample, one computes the Mahalanobis distance to each class, and classifies the test point as belonging to that class for which the Mahalanobis distance is minimal. So Mahalanobis distance is calculated as follows [Jose2000]:

$$MD = transpose(x-\mu)\times\sum^{-1}\times(x-\mu) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Where $\sum$ is the covariance matrix of the classes, $\sum^{-1}$ is the inverse of the covariance matrix, and μ is the mean for each class.



4. Experimental Results and Discussion

The matalab 7 language have been used to execute the recognition system which based on data consists of group for the twenty eight Arabic alphabets, each group was written by 36 writers from different ages and educational backgrounds. Each group is divide into 8 images for train and 28 images for test. An 64×64 image was used as input image, Then the preprocessing operations have been applied for an input image, After that the 1 level haar wavelet have been used to extract the wavelet coefficients, then 3 features for 8 zones (42 features for an input image) have been extracted. Table 2 show the recognition accuracy for each character. Table 3 show the less recognition accuracy without using only haar wavelet.

5. Conclussion

A simple off-line handwritten Arabic character recognition system using a new type of feature extraction namely, Haar Wavelet based zoning is proposed. The result obtained is comparable with similar works but without using haar wavelet. In this recognition system an average recognition rate of 73% has been obtained with fewer trian images .It has been found that the haar wavelet has given the highest recognition accuracy. As the size and quality of database is major factor influencing handwritten Arabic character recognition systems, so relatively large database and new classifier can be used in the future work. This will help to enhance the recognition accuracy. By adding some more features can also be helpful to enhance the recognition accuracy. It has been observed in this work that certain characters have confused with other characters during recognition process. It has been found that for character د and ب ,recognition accuracy is least.

Table 1. Shapes of Arabic Characters in different positions.

No	Character Name		Isolated	Connected		
				Beginning	*Middle*	*End*
1	Alif	ألف	ا	ا	ـا	ـا
2	Baa	باء	ب	بـ	ـبـ	ـب
3	Taa	تاء	ت	تـ	ـتـ	ـت
4	Thaa	ثاء	ث	ثـ	ـثـ	ـث
5	Jeem	جيم	ج	جـ	ـجـ	ـج
6	Haa	حاء	ح	حـ	ـحـ	ـح
7	Khaa	خاء	خ	خـ	ـخـ	ـخ
8	Daal	دال	د	د	ـد	ـد
9	Thaal	ذال	ذ	ذ	ـذ	ـذ
10	Raa	راي	ر	ر	ـر	ـر
11	Zaay	زاي	ز	ز	ـز	ـز
12	Seen	سين	س	سـ	ـسـ	ـس
13	Sheen	شين	ش	شـ	ـشـ	ـش
14	Saad	صاد	ص	صـ	ـصـ	ـص
15	Dhaad	ضاد	ض	ضـ	ـضـ	ـض
16	Ttaa	طاء	ط	طـ	ـطـ	ـط
17	Dthaa	ظاء	ظ	ظـ	ـظـ	ـظ
18	Ain	عين	ع	عـ	ـعـ	ـع
19	Ghen	غين	غ	غـ	ـغـ	ـغ
20	Faa	فاء	ف	فـ	ـفـ	ـف
21	Qaf	قاف	ق	قـ	ـقـ	ـق
22	Kaf	كاف	ك	كـ	ـكـ	ـك
23	Lam	لام	ل	لـ	ـلـ	ـل
24	Mem	ميم	م	مـ	ـمـ	ـم
25	Noon	نون	ن	نـ	ـنـ	ـن
26	Haa	هاء	ه	هـ	ـهـ	ـه
27	Wow	واو	و	و	ـو	ـو
28	Yaa	ياء	ي	يـ	ـيـ	ـي

Table (2) The Recognition Accuracy using Haar Wavelet Based Zoning

	Character		Accuracy%		Character		Accuracy%
1	أ	Alif	95.67	15	ض	Dthad	66.80
2	ب	Baa	57.03	16	ط	Ttaa	66.05
3	ت	Taa	75.77	17	ظ	Dthaa	58.00
4	ث	Thaa	88.55	18	ع	Ain	68.89
5	ج	Jeem	85.88	19	غ	Ghen	62.21
6	ح	Hhaa	93.21	20	ف	Faa	61.80
7	خ	Khaa	72.27	21	ق	Qaf	67.25
8	د	Dal	60.22	22	ك	Kaf	84.22
9	ذ	Theal	65.79	23	ل	Lam	73.33
10	ر	Raa	70.00	24	م	Meem	79.78
11	ز	Zaay	68.45	25	ن	Noon	59.12
12	س	Seen	71.56	26	هـ	Haa	82.66
13	ش	Sheen	89.00	27	و	Waw	87.00
14	ص	Sad	62.22	28	ي	Yaa	80.63
Average Accuracy							73.33

Table (3) The Recognition Accuracy Without Using Haar Wavelet

	Character		Accuracy%		Character		Accuracy%
1	أ	Alif	90.22	15	ض	Dthad	59.99
2	ب	Baa	53.46	16	ط	Ttaa	61.00
3	ت	Taa	65.67	17	ظ	Dthaa	53.41
4	ث	Thaa	80.21	18	ع	Ain	66.63
5	ج	Jeem	75.13	19	غ	Ghen	62.15
6	ح	Hhaa	90.78	20	ف	Faa	62.68
7	خ	Khaa	71.90	21	ق	Qaf	62.27
8	د	Dal	57.34	22	ك	Kaf	79.56
9	ذ	Theal	59.44	23	ل	Lam	71.51
10	ر	Raa	66.80	24	م	Meem	78.89
11	ز	Zaay	65.76	25	ن	Noon	54.73
12	س	Seen	70.72	26	هـ	Haa	78.00
13	ش	Sheen	83.18	27	و	Waw	80.16
14	ص	Sad	60.00	28	ي	Yaa	75.42
Average Accuracy							69.17

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