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Recognition of secondary characters in handwritten Arabic using Fuzzy Logic

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Abstract

Arabic language is characterized by extensive use of dots or secondary characters associated with main body or primary characters. More than half of the Arabic characters can only be distinguished by these secondary characters. Hence recognition of these characters has a vital importance in Arabic OCR. In printed text the problem is much easier than handwritten text because of the variety of shapes and the minute sizes of these secondary characters. In this paper the use of fuzzy logic in recognition of these secondary characters is presented. Features like width, length, number of pixels and height-to-width ratio are used for recognition of these characters. Membership functions for fuzzy logic treatment are derived from handwritten data and are used in the fuzzy rules. The secondary characters may give even further information for recognition of the characters.

I. INTRODUCTION

The two fundamental approaches to character recognition are feature classification and template matching. Template matching techniques are more sensitive to font and size variation of the characters and hence are not suitable for character recognition from noisy document images or handwritten.

However, selection and extraction of useful features is not always straightforward. It may be mentioned that human beings are more efficient than computers in handling complex recognition problems including character recognition from document images. Human reasoning is somewhat fuzzy in nature, which enables us to combine even visually degraded features in the brain using millions of neurons working in parallel. Fuzzy sets have the ability to model vagueness and ambiguity in data, which is encountered in character recognition as well as in other pattern recognition problems [1].

Fuzzy logic is a class of multivalent, generally continuous-valued logic based on the theory of fuzzy sets initially proposed by Lotfi Zadeh in 1965. He extended the two-valued logic, defined by the binary pair {0,1}, to the whole continuous interval {0,1}, thereby introducing a gradual transition from falsehood to truth. The function that ties a number to each element x of the universe is called the *membership function* $\mu(x)$. Fuzzy logic is concerned with the theoretic operations allowed on fuzzy sets, how these operations are performed and interpreted, and the nature of fundamental fuzziness. Most fuzzy logics are based on the min-max or the bounded arithmetic sum rules for set implication [2].

This paper will use the fuzzy logic in recognition of secondary characters in Arabic handwritten text.

II. CHARACTERISTICS OF ARABIC LANGUAGE

The Arabic character set is composed of 28 basic characters. 15 of them have dots and 13 are without dots. Each character may have up to four different forms according to its location in the word; the initial, the middle, the final or the stand alone forms. Dots above and below the characters, play a major role in the distinction between some characters that differ only by the number or location of dots. As an example the letters: ب ت ث ي ن ; in their middle form, all these five letters are written the same way as: ـبـ ـتـ ـثـ ـيـ ـنـ . They differ only by the number or the locations of the dots.

There are four characters which may take the zigzag shaped secondary character "Hamzah ء". Those are "Alif إ أ ", "Waw ؤ" , "Yaa ئ " and "Kaf ك ". The character "Alif" may have the "Hamzah" above or below it. The character "Kaf" does not have the secondary in its initial or middle forms but rather in its final and stand alone forms. The "Hamzah" may appear as a stand alone character and hence can be considered as extra character as well as a secondary character. There are also some other secondary characters used above and below the characters to indicate vowels (Fathah, Kasrah, Dhammah, Tanween, Maddah) but we shall not consider them in this study. Table 1 gives details of all secondary characters.

Arabic characters do not have fixed width or fixed size, even in printed form for the same font. Six of the characters (ا د ذ ر ز و) don't connect from the left side, Hence there are only two forms for these characters, while the rest have four forms.

III. ARABIC CHARACTER RECOGNITION

Survey of Arabic OCR research has been made in some literature [3,4]. Arabic OCR should take into account the special nature and characteristics of Arabic handwriting. Special attention should be paid to the nature of division of Arabic words into sub-word.

TABLE 1 SECONDARY CHARACTERS

	Secondary Name	**Example**	**Remarks**
1	One upper dot	خ ذ ز ض ظ غ ف ن	For all shapes of the 8 letters
2	Two upper dots	ت ق ة ـة	For all shapes of the 2 letters and the "Ending Taa"
3	Three upper dots	ش ث	For all the shapes of the 2 letters
4	One lower dot	ب جـ ـجـ	For all the shapes of ب and middle and initial for ج
5	Two lower dots	ي	For all shapes
6	One middle dot	ج ـج	For final and stand alone
7	Upper Hamzah	ك ـك أ ؤ ئ	With ا و ي and ك (end and stand alone)
8	Lower Hamzah	إ	With ا
9	Shaddah	ّ	With all letters except ا
10	Maddah	آ	With ا
11	Sord like Alef	' 'ى	As hidden alef and with ى
12	Fathah	ـً	Upper with any letter
13	Kasrah	ـِ	Lower with any letter
14	Dhammah	ـُ	Upper with any letter
15	Sukun	ـْ	Upper with any letter
16	Tanween Fatih	ً	Upper at end of word
17	Tanween Kasir	ٍ	Lower at end of word
18	Tanween Dhamm	ٌ	Upper at end of word
19	Combinations	ـَّ ـُّ ـِّ ـًّ ـٍّ ـٌّ	Shaddah with other secondary characters

A novel approach for the Arabic character recognition based on statistical analysis of a typical Arabic text has been presented to indicate the importance of sub-word recognition rather than word in Arabic OCR system [5]. Results showed that the sub-word in Arabic language is the basic pictorial block rather than the word. The method is applied for the recognition of some Arabic characters in their stand-alone form. An off-line recognition system based on the selected features has been built[6]. The system was trained and tested with realistic samples of handwritten Arabic characters. Evaluation of the importance and accuracy of the selected features was made.

Two kinds of features are generally recognized in character recognition namely: quantitative features and qualitative features.

In quantitative features, the simplest feature is the black pixel count. Other features are: character height, character width, character area, short line segment count; character weight above and below the base line, dot count, aspect ratio (relationship between width and height of a character), horizontal and vertical projections; moments and moments invariant. Fourier descriptors, major connectivity directions, end points, the relative distance between the start and end points of a stroke, etc.

The qualitative features represent the structure of the entire character or the stroke. Ideally, feature forming structures are assigned a code instead of a value. Examples of the qualitative features are: the branch point count codes, branch attributes, closed curves, open curves, corner point count codes, crossing code, crossing point, crossing number, Freeman code, dot positions, end-point codes, end-point count code, junction points, loop counts, loop position, secondary strokes, topological relations, topological description, layout context (base line information and location of one character with respect to its neighbors), (character position relative to the base line); character's position within a word (initial, last, middle, or stand alone character), character connectivity, boundary analysis (outer boundary shape), projection profile (position of peaks and valleys in the horizontal projection), connected component analysis (connected component code), vertical and horizontal bars, curves directions of opening, etc.[3]

Thinning is usually one of the major steps in the preprocessing stage before feature extraction is made. But as we shall see thinning is not useful for secondary character recognition.

IV. REVIEW OF USE OF FUZZY LOGIC IN OCR

Fuzzy logic has been used recently in a variety of ways to aid character recognition. Recognition strategies for the isolated handwritten English characters (A to Z. a to z) is performed by the preprocessing of characters comprises bounding of characters for translation invariance and normalization of characters for size invariance. The variability in a character shape has been taken into account by devising a fuzzy logic based approach using normalized angle features [7]. On the other hand, a fuzzy language for the syntactic description of handwritten symbols has been used. It incorporated the fuzzy logic techniques to describe the syntactic relations of the semantic features extracted from a symbol pattern. The rule-base represents the compact feature information extracted from a small number of character prototypes and covers various handwriting styles [8]. A handwritten Chinese character recognition method based on primitive and compound fuzzy features using neural network model has been proposed. The primitive features are extracted in local and global view. Since handwritten Chinese characters vary a great deal, the fuzzy concept is used to extract the compound features in structural view. The use of fuzzy set theory in feature extraction and the neural network model as a classifier is helpful for reducing distortions, noise and variations. In spite of the poor thinning, a good recognition rate was obtained. [9]

As for the recognition of handwritten numerals, fuzzy logic has been used in fuzzy techniques. Modification of fuzzy density calculation resulted in better recognition rate. Test conducted on a large set of handwritten numeral data yielded high recognition rate with this technique. [10]

In word recognition, without any segmentation to characters, an unconstrained Farsi handwritten word recognition system based on fuzzy vector quantization (FVQ) and hidden Markov model (HMM) for reading city names in postal addresses is reported [11].

A fuzzy set is defined on the Hough transform of character pattern pixels from which additional fuzzy sets are synthesized using t-norms. A multilayer perceptron trained with a number of linguistic set memberships derived from these t-norms had recognized characters of Bengali scripts by their similarities to different fuzzy pattern classes [12]. A multi-stage character recognition system for Bengali script using fuzzy features and multilayer perceptrons has been developed. The fuzzy features are extracted from Hough transform of a character pattern pixels. A number of fuzzy sets on the Hough transform accumulator cells were first defined. The fuzzy sets are then combined by t-norms to generate feature vectors from each character. A set of fuzzy linguistic vectors is next generated from these feature vectors. The perceptron used for classification have the fuzzy features as inputs and its outputs represent the belongingness of an input pattern to different fuzzy character pattern classes. High recognition accuracy of the system has been obtained[12,13].

A neuro-fuzzy system for character recognition using a fuzzy Hough transform technique has been reported. For each character pattern, membership values are determined for a number of fuzzy sets defined on the standard Hough transform accumulator cells. These basic fuzzy sets are combined by t-norms to synthesize additional fuzzy sets whose heights form an n-dimensional feature vector for the pattern. A 3n-dimensional fuzzy linguistic vector is generated from the n-dimensional feature vector by defining three linguistic fuzzy sets, namely, weak, moderate and strong. The linguistic set membership functions are derived from the Butterworth polynomials and are similar to the gain functions of low-pass, band-pass and high-pass filters, respectively. A multilayer perceptron (MLP) is trained with the fuzzy linguistic vectors by the back propagation of errors. The MLP outputs represent fuzzy sets denoting similarity of an input feature vector to a number of character pattern classes. High recognition accuracy of the system was reported [2].

Neuro-fuzzy systems were used in more than one way. A neural network classifier which is based on geometrical fuzzy sets has been reported. Voronoi diagram has been used for training patterns leading to the identification of regions belonging exclusively to one of the pattern classes. The resulting scheme is a constructive algorithm that defines fuzzy clusters of patterns. Based on observations concerning the grade of membership of the training patterns to the created regions, decision probabilities are computed through which the final classification is performed 14]. Another method which utilizes both neural networks and fuzzy logic techniques, and is independent of font, is used for printed and handwritten text recognition. In this method, the binary image of the character is partitioned into a fixed number of sub-images called boxes. The features consist of vector distance from each box to a fixed point. The vector of distances of all the pixels lying in a particular box, from the fixed point are calculated and added up and normalized by the number of pixels within that box. Both neural networks and fuzzy logic techniques are used for recognition and recognition rates are found to be quite high. The methods are independent of font and size of character [15].

Some document management system are based on neuro-fuzzy systems and are used to support simple OCR that inherits fine properties of ART architectures, such as fast and incremental learning, stability and modularity.[16]

A method which combines both wavelet packet transform with neuro-fuzzy approach is used for automatic handwritten character recognition. The fuzzy logic system is used for classification purpose and a neural network system is used for recognition purposes. Characteristic features are extracted by taking wavelet packet transform using best-basis algorithm and are given as input to the fuzzy classifier where they are fuzzified and classified using IF ... THEN rules, and given to a neural network recognition system [17].

Stroke-based neuro-fuzzy system for recognition of handwritten Chinese characters consisting of three main components: stroke extraction, feature extraction, and recognition. Stroke extraction applies a run-length based method to extract strokes from the image of a given character. Various fuzzy features of the extracted strokes, including slope, length, location, and cross relation, are obtained by the feature extraction module. A neural network, using a two-stage training algorithm, is used to recognize characters. Experiments have shown that this system is effective [18].

Fuzzy logic has been used for other purposes related to OCR, like skew angle estimation for complex address images. It was tested on a variety of post office parcel images including both machine print and handwritten addresses. The testing results showed a good successful rate [19]. In another attempt, a pattern recognition approach to robust word boundary detection in adverse acoustic noise conditions is proposed. The algorithm uses four simple differential parameters calculated in the time domain and pattern matching based on a set of six fuzzy rules extracted by a hybrid learning tool. The experimental results demonstrated that the new endpoint detector outperforms traditional methods, in particular in the presence of high levels of background noise [20].

A method to segment characters and numbers in presence of colored background, texture and noise has been also reported. The method is based on the concept of the fuzzy connectivity and it exploits both intensity information and continuity of direction which characterize structures belonging to the document. The final result of this process is a grey levels image (the "connectedness" image); where every value represents the degree of membership of the pixel to the object searched [21].

As the presence of extra ink impairs recognition, classification of extra ink instead of a letter class, has been tried using fuzzy measure. This was done first by defining initial crisp evaluation to filter out unambiguous extra ink strokes and then the fuzzy measure was applied [22].

Classification of text and image using statistical features (mean and standard deviation of pixel color values) is found to be a simple yet powerful method for text and image segmentation. The features constitute a systematic structure that segregates one from another. This segregation is identified in the form of class clustering by means of Fuzzy C-Mean method, which determined each cluster location using maximum membership defuzzification and neighborhood smoothing techniques. The method can then be applied to classify text, image, and background areas in OCR applications for elaborated open document systems [23].

A fuzzy representation for isolated character description has been reported. This representation maps a character from its original sequence of 2D coordinates into a fuzzy vector space that can thereafter serve as input to any artificial neural network classifier [24].

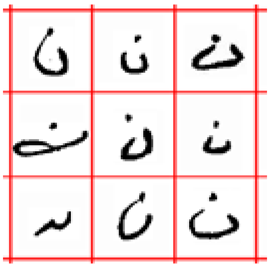
A structural approach using fuzzy relations for recognizing handwritten isolated Arabic characters has been performed [25]. Each input pattern was divided into sub-patterns (strokes) by feature points; end points, branch points, intersections and maximum curvatures point, etc. The number of sub-patterns varies from one to six depending on the input character. The sub-pattern are then represented in terms of similarity to primitive elements (straight line, circle and diacritical point). The algorithm has been tested on a small number of handwritten samples. Other work may be found elsewhere [26-32]

V. SECONDARY CHARACTERS AND FUZZINESS

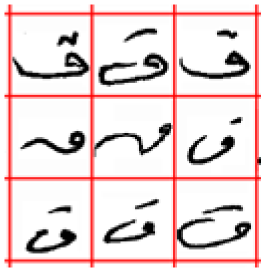
The processing of handwritten characters in this paper is based on data base from 48 different individuals writing in an unrestricted way. The writing has then been manually segmented and put in separate files [33]. The separation also was performed on dots, numerals and signs.

From study of the available data mentioned above it has been noticed that the presence or absence of dots is a fuzzy feature because:

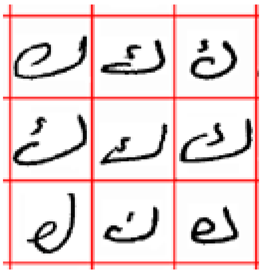
(i) Some writers are used to write some letters with or without dots e.g ق & ن. Figures 1a shows 9 characters written by 9 different writers for the character ن . It is clearly seen that some of the writers wrote the character without an upper dot and some others joined the dot with the main part of the character. Figure 1b shows the character ق written also by 9 different writers. Here also some writers wrote the character without the upper two dots. Figure 1c shows the ك character. It is seen that some writers joined the secondary of the character with the main body of the character in such a way that it makes the looks like a Hamzah while in some other cases it does not look like a joined Hamzah but rather the whole character with its secondary looks in different shape.



(a)



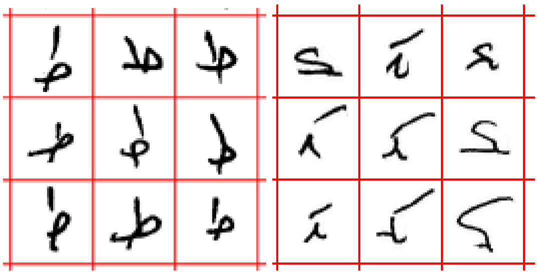
(b)



(c)

Figure 1 (a) ن (b) ق (c) ك by 9 different writers

(ii) Primary part of some characters is written in such a way to confuse with dots e.g. ط ، ظ ، ـكـ. This is another source of uncertainty in the secondary characters as a result of the casual way of writing some parts of characters without dots so as to look like two separate identities. Figure 2a shows the character ط which consist of a lower part with a loop and an upper vertical stroke. This stroke may not be joined by some writers to the main part of the characters as shown. Figure 2b shows the character ـكـ in its middle shape of ك. It is also clear that this character may be written by some writers so that its upper secondary part is separated from the lower primary part of the character. Note also that characters like ظ may appear to have two secondary characters; one as upper dot and the other is confused as mentioned in the ط .



(a) (b)

Figure 2 (a) ط (b) ك by 9 different writers

(iii) Dots sometimes are joined un-intentionally with the primary part as can be noticed from one of the ن in figure 1a

(iv) Dots sometimes are so small that they are considered as noise.

The second fuzzy thing in the dots is the number of dots. It is a fuzzy feature for the following reasons:

(i) For the case of upper secondary parts, the one, two or three dots may be confused with each other or with the Hamzah.

(ii) For the case of lower secondary part, the one or two dots may be confused with each other or with Hamzah as there is no character with 3 lower dots.

(iii) The number of pixels comprising the dots is so little that they are easy to confuse with each other. It is difficult to find good algorithms to distinguish between them in a clear cut way. This is because there are limited number of features to be used for secondary characters recognition, namely, width, height, height to width ratio or area.

(iv) Thinning of dots may be of no use because of their small sizes and the big distortion occurring as a result.

As mentioned above, recognition of secondary characters is an important step for recognition of more than half of the Arabic alphabets. In order to do that, the secondary parts, to be first separated from the primary part of the characters.

This step although it is straight forward in printed text, it is not so with handwritten text. The secondary characters which we are going to consider in this paper are the one, two and three upper dots, the one, and two lower dots and the upper and lower "Hamzah", i.e. 1-8 of Table 1. The secondary characters 9-11 are also in use in common handwriting, while the rest are used only in "Tashkeel diacritical mark" form of writing and are common in Morocco, Algeria and Tunisia as well as religious texts and specialized Arabic language books of grammar and literature.

VI. RECOGNITION OF SECONDARY CHARACTERS

The spot containing the secondary character can be separated by simple algorithms. However these spots may or may not be dots or Hamzah as mentioned above. Hence their belonging to one of these secondary characters is a fuzzy relationship.

The characters which seem to be with no secondary part may also be one of the dotted characters with the dots badly written and mixed with the main body of the character. Hence the relationship is fuzzy.

The distinction between the upper one dot, two dots, three dots and the Hamzah is going to be shown later with some details as an example on the fuzzy treatment of the subject. Figure 3 shows the upper two dots written by 48 different writers. It is shown that different people may write these dots differently. Some write them as two separate dots, some write them as a dash and some others will write them as zigzag, etc. It has been noticed even that the style of writing the upper two dots differs from the style of writing the lower two dots. Figure 4 shows the upper 3 dots which clearly indicate the similarity of some of them with the two dots of figure 2. This makes the recognition more difficult.

Figures 5 shows the Hamzah shapes and its association with ا و ي . This in addition to figure 1c indicate various Hamzah shapes and their primary part of the characters.

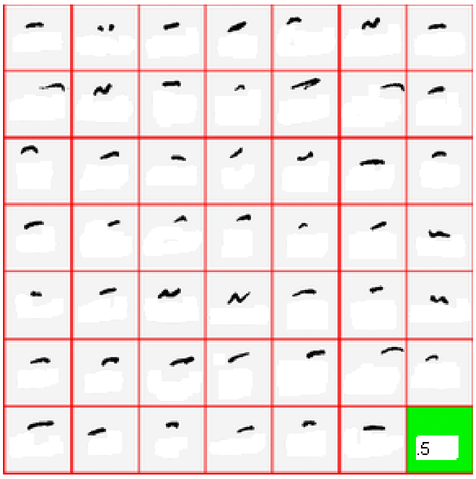


Figure 3 Two upper dots by 48 different writers

Figure 4 Three upper dots by 48 different writers

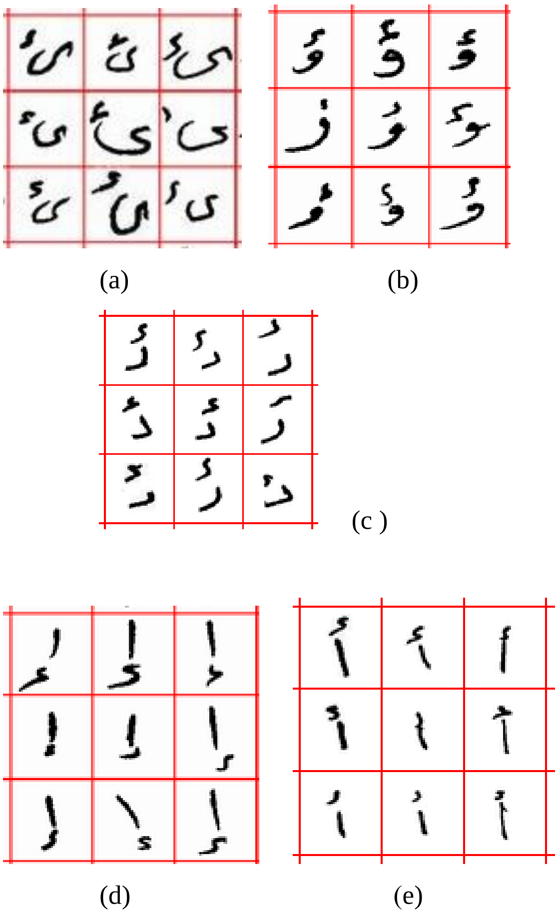


Figure 5 (a) ئ (b) ؤ (c) ـئ (d) إ (e) أ for 9 different writers

TABLE 2 SECONDARY CHARACTERS DIMENSIONS

	One dot up	Two dots up	Three dots up	One dot down	Two dots down	Hamza
Max. Height	8	8	14	7	10	31
Min. height	3	3	3	3	3	7
Average Height	5	4.5	9.8	4.3	5	13
Max. width	7	16	14	7	16	38
Min. width	3	3	4	3	7	16
Average width	4	9	9.7	4	11	28
Max. No. of pixels	27	39	86	34	45	95
Min. No. of pixels	11	15	30	10	21	42
Average No. of pixels	17.4	25.2	50	17	33	63

VIII. SELECTION OF MEMBERSHIP FUNCTIONS

The membership function shape is an important step in building the fuzzy logic system for any problem. The features selected here are the height, width and total number of pixels. Other features may also be selected to build a robust system. The measurement of each of these features in pixels may vary from one document to other; however they are inter-related with each other and with the average size of words, characters and document as a whole. This problem of normalization will not be discussed here.

Table 2 shows the parameters obtained from the data base under consideration. The maximum, minimum and average number of pixels is helpful in selecting the shape of the membership function. However the spectrum of number of pixels may give further information to better select the membership function.

VII. INFERENCE FUZZY RULES

Rules used for the distinction between one dot, two dots, three dots and the Hamzah gave the results given in Table 3.

The structure of the fuzzy rules is given below:

If (height is M1) & (width is M2) & (area is M3) then the character is …

Where the fuzzy membership function Mi are defined on their respective universe of discourses. Look Figures 6 and 7.

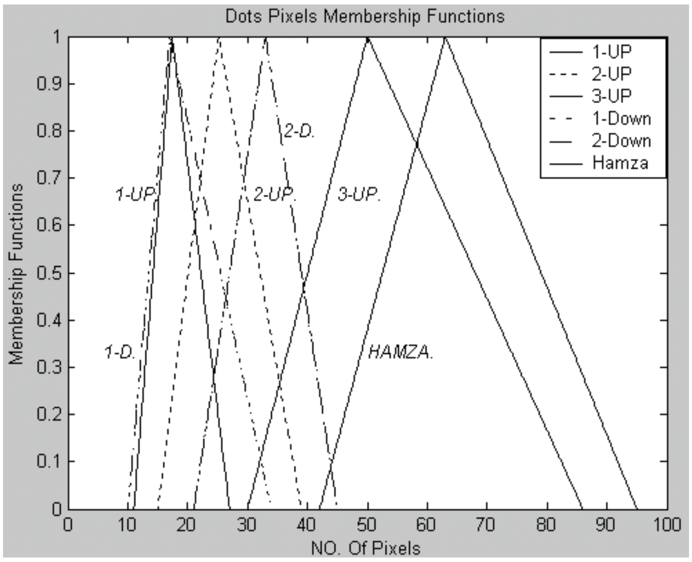


Figure 6 Membership Function for width

There are several methods of inference in compositional fuzzy systems; among which are: the min-max (Mamdani) and the fuzzy additive method [1].

In the min-max method which is used here, the consequent membership function is restricted to the minimum of the predicate truth and the compound result is the maximum of all these fuzzy sets

Defuzification or fuzzy decoding transforms a fuzzy quantity into a crisp one. There are many methods for defuzzification [1] and the Max-Membership principle method was used in the present research, which chooses the element with the maximum μ value

It is clear that confusion between different secondary characters is there and hence further necessity for more features, statistical treatment or context dependence rules. All these may be treated within the fuzzy logic rule based system.

Recognition of Secondary Part Features Aiding Primary Part Recognition

Recognition of primary part of the characters with secondary part need to be first separated from the secondary part and treated as a character with no secondary part e.g. خ ج ح are

TABLE 3 CHARACTERS RECOGNITON RATES

Letters	One-dot	Two-dot	Three	Hamza	No-dot
إ	21%	2%	0	77%	0
أ	63%	15%	13%	6%	4%
ب	98%	0	0	0	2%
ت	8%	79%	4%	0	0
ث	10%	31%	50%	6%	3%
ج	92%	0	2%	0	6%
خ	98%	0	0	0	2%
ذ	98%	0	0	2%	0
ز	100%	0	0	0	0
ش	10%	31%	54%	2%	2%
ض	98%	0	2%	0	0
ط	21%	4%	0	29%	46%
ظ	48%	4%	4%	27%	17%
غ	94%	0	4%	0	2%
ف	100%	0	0	0	0
ق	15%	52%	19%	0	14%
ن	79%	4%	6%	8%	3%
ؤ	17%	21%	42%	20%	0
ئ	13%	10%	42%	31%	4%
ي	17%	77%	0	6%	0

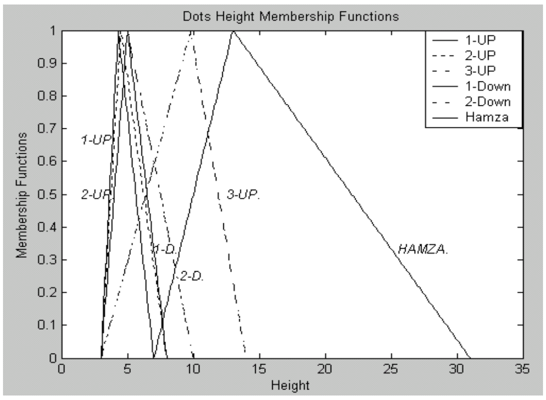


Figure 7 Membership function for height

treated in the same way after removal of the dots. Once the character is defined as one of these three, then the existence of the upper dot, lower dot or the nonexistence of any, define which of the three characters is required. However the position of the secondary characters compared to the primary are useful features for recognition of some characters e.g. upper dot of the ف is shifted to the right, while for the ن it is almost at the center. This will add an extra feature for the recognition of these characters which can add to the fuzzy rules extra information.

To enhance the recognition rate of an OCR system, syntactic, semantic, morphological, contextual and statistical properties of the Arabic language have to be used.

IX. CONCLUSION

This paper introduced a method for recognition of the secondary parts of handwritten Arabic characters. The proposed algorithm combined a structural and statistical method for feature extraction and a modeling and classification technique based on fuzzy logic. Features were extracted from the complement part of a character. The features were modeled by fuzzy linguistic values which provided a more expressive system for the characters. Promising results are shown. Further morphological, contextual and statistical information shall enhance recognition rates.

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