A New Approach for the Extraction of Handwriting Perceptual Codes using Fuzzy Logic

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Abstract

In this paper we present a new method to extract the elementary perceptual codes from on-line handwriting scripts. This approach uses the advantages of fuzzy sets theory to classify the on-line handwriting strokes into elementary perceptual codes and the Beta-elliptic model for the generation of complex handwriting movements. Human perceptual system is based on some basic features in order to read, write and recognize handwriting. These features are the elementary perceptual codes (EPC) which are on the base to identify patterns. The writing process implies the use of many constraints including the psychological and the physiological ones of the writer. This new method has been tested on the developed data base containing characters, digits and Arabic texts. The achieved results show successful representations of handwritten script with EPCs. Good recognition rates are also reached where the elementary perceptual codes are applied as the characteristics vector of an on-line handwriting Arabic recognition system.

Keywords: Fuzzy Logic, Handwriting generation, Beta-elliptic model, Perceptual codes, Handwriting font recognition.

1. Introduction

Handwriting is a common and natural form of communication for human being; we can see, perceive, read, write, recognize, and interpret a handwritten script in different forms and constraints. Today some of the major research challenges in on-line and off-line methods of handwriting recognition are inspired from the human reading /writing system [5].

Some psychophysical aspects of the generation and perception of handwriting highlight the different sources of variability that make handwriting segmentation and analysis difficult [16] [20]. The human perceptual system function successfully even when scripts possess a certain vagueness, noise and imprecision. It allows selecting some basic perceptual features which identify the handwriting while ignoring the rest of the uncertainties [1] [2] [5].

In order to make machines capable to read, to understand and to recognize the handwriting, it is necessary to study the manner that the human does this task easily. Perception starts with the detection of basic features that are gathered together in order to identify the pattern. In this paper, we opt to extract these basic features which are the elementary perceptual codes (EPCs) using fuzzy logic.

Based on the Beta-elliptic model for the generation of complex handwriting movements, the proposed approach uses the concepts of fuzzy logic to define the different intervals where does the static parameter corresponding to the deviation angle belongs. By this means a handwriting script is composed of elementary components called strokes approximated by elliptic strokes and these ones are transformed into EPCs with different fuzzy logic rates.

The aim of this study is to associate for each elliptic stroke an EPC with a certain degree of belongness and to use the EPCs as the characteristics vector of an on-line Arabic font recognition system.

The organization of this paper is as follows: in section 2, the proposed fuzzy model for the extraction of the different EPCs is presented. Then, we present the adequacy of the fuzzy perceptual model for the case of complex handwriting movements and examine some computer simulations. In section 4, we present a recognition system for on-line Arabic texts based on the extracted EPCs. Some applications of the obtained perceptual codes are proposed to be used in the conclusion.

2. The fuzzy perceptual model

Handwriting is an individual skill, developed to facilitate human interaction. It consists of drawing graphical marks on a surface with purpose to communicate message or idea. Many researches in different fields such as biology, neurophysiology, cognitive sciences and linguistics, try to know the manner that the human perceptual system exploits to read and write manuscripts, and several reading and writing models have been developed [5] [14] .

Reviewing the literature of the developed perceptual models, little research has been done for the on-line handwriting scripts. The majority of the developed models treat the off-line case of handwriting. We note some of these models: Snoussi S. [19], Pinales J.R. [10], Miled H. [8], Côté M. [14], Lecolinet E. [4]. For on-line handwriting, we mark few models such as Oudot L. model [12] and Anquetil E. model [3]. Our proposed method treats the on-line handwriting case.

After the review of different reading models inspired from the human system, we note that, common basic features are necessary to understand handwriting.

The generation of handwriting scripts is an important research field which aim to study and analysis the complex generated human movements. Writing a simple script with different forms and different orientations is the result of the execution of many learned programs. Therefore, to produce handwriting many neuromuscular networks are implicated. Based on these facts, we use the Beta-elliptic model for the generation of handwriting scripts.

Handwriting scripts are considered as a superposition of elementary strokes which are overlapped in time. In addition, on-line handwriting is generated via kinematic and static parameters [6]. These parameters reflect both the global timing properties of the neuromuscular networks involved in generating the movement and the global geometric properties of the set of muscles and joints recruited to execute the movement. Using the geometric parameters which indicate the curvature and direction of each stroke, we determine the corresponding elementary perceptual code. We investigate the fuzzy logic tools to determine the membership degrees of each stroke to the different deviations [11]. The architecture of the proposed model is illustrated in Figure 1.

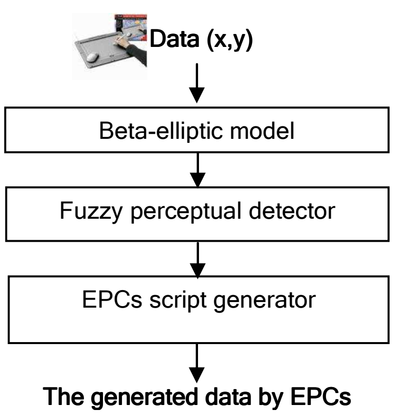

Figure 1. The architecture of the fuzzy perceptual model.

2.1 The Beta-elliptic model for the generation of handwriting scripts

The Beta-elliptic model is based on some assumptions: Firstly, it considered that handwriting movement, like any other highly skilled motor process, is partially programmed in advance. Secondly, movements are represented and planned in the velocity domain since the most widely accepted invariant in movement generation is the Beta shape of the velocity profiles. In its simplest form, the model is based on a Beta equation that describes the velocity profile in the kinematic domain and an elliptic equation that characterizes the trajectory of a simple movement [6] [7] [13].

The Beta function is defined as follows (see equation 1).

$$\beta(t,p,q,t_0,t_1)=\begin{cases}\left(\frac{t-t_0}{t_c-t_0}\right)^p\left(\frac{t_1-t}{t_1-t_c}\right)^q & \text{If } t\in\ ]t_0,t_1[\\ 0 & \text{If not}\end{cases} \qquad (1)$$

$p, q,\ t_0 < t_1 \in \mathcal{R}$

$$t_c=\frac{p*t_1+q*t_0}{p+q} \qquad p=q*\left(\frac{t_1-t_c}{t_c-t_0}\right)$$

The curvilinear velocity is as follows (see equation 2):

$$V(t)=\left((dx/dt)^2+(dy/dt)^2\right)^{1/2} \qquad (2)$$

The different elliptic parameters are (x_0, y_0, a, b, θ), which are respectively the coordinates of the ellipse center, big and small axes of the ellipse, and the angle θ that defines the deviation of the elliptic arc and the horizontal axe which is obtained by the following equation (see equation 3), where (X_0,Y_0) and (X_1,Y_1) are respectively the coordinates of the centre of the ellipsis and the starting point of the elliptic stroke.

$$\theta = \text{Arctg}\left(\frac{Y_1-Y_0}{X_1-X_0}\right) \qquad (3)$$

The architecture of the Beta-elliptic model is presented in Figure 2.

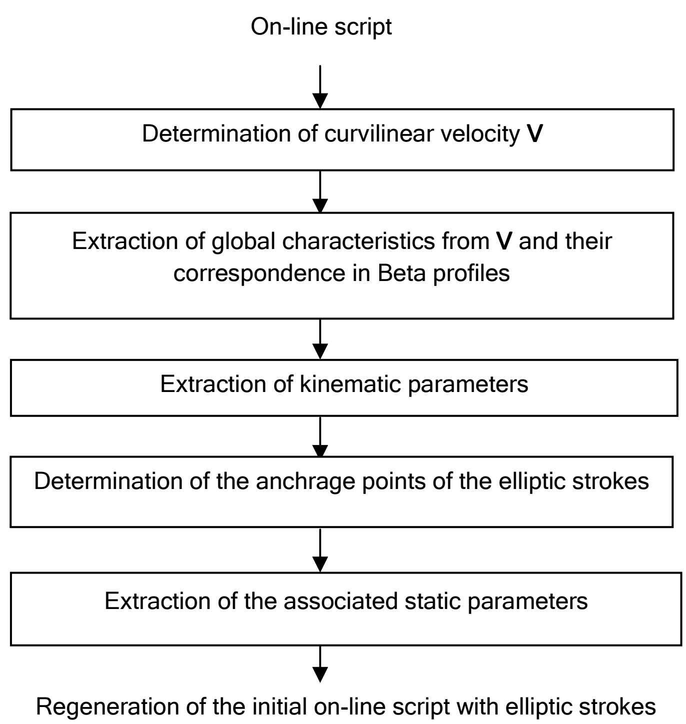

Figure 2. The architecture of the Beta-elliptic model.

Using the Beta-elliptic model, an on-line handwriting script is segmented to different elliptic strokes. These ones are approximated by elliptic strokes and classified into elementary perceptual codes as detailed in the following section.

2.2 The fuzzy perceptual detector

Reviewing the reading models such as: the Pandemonium [20], McClelland and Rumlehart [14], we note that there are basic features necessary to read, to write and to recognize a manuscript. The human perceptual system interprets these features to identify handwriting even when some information is missed. We try to approximate these latest by the elementary perceptual codes (EPCs) and we have four EPCs (see Table1). As a consequence handwriting script is described by a sequence of EPCs (see equation 4):

$$\text{Handwriting} = \{EPC_{1j}, EPC_{2j}, \ldots, EPCij, \ldots, EPC_{nj}\} \quad (4)$$

With n: the total number of strokes defined in the script and j: {1, 2, 3, 4}.

Table 1. The elementary perceptual codes.

Elementary Perceptual Code (EPC)	Shape
EPC_1 : Valley	—
EPC_2 : Left oblique shaft	/
EPC_3 : Shaft	|
EPC_4 : Right oblique shaft	\

Because of the different constraints that are involved in the writing process, the analysis of handwriting show different properties such as style, speed, position, size, orientation, lack of information's… These characteristics affect the generated form of cursive script and make difficult its treatment and analysis.

The new proposed method starts with the segmentation of the on-line script into a sequence of elliptic strokes based on the kinematic parameters extracted with the Beta model.

The main idea of this paper is to associate for each elliptic stroke an EPC with a certain membership degree. For example, for a simple stroke which is vertically aligned we can associate solely the EPC *Shaft*, but if it has a certain negative deviation, it can be perceived such as a *Shaft* or a *Left oblique shaft* as depicted in Figure 3, where the dotted curve correspond to the elliptic stroke. To resolve the problems of fuzzy perception and the uncertainty of assessed EPC, we opt to use fuzzy logic representation [1] [11]. This implies that for each stroke a certain belongingness degree will be allotted.

To evaluate the fuzzy membership degrees of the different strokes, the deviation angle extracted by the Beta-elliptic model is required.

By the means of the fuzzy perceptual detector, each stroke of the segmented on-line script is codified into EPCs with different membership degrees.

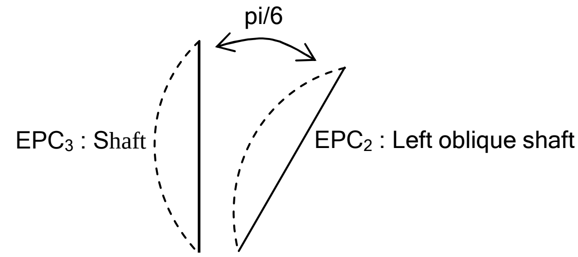

Figure 3. Example of fuzzy perception: Shaft or Left oblique shaft.

The architecture of the fuzzy perceptual detector is presented in the Figure 4.

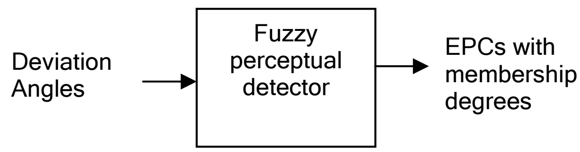

Figure 4. The architecture of the fuzzy detector.

The linguistic values associated to the deviation angles are represented in the regions of the trigonometric circle which is divided in eight proposed regions (see Table2).

Table 2. The fuzzy sub-sets and the associated linguistic values.

N°	Fuzzy sub-sets	Linguistic value
1	[-pi ; -7pi/8]	Approximately Negative pi (ANP)
2	[-7pi/8 ; -5pi/8]	Small Negative (SN)
3	[-5pi/8 ; -3pi/8]	Medium Negative (MN)
4	[-3pi/8 ; -pi/8]	High Negative (HN)
5	[-pi/8 ; pi/8]	Approximately Zero (AZ)
6	[pi/8 ; 3pi/8]	Small Positive (SP)
7	[3pi/8; 5pi/8]	Medium Positive (MP)
8	[5pi/8 ; 7pi/8]	High Positive (HP)
9	[7pi/8 ; pi]	Approximately Positive pi (APP)

In constraint to Freeman's chain code as shown in Figure 5 (a) [1], we don't use only eight directions, but the whole region contains a set of directions as illustrated in Figure 5 (b).

The sense of writing direction is an interesting property for handwriting segmentation problems; a human can write from the right to the left or in the other sense. When the writer try from the right to the left or from the left to the right, a defined stroke will belong to only one EPC or to both consecutive EPCs with appropriate membership degrees.

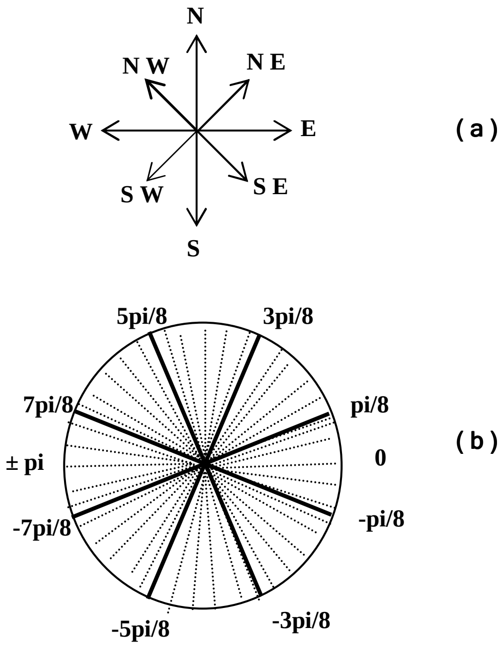

Figure 5. (a) : Freeman's chain code, (b) : the proposed regions.

The detailed architecture of the proposed fuzzy perceptual detector is presented in Figure 6. It is composed of eight sub-fuzzy-detectors, S-F-D_i : i from 1 to 8.

The input of the fuzzy perceptual detector is the deviation angle θ of generated elliptic stroke, and the outputs are a list of membership degrees of the corresponding EPCs. According to the value of the input, the corresponding S-F-D_i is activated.

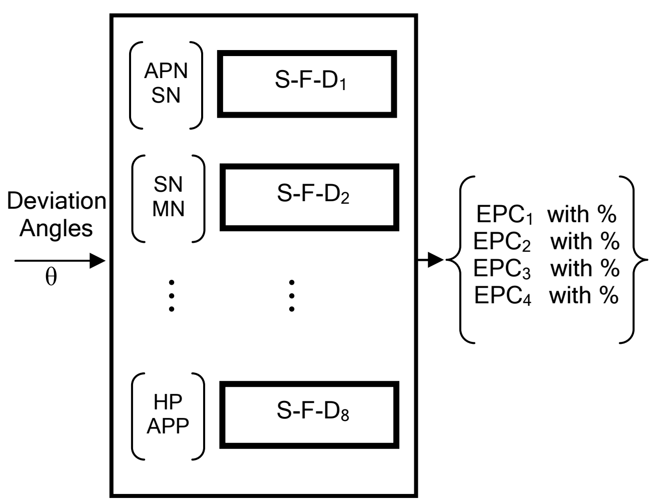

Figure 6. The detailed architecture of the fuzzy perceptual detector.

As detailed in Table2, there are associated nine fuzzy sub-sets of a deviation angle θ.

For both successive fuzzy sub-sets, an S-F-D_i is associated, so we obtain eight ones.

The input of each S-F-D_i is the deviation angle θ of elliptic strokes. The outputs are two EPCs with different membership degrees.

The S-F-D_i have the same architecture, for an appropriate input θ, correspond outputs "EPCs" with membership degrees. For example, if we consider the S-F-D_2, as presented in Figure 7, the outputs are the EPC_2: Left oblique shaft and the EPC_3: Shaft with respective membership degree.

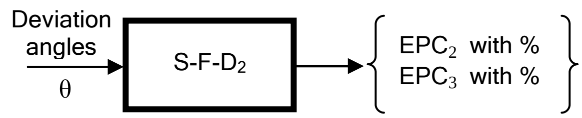

Figure 7. Architecture of the S-F-D_2.

For the same example of the S-F-D_2, the following Figure (figure 8) presents the associated fuzzy sub-sets of the input variable θ, which are SN: Small Negative and MN: Medium Negative as mentioned in Table2.

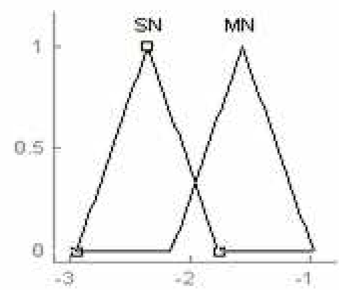

Figure 8. The fuzzy sets associated to the input variable θ of the S-F-D_2.

For each S-F-D_i, we define two fuzzy rules written in the following forms:

- **if** (θ is ANP) **then** EPC is Valley or Left oblique shaft.
- **if** (θ is SN) **then** EPC is Left oblique shaft or Shaft.
- **if** (θ is MN) **then** EPC is Shaft or Right oblique shaft.

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3. Experimental and simulation results

In order to test the validity of our fuzzy perceptual model, we have developed a large lexicon containing digits, characters and words in Arabic and Western language. This lexicon is acquired by different writers using a digitizing tablet. Different samples of scripts can be retrieved with or without pen ups. The following Figure presents the digit "3" generated by both elliptic strokes and elementary perceptual codes.

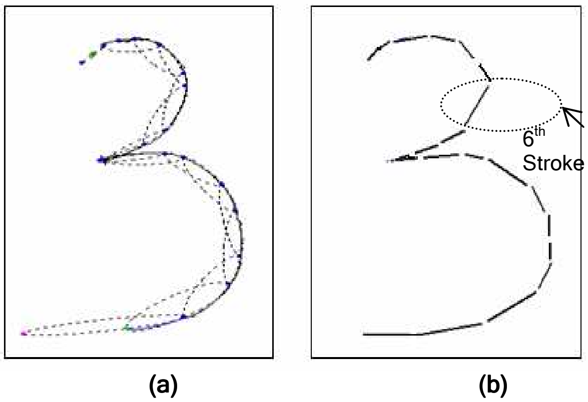

Figure 9. The digit ‘’ 3’’ generated by : (a) : elliptic strokes, (b) : elementary perceptual codes.

The digit “3” is composed by nineteen strokes. The 6th stroke can be perceived as a *Left oblique shaft* or a *Shaft* with respective membership degrees as depicted in Table3. We note that there are some strokes which belong to only one EPC by the way the problem of fuzzy perception is missed.

Table 3. The membership degrees associated to the different strokes of the digit “3”

Stroke N°	Valley %	Left oblique shaft %	Shaft %	Right oblique shaft %
1	16.59	83.41	0	0
2	100	0	0	0
3	72.60	0	0	27.40
4	0	0	100	0
5	0	20.88	79.12	0
6	36.40	63.60	0	0
7	56.74	43.26	0	0
8	0	0	100	0
9	100	0	0	0
10	100	0	0	0
11	36.32	0	0	63.68
12	0	0	0	100
13	0	0	88.77	11.23
14	0	0	100	0
15	0	100	0	0
16	17.48	82.52	0	0
17	86.10	13.90	0	0
18	100	0	0	0
19	100	0	0	0

4. Application: Arabic font recognition system

To validate the proposed model, we are interested to Arabic texts written with calligraphy forms. The Arabic calligraphy is the art of drawing the different signs of writing in decorated forms in order to make pleasure to the eyes [9]. We have different calligraphy styles which vary with the region and the period when they appeared, and the material used to be written. From these styles, we motion: Old coufique, Occidental coufique, Oriental coufique, Diwani, Diwani Djali, Naskhi, Perse (Farsi), Thoulouth, Roqa and Maghrebi. Some examples of Arabic calligraphy styles are illustrated in Figure 10.

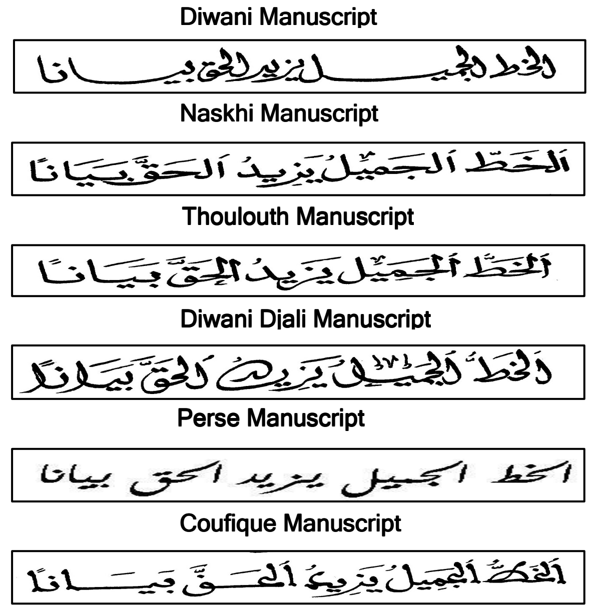

Figure 10. Examples of Arabic calligraphy fonts.

The proposed system for the on-line handwriting Arabic recognition style is a system that has a similar architecture such as an on-line handwriting recognition system. As presented in Figure 11, an Arabic text is obtained by using a digital tablet.

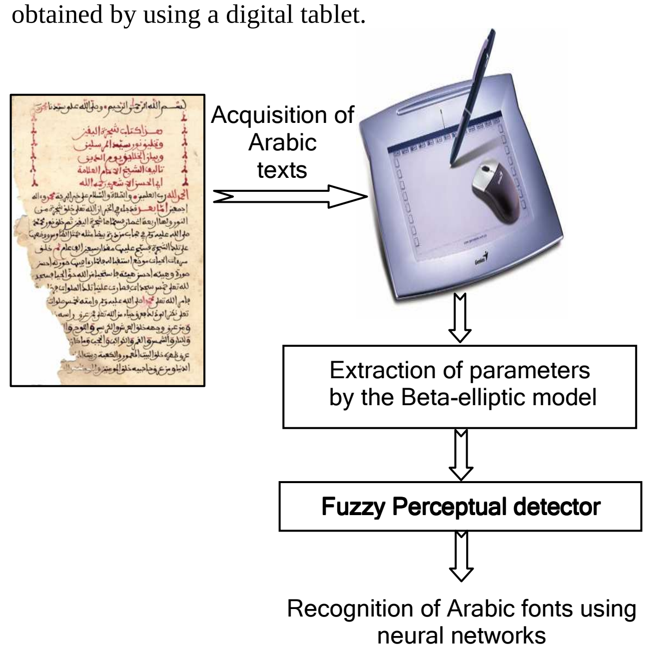

Figure 11. Architecture of on-line Arabic fonts recognition system.

By the means of the Beta-elliptic model, we extract the necessary parameters which correspond to the input of the fuzzy perceptual detector. The extracted parameters and the membership degrees of EPCs will be used as inputs of the on-line Arabic fonts recognition system.

For the recognition of Arabic texts in two different styles, we use a neural network composed of two OCONs (One Class One Network), to each style is associated a class that correspond to Multi-Layer-Perceptron Neural Networks [13] [15] [17] [18]. The architecture of our neural system is presented in Figure 12.

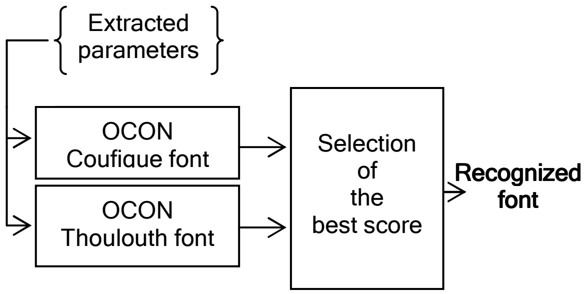

Figure 12. Global architecture of the neural network system.

In order to test the performance of the recognition system, we have developed a data base containing 200 Arabic texts written by ten writers and with two different fonts: Coufique and Thoulouth. The data base is obtained by different writers. The global recognition rate is approximately 89%. The detailed of the different rates are illustrated in Table 4, for the writing font Thoulouth we obtain up to 90%.

Table 4. Recognition rate of each Arabic font.

Font	Coufique	Thoulouth
Rate %	88	90.66

Using EPCs with different membership degrees, good global recognition rate is obtained.

5. Conclusions

In this paper, we present a new fuzzy model inspired from the human perceptual system to extract the elementary perceptual codes (EPCs: *Valley*, *Left oblique shaft, Shaft, Right oblique shaft*). This model is based on the Beta-elliptic model for the generation of on-line handwriting scripts and the advantages of the fuzzy sets theory that permit to allocate for each elliptic stroke an elementary perceptual code with a certain membership degree. The proposed model is successfully tested on a large developed lexicon. The obtained results show that the new method has been successfully used for the segmentation and the recognition of on-line handwriting. As application to our proposed model, an on-line handwriting Arabic recognition system was developed and good global recognition rate is obtained. The proposed approach is effective in automatic recognition of Arabic handwriting fonts and good recognition rate was obtained. These EPCs can be grouped to generate more global ones, which can reduce the number of the initial acquired information and be helpful for the analysis and the segmentation handwriting problems.

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