Recognition of Farsi Handwritten Numbers Using the Fuzzy Method

Mansoreh Sharizfadeh *sharifzade@yahoo.com*
Faculty of Engineering
University of Hormozgan
Bandar Abbas, 74318, Iran

Shahpour Alirezaee *Sh_alirezaee@yahoo.com*
Faculty of engineering
Razi University
Kermanshah, 74555, Iran

Abstract

There are wide varieties of handwritten characters which differ not only from person to person but also from the state of mood of the same person. Nevertheless humans are trained to extract the specific features characterizing a symbol. This paper aims to introduce fuzziness in the definition of the proposed pattern features, which provides the enhancement to the handwritten character information to be stored. Some novel shape features in fuzzy linguistic domain are proposed. The experimental results indicate 95 % accuracy on recognition of Farsi numbers over the selected database.

Keywords: Character Recognition, Farsi Handwriting Numbers, Fuzzy Method, Geometrical Features.

1. INTRODUCTION

The objective of the Handwritten Character Recognition is the recognition of data that describe handwritten objects. On-line handwritten recognition deals with a time ordered sequence of data for different persons from various backgrounds e.g. nationality, education or profession. Development of such a system is only possible if the character prototypes are defined with a flexible rule base including only handwriting style independent features. The primary goal of our methodology is to represent the handwriting information into a minimum number of meaningful features. These features are subsequently stored into a compact database.

Many methodologies have been developed for the recognition of handwritten characters. Some of the more recent methodologies include the use of Bayesian inference (Cheung and Yeung, 2002), Neural Networks (Koerich and Leydier, 2002; Lee and Kim, 1995), Fuzzy Logic (Malaviya and Peters, 1995) and Genetic Algorithms (Kim and Kim, 2000). When compared with other description methods, fuzzy description is probably the most efficient in terms of computational usage. Due to this reason, fuzzy logic is an appropriate method for online character recognition[1],[2]. The proposed method achieves the flexibility in recognizing varied handwritings by using linguistic fuzzy rules.

The human visual sense is selectively activated in response to curved lines and other geometrical characteristics [2]. These features themselves contain certain vagueness in terms of their definition. The human recognition system is most accurate in grasping the typical geometrical features of handwritten characters while ignoring the vagueness. To compensate these inherent geometrical shape distortions existing in the different handwriting styles we have applied the fuzzy set theory [8]. By use of fuzzy technique we integrate the existing vagueness into membership function of basic structural features. These possibilities are then estimated and further processed with fuzzy aggregation techniques.

This paper has been organized as follows. First, a quick glance on fuzzy linguistic modeling is given and some definition and general consideration related to shape recognition are presented. Shape recognition using the fuzzy feature will be described in the fourth section. In this section we will have a complete presentation on the fuzzy features for shape recognition. Then the proposed method will be presented in the fifth section. Experimental results will be discussed in the sixth section. Finally the conclusion of the presented method and the related performance will be discussed in the last section.

2. THEORY OF FUZZY LINGUISTIC MODELING

The linguistic variable is the core of the fuzzy modeling technique. Through the introduction of linguistic descriptors, phenomena which are too complex or too ill defined to be susceptible to be described by exact quantitative terms can be defined with ease. Therefore a linguistic variable can be either regarded as a variable whose value belongs to a fuzzy set or as a variable whose values are defined by linguistic terms.

Each linguistic term has a meaning associated to it by a fuzzy set. Membership functions of a given linguistic term A can be formulated such as the members of universal set X fall within a specified range [0,1] and indicate the membership grade mA(x) of these elements in question. Definition of a Fuzzy linguistic is as follows:

"A linguistic variable x is identified by its name and characterized by a term set T(F(x)), where F(x) denotes the fuzzy membership function."

For example, if a linguistic variable xhp, which stands for “handwriting property x” is taken as a general example, its term set could be represented as T(F(xhp)) = { Zero, Very Very Low, Very Low, Low, Medium, High, Very High, Very Very High, Excellent}

Definition of the fuzzy sets can be categorized into the discrete and continues values. In case of discrete values numerical vectors are used for assignments of grades of memberships. The second method, for continuous values, which is accomplished with the help of membership assignment in functional form. Typically used membership functions are S- or P-shaped, bell-shaped, triangular and trapezoidal function. The most widely used fuzzy membership function is the triangular membership function, whose shapes are variations of a triangle.

3. COMBINING FEATURES WITH FUZZY AGGREGATION

Fuzzy aggregation mechanism aims to find an overall measure of certain fuzzy information from an uncertain and imprecise information data. The selection of meaningful features from a given set of handwriting data is dependent on the possible relationships among these feature categories. The meaningful feature designates the features with a good discrimination factor. To make a hierarchical structure a two phase aggregation scheme has been developed which is based on the union and weighted generalized mean aggregation connectives. The wide ranges of these connectives provide flexibility in finding the most suitable output feature set.

4. SHAPE RECOGNITION

The shape is considered as the primal geometrical property for extracting pattern recognition features. The daily life objects are mostly recognized because of their specific shapes. The perception of shapes can be viewed as a collective cognition of the properties like size, form, symmetry and orientation.Thus a fuzzy approach to shape analysis incorporating imprecise concepts merits consideration.

The definition of a shape in terms of linguistic description like “curve is long / round/ thin” etc. is easily related by the humans to known patterns. But it is quite vague to define the shape of the objects by these descriptors as there is an obvious incompatibility with numerical processing methods. A closer look at these descriptors show that geometrical, positional and global features provide some insight about the shape itself provided they can be related to linguistic attributes or terms. For example “curve” or “circle” or “line” have a well-defined geometric description but the definition of terms like “long”, “thin” “round” are more difficult to be expressed by formulas without the semantic power offered by the fuzzy set theory. Thus if we take again the circle example the shape description “the circle is round” is a fuzzy syntactic rule where circle is the linguistic variable and round is one of the possible linguistic terms associated to the circle with a membership defined for e.g. by Eq. 8. Our proposed approach collects the shape information through the extraction of geometric, positional and global features and expresses this information in the set theoretic fuzzy manner.

In the following subsections the computation and the properties of these features are described. While the global features characterize the pattern as a whole, e.g. aspect-ratio, the geometric and positional features describe local aspects for each identified sub-pattern. The extraction of predefined sub-pattern is done through a rough segmentation step in which abrupt changes in shape are used as discriminator.

To find or identify certain shape features we have first to define our universe of discourse. In our case this is the smallest rectangle in which the unknown character fits. This rectangle is defined by four parameters:

4.1 Positional Features

The positional features determine the relative position of the global or geometrical feature in the given rectangular window and are defined in the universe of discourse [0,1]. The two dimensional universe of discourse is divided into six linguistic terms: {Left, Centre, Right} and {Top, Middle, Bottom}. These are associated to the fuzzy linguistic variable or feature Vertical Position (VP) and Horizontal Position (HP) and express the relative position of a point, region, or segment to the centroid (xm,ym) of the analysed character.
These linguistic terms can be combined creating additional linguistic terms, e.g. “circle to the left-centre” and “line right-top-centre” which could identify a “d”. Just by interchanging the linguistic term “left” with “right”, “circle to the right-centre” and “line left-top-centre” the renewed description would correspond to a “b”.

4.2 Global Features

The global features describe the character as a whole and can be used for the pre-classification of the character. These shape features represent the global approximation of the shape. One method of shape classification relay on global features, e.g. area, compactness. These shape features are the global approximation of the shape. In other words information about the shape from all portions combines to form the global description.
The basic idea is to follow human visual modeling and to reproduce geometrical features in comprehensive terms. In this paper we have used the Start-point and End-point as follows.

Start-point and End-point

The starting point and the ending point of the character can be described related to the defined universe of discourse:

$$\mu_{S\_Y} = \frac{y_0 - y_{\min}}{y_{\max} - y_{\min}}$$

$$\mu_{S\_X} = \frac{x_0 - x_{\min}}{x_{\max} - x_{\min}}$$

$$\mu_{E\_Y} = \frac{y_N - y_{\min}}{y_{\max} - y_{\min}}$$

$$\mu_{E\_X} = \frac{x_N - x_{\min}}{x_{\max} - x_{\min}}.$$

where $(x_0, y_0), (x_N, y_N)$ are the coordinates of the start and end point of the handwriting profile and $x_{\min}, x_{\max}, y_{\min}, y_{\max}$ are the borders of the universe of discourse. The values of μ_{S_X}, μ_{S_Y} are scaled to fit into a range of: [0:Left, 1:Right] and [0:Bottom, 1:Top] respectively. Fig.1 presents this feature.

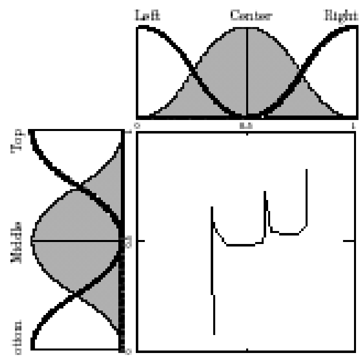


FIGURE1: Start-point and End-point feature

4.3 Geometric Features

We defined two classes of local geometric features: straight-line and curved-line. A segment description based on these two feature classes could be e.g. {class Arc, feature C-like} or {class Straight Line, feature Vertical Line,}.

The first step is the classification of the unknown segment to one of these geometric classes. This process is done through a fuzzy measure of “arced-ness” and “straight-ness”. As each class has several features (subclasses) the next step is to measure the belonging of the unknown segment to all subclasses. Due to the “fuzzy” nature of handwritten characters several solution are possible. The defined features (subclasses) form several fuzzy sets which are related thus covering the whole space of possible pattern distortions. We have applied two kinds of the geometrical features, measure of arced-ness and straight-ness, as follows.

Measure of arced-ness and straight-ness

The shape of a given segmented sub-patterns can be classified to the class of “straight line” or “arced line”. Pal and Majumder showed that the measure of straight-ness of a segment is determined by fitting a straight line with the minimum least squares error. Similarly in a given segment, ratio of the distance between end points to its total arc length shows its arced-ness. In other words if the distance between the end points is nearly equal to the total arc length, it is possibly a straight line. Otherwise if the arc length is much greater than the distance between the end-points then it is very likely a curve. Here it is assumed that the curve is monotonous. If we consider the measure of arced-ness and the measure of straight-ness to be two complementary fuzzy linguistic terms of the fuzzy linguistic variable shape and their definition for a segment is the relative deviation in the arc-length from the length of a straight line joining its end-points, then these two measures can be expressed as follows:

$$\mu_{Arc}(S_j) = \left(1 - \frac{d_{P_{j0} p_{jk_j}}}{\sum_{k=0}^{k_j - 1} d_{p_{jk} p_{j(k+1)}}}\right)^{\beta}$$

$$\mu_{\text{Straightness}}(S_j) = \left(\frac{d_{P_{j0} p_{jk_j}}}{\sum_{k=0}^{k_j - 1} d_{p_{jk} p_{j(k+1)}}}\right)^{\beta}$$

where β is a real positive number. This fuzziness factor β introduces a compression or expansion of the defined fuzzy membership function enables to adapt the relation to the respective operating range. Based on experimental test results the suitable value of β is chosen 0.5 for the arced-ness and 1 for straight-ness. The results indicate, for Farsi numbers, 0.3 for the arced-ness and 1.4 for straight-ness achieve the best recognition rate.

4.3.1 Class of Fuzzy Straight Lines

If a segment is identified as a straight line then the orientation or the angle of inclination of this segment distinguishes it further into one of the following features: vertical line, horizontal line, positive slant, and negative slant. The corresponding membership function as $\Lambda(\varphi, B, C)$ (Eq. 6) where φ represents the angle of orientation of the straight line, the bandwidth b is 90o and at c the membership value is maximum which is unity.

Vertical line: VL

A vertical line (|) has an ideal orientation of 90o or 270o. Therefore the fuzzy linguistic term *vertical line* is defined as a triangular membership function $\Lambda(\varphi;b,c)$ by the following equation:

$$\mu_{VL}(\varphi) = \mathrm{MAX}(\Lambda(\varphi, 90^\circ, 90^\circ), \Lambda(\varphi, 90^\circ, 270^\circ))$$

Horizontal line: HL

A horizontal line ( ) has an ideal orientation of 0o,180o or 360o. Therefore a fuzzy *horizontal line* is defined by a triangular membership function by the following equation.

$$\mu_{HL}(\varphi) = \mathrm{MAX}(\mathrm{MAX}(\Lambda(\varphi, 90^\circ, 0^\circ)\ \Lambda(\varphi, 90^\circ, 180^\circ), \Lambda(\varphi, 90^\circ, 360^\circ)))$$

Positive Slant: PS

A positive slant (/) has an ideal orientation of 45o or 225o. Therefore a *fuzzy positive slant* is defined as a
triangular membership function by the following equation:

$$\mu_{PS}(\varphi) = MAX(\Lambda(\varphi, 90^\circ, 45^\circ), \Lambda(\varphi, 90^\circ, 225^\circ))$$

Negative Slant: NS

A negative slant (\) has an ideal orientation of 135o or 315o. Therefore a *fuzzy negative slant* is defined as a triangular membership function:

$$\mu_{NS}(\varphi) = \mathrm{MAX}(\Lambda(\varphi, 90^\circ, 135^\circ), \Lambda(\varphi, 90^\circ, 315^\circ))$$

4.3.2 Class of Fuzzy Curved Lines

Due to the wide range of possible shapes and forms, distinguishing curved lines is a more complex task. From the large number of possible curved shape features we selected the shapes which are frequent in handwriting patterns. We divided these curves into four categories namely Circles, S or Z types of curves, loops and open arcs. While the first two classes correspond each to a linguistic term describing the shape, loops and open circles are described by several primitive linguistic terms dependent on their crossing point or the position of their starting and ending point.

Most curves in handwritten characters are wholly or partially monotone convex. Depending on the missing part and the length of the arc we can define them as: vertical curves (E,.), horizontal curves (C,E), hockey and walking sticks. The distinction of these shape categories is accomplished by using the angle of rotation, the angle of slope joining the end points of the segment, measure of arced-ness, the relative length and the area covered by the segment. All of these measures are relative and normalized in the fuzzy domain of discourse [0,1], and can be combined with the fuzzy aggregation operators.

The output of this evaluation can classify a segment to several features and by this associate several possible meanings to its shape. The decision for one of these classes can be done at a later stage by adding contextual information or linking it to global or segment related features. In case of unavailability of contextual relation, maximum grade of membership is considered as the best choice. In the following we present the structure of the feature primitives and the corresponding fuzzy membership function.

Simple curve features

First we introduce some primitive features which through the fuzzy aggregation process form features of the defined curve categories. The category of the horizontal (C,E) and vertical curves (E,.) can be described by the convexity. In case of a vertical curve (E,.), a vertical line joins the end points of the curve and in case of a horizontal curve(C,E), a horizontal line joins the end points of this curve.

Vertical curve (VC) The line joining the end-points of vertical type of curves (e.g. E,.) has typically an inclination of 90o or 270o. Therefore a fuzzy vertical curve is defined as a triangular membership function L(j;b,c): Based on the definition of the vertical and horizontal curve additional information about the direction of the convexity of the curve we can identify the shape to one of the defined categories.

Vertical Curve (VC)

The line joining the end-points of vertical type of curves (e.g.□.□) has typically an inclination of 90o or 270o. Therefore a fuzzy vertical curve is defined as a triangular membership function □(□;b,c):

$$\mu_{VC}(\varphi) = \mathrm{MAX}(\Lambda(\varphi, 180^\circ, 90^\circ), \Lambda(\varphi, 180^\circ, 270^\circ)) \qquad . \text{!!}$$

Horizontal Curve (HC)

The line joining the end-points of horizontal type of curves (e.g.□.□) has typically an inclination of 0o,180o or 360o. Therefore a fuzzy horizontal curve is defined as a triangular membership function□(□;b,c):

$$\mu_{HC}(\varphi) = \mathrm{MAX}(\mathrm{MAX}(\Lambda(\varphi, 180^\circ, 0^\circ) \\ \Lambda(\varphi, 180^\circ, 180^\circ), \Lambda(\varphi, 180^\circ, 360^\circ))) \qquad . \text{ı□.}$$

Based on the definition of the vertical and horizontal curve additional information about the direction of the convexity of the curve we can identify the shape to one of the defined categories.

C-like Curve (CL)

To distinguish a C-like curve from a D-like curve, both vertical curves, we use the qualitative statement of the left or right convexity direction. In a curve which is of vertical type (VC), if the global minimum of horizontal projections xmin is relatively much lower than the weighted average of x projections, wS, wE, of its endpoints, xS, xE then it is very likely to be a C-like curve. is the binary function which possess the truth values over the whole segment regarding the point position. That means, if a segment point is on the left hand side of the median of the end point x-projections, then this binary function is equal to 1, else it is 0. The summation function is then normalized to the universe of fuzzy discourse [0,1].

$$\mu_{CL} = \min\left(1, \frac{\sum_{i=0}^{n} l_{x_i}}{n}\right)$$

$$\text{where} \qquad l_{x_i} = \begin{cases} 1, if\,(x_i < (x_S + x_E)/2) \\ 0, else \end{cases}$$

D-like Ccurve (DL)

Symmetric to the given definition for the C-like curve, we define the D-like curve. In a curve which is of type vertical (VC), if the global maximum of horizontal projections xmax is relatively much higher than a weighted average of x projections of its end-points xS,xE, then it is very likely to be a D-like curve. This statement is represented by the summation of a binary function , which possess the truth values over the whole segment regarding the point position. That means, if a segment point is on the right hand side of the median of the end point x-projections, then this binary function is equal to 1, else it is 0. The summation function is then normalized to the universe of fuzzy discourse [0,1].

$$\mu_{DL} = \min\left(1, \frac{\sum_{i=0}^{n} r_{x_i}}{n}\right)$$

$$\text{where} \qquad r_{x_i} = \begin{cases} 1, if\,(x_i > (x_S + x_E)/2) \\ 0, else \end{cases}$$

A-like curve (AL)

Same as for the two vertical curves C- and D-like, the two horizontal curves A- and U-like differ in the direction of their upward or downward convexity. While for C- and D-like the x projection was of great importance for A-like curves the y projection and their distribution is the main identification factor. In a curve which is of type horizontal (HC), if the global maximum of vertical projections ymax is relatively much higher than the weighted average (wS, wE) of y projections of its end points (yS, yE), then it is very likely to be an A-like curve. As for the above presented features, A-like can be identified with help of the binary function . The segment points have to be above the median of the end point y-projections, to be counted. The summation function is then normalized to the universe of fuzzy discourse [0,1].

$$\mu_{AL} = \min\left(1, \frac{\sum_{i=0}^{n} a_{y_i}}{n}\right)$$

$$\text{where} \quad a_{y_i} = \begin{cases} 1, if\,(y_i > (y_S + y_E)/2) \\ 0, else \end{cases}$$

U-like Curve (UC)

In a curve which is of type horizontal (HC), if the global minimum of the vertical projections ymin is relatively much lower than the weighted average (wS, wE) of y projections of its end-points (yS, yE), then it is very likely to be a U-like curve. This is represented by the summation of a binary function . That means, if a segment point is below the median of the end point y-projections, then this binary function is equal to 1, else it is 0. The summation function is then normalized to the universe of fuzzy discourse [0,1].

$$\mu_{UL} = \min\left(1, \frac{\sum_{i=0}^{n} b_{y_i}}{n}\right)$$

$$\text{where} \quad b_{y_i} = \begin{cases} 1, if\,(y_i < (y_S + y_E)/2) \\ 0, else \end{cases}$$

5. PROPOSED METHOD

The main idea of the proposed method consists five blocks as follows:

1. Number Segmentation
2. Feature extraction
3. Fuzzy feature combination
4. Training and recognition

Figure 2 shows the diagram of the proposed method which will be presented in more details in the next sections.

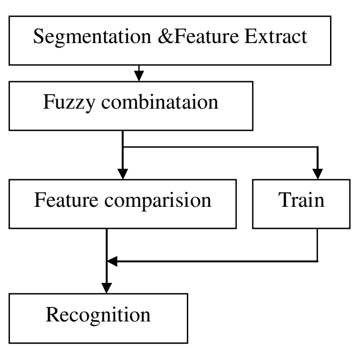


FIGURE 2: Diagram of the proposed method

5.1 Number Segmentation

In this stage the characters should be segmented and bounded by a box. We have applied the traditional bounding box methods and the results of this stage will send to the feature extraction block.

5.2 Feature Extraction

Feature extraction methods can be classified to structural and statistical features. In this paper we have extracted the structural or shape-based features. We have extracted several temporal and geometrical features and describe them with the Fuzzy method which will be described in more details.

5.3 Fuzzy Aggregation Feature Combination

The main objective of the fuzzy aggregation mechanism is to find an overall measure of certain fuzzy information from an uncertain and imprecise information data. The selection of meaningful features from a given set of handwriting data is dependent on the possible relationships among these feature categories. The meaningful feature designates the features with a good discrimination factor. To make a hierarchical structure a two phase aggregation scheme has been developed which is based on the union and weighted generalized mean aggregation connectives. The wide range of these connectives provides flexibility in finding the most suitable output feature set.

In this stage the local extracted features are aggregated to create a proper feature set. These feature sets are uniquely describe a symbol. A selected subset of Fuzzy aggregated and combined extracted features can form a unique feature for each symbol.

In the proposed method first we find the measure of arced-ness and straight-ness then these features are combined with the vertical line(VL), Horizontal line(HL), Positive Slant(PS) and Negative Slant(NS) features and the maximum value will be kept. Then the curve shaped features are combined and the maximum value is extracted. Finally the maximum of two combined values are considered as the shape feature and the maximum fuzzy value of that will be stored.

As the above statements, local extracted features will be combined in an efficient manner to achieve the best recognition rate. These features should uniquely represent each symbol. In this paper the memdanian product is applied to combine the features. This value is achieved by multiplication of straight line measure with each of line features. In the same manner for curves each feature is extracted from multiplication of arc measure with any extracted curve features as follows:

$$\mu_{AggLine1} = \mu_{Straightness} * \mu_{VL}$$

$$\mu_{AggLine2} = \mu_{Straightness} * \mu_{HL}$$

$$\mu_{AggLine3} = \mu_{Straightness} * \mu_{PS}$$

$$\mu_{AggLine4} = \mu_{Straightness} * \mu_{NS}$$

$$\mu_{AggArc1} = \mu_{ArcHC} * \mu_{CL}$$

$$\mu_{AggArc2} = \mu_{ArcVC} * \mu_{UL}$$

$$\mu_{AggArc3} = \mu_{ArcVC} * \mu_{AL}$$

$$\mu_{AggArc4} = \mu_{ArcHC} * \mu_{DL}$$

In the next stage

$$\mu_{AggArc}(i) = \mu_{aggArc}(i) * \mu_{Arc}$$

5.4 Training

In this stage for preparing the database, we have selected 40 people with different knowledge and ages. For this reason we have asked them to write numbers zero to nine several times. These people have written the farsi numbers "zero" to "nine" and the system automatically segmented and extracted the related features. If the sample existed then the number is recognized else maximum of curveness and linearity, the related fuzzy value, segment numbers and temporal features are used to train as a new value and is stored.

5.5 Recognition

In the recognition stage, first percent of the stored numbers in the database and the under recognition number are obtained for recognition, extracted feature values of the tested number are compared with the database value and the number is recognized. In this stage, each number is represented based on the structural features. If these features matched with one of the numbers in the database then the number is recognized. For maximizing the recognition rate in the farsi numbers, we have selected nine linguistic variaibles as follows:
{Zero, VeryVeryLow, VeryLow, Low, Medium, High, VeryHigh, VeryVeryHigh, Excellent}
The membership functions of these linguistic terms can be seen in Fig.3 . In this stage for recognizing the number "seven" and "eight", we have used the temporal features as well as the geometrical features. Table 1 shows a sample of fuzzy terms for recognition of numbers.

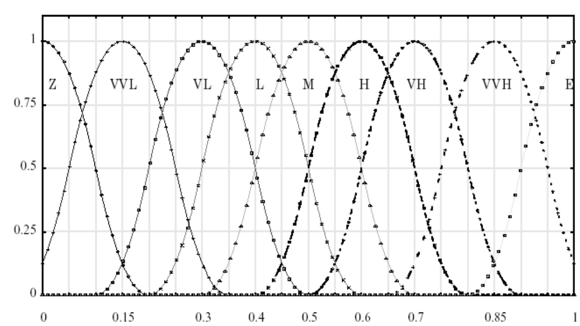


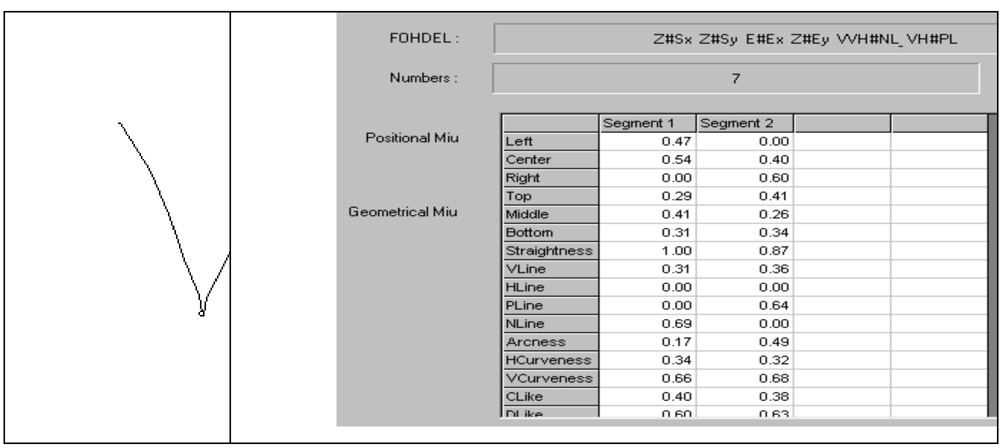
FIGURE 3: The membership functions of these linguistic terms

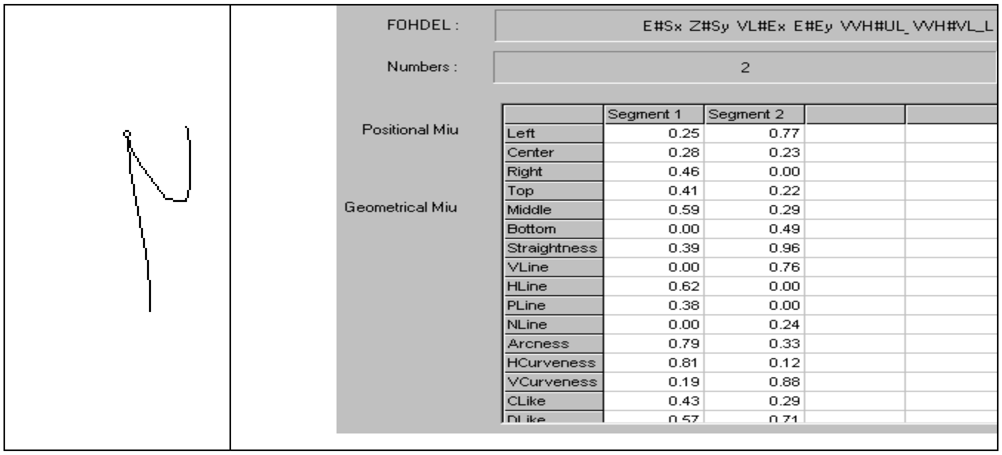
TABLE 1:. A sample of fuzzy terms for recognition of numbers.

Number	Fuzzy term	Term description
Two	VVH#UL_T, VVH#VL_L	A u-type curvein the upper part, A "T" with the highest curvness, A vertical line at the left of "L" with the highest linearity
Three	VVH#UL,VH#UL_C, E#VL_L	A u-type curvein the upper part, A u-type curve in the center of "C" with the highest curvness, A vertical line at the left of "L" with the high linearity
Seven	E#Ex, Z#Ey, VVH#NL, VH#PL	A negative slope line(NL) with the high linearity, A positive slope line(PL) with the high linearity, EX and EY represent the start and end points in the xy coordination.

6. EXPERIMENTAL RESULTS

For testing the proposed method, we have prepared a database. We have asked 50 people to write Farsi numbers 10 times with restriction and 10 times without any restriction. The proposed method indicates around 95% recognition rate over the restricted database and 74% over the non-restricted sample set. Figure 4 shows a sample of the program execution.





	Segment 1	Segment 2		
Left	0.25	0.77		
Center	0.28	0.23		
Right	0.46	0.00		
Top	0.41	0.22		
Middle	0.59	0.29		
Bottom	0.00	0.49		
Straightness	0.39	0.96		
VLine	0.00	0.76		
HLine	0.62	0.00		
PLine	0.38	0.00		
NLine	0.00	0.24		
Arcness	0.79	0.33		
HCurveness	0.81	0.12		
VCurveness	0.19	0.88		
CLike	0.43	0.29		
DLike	0.57	0.71		

FIGURE 4: A sample of the program execution

7. CONCLUSION

In this paper we introduced fuzziness in the definition of the proposed pattern features for Farsi numbers, which provided the enhancement to the handwritten character information to be stored. The proposed method was applied on the related database for the Farsi handwritten numbers. The experimental results indicate 95% accuracy on recognition of Farsi numbers over the selected database.

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