The PerTOHS Theory for On-Line Handwriting Segmentation

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Abstract

In this paper, we present PerTOHS theory for on-line handwriting segmentation, based on the fact that in order to identify patterns, our human perceptual system is based on basic features called perceptual codes. Analysing handwriting, we notice the existence of elementary and global ones. Perceptual organization of elementary perceptual codes in various constraints generates global ones, and to obtain different forms of handwriting, we proceed by combining them. We develop a new approach to improve handwriting segmentation via perceptual codes. The proposed architecture uses the Beta-elliptic model for the generation of on-line handwriting scripts, the fuzzy set theory to detect the elementary perceptual codes and the genetic algorithms for the global perceptual ones. This theory has been tested on the developed MAYASTROUN database, and IRONOFF database. The achieved results show successful representations of handwritten script via perceptual codes and good segmentation rate is obtained.

Keywords: *PerTOHS theory, Perceptual codes, On-line handwriting segmentation, Beta-elliptic model, Fuzzy theory, Genetic algorithms.*

1. Introduction

Since the appearance of computers, man has always tried to give this machine the similar behavior. He wants to make it capable to understand, to read, to write, to segment and to recognize automatically the handwriting, in order to do this task, it is important to study the manner that we do it. So many studies are made to analyse the nature of handwriting inspired from the human perceptual system, in this purpose several theories of visual perception are reviewed, in addition to some reading/writing models [20,26,33,34,39].

This paper presents PerTOHS, the new perceptual theory for on-line handwriting segmentation. The basic idea for PerTOHS theory is that handwriting is a sequence of basic features corresponding to perceptual codes. Analysing handwriting, we note the existence of two types of perceptual codes, the first one corresponds to elementary perceptual codes (EPCs), which are perceptually grouped to form global ones (GPCs). To validate our appraoch, we propose an architecture for PerTOHS theory uses in the first stage the Beta-elliptic model for the generation of complex handwriting movements, for the perceptual encoding system, we use the concepts of fuzzy logic to define the different intervals where the static parameter corresponding to the deviation angle belongs, and the genetic algorithms to detect GPCs. By this way a handwriting script is composed of elementary components approximated by elliptic strokes and these ones are transformed to EPCs with different fuzzy logic membership degrees, then, these EPCs are combined in order to obtain GPCs. The segmentation of handwriting is an important step for its analysis and it allows its decomposition into sub-patterns, features and primitives. Different studies on handwriting segmentation are presented in the following works [3, 11, 12, 13, 37, 42, 43, 47].

We are interested to improve the field of on-line handwriting segmentation, where some related works are exposed in the following studies [1, 18, 27, 40].

The organization of this paper is as follows: in section 2, we present an overview of theories of visual perception and some reading/writing models. In section 3, we describe PerTOHS theory for on-line handwriting segmentation. Then, we detail elementary and global perceptual codes used to segment handwriting. Next, we deal with the presentation of PerTOHS architecture. Section 4, examine some experimental and simulation results on on-line handwriting. Finally conclusions and future works are mentioned.

2. Overview

In literature, some studies were made in order to understand perception. The study of visual perception offers considerable evidence that the world, the image, or the handwriting is not given but constructed and programmed in advance. The aim of this part is to introduce general theoretical approaches in visual perception. In the literature, we mark the existence of different theories of visual perception treating the case of objects forms and images. In the seventeenth century, the first one is the empiricism theory started in the Greek area with Aristote in which experience is the only source of cognition, so our cognitions are derived from experiences. In the same period we have also the appearance of the rationalism theory. In the twentieth century, some theories appeared. Behaviourism theory considers that Human is assimilated to a black box, and her sensation is the result of an environment stimulus. The founders of this psychological movement are Thorndike, Watson and Skinner. They hope with this movement to make psychology an experimental science. For the same period, the Gestalt theory or "form as a whole" appeared. Similar elements (figure) are contrasted with dissimilar elements (ground) to give the impression of a whole. The meaning of the word *gestalt* is global form or organised form. This theory was founded in 1910 by Wertheimer. He says that "*a set is different from the sum of their parts*". Koffka once asked a famous question "*Why do things look as they do?*". People organize what they see and the context is very important in perception. This approach emphasizes that we perceive objects as well-organized patterns rather than separate component parts. The perceptual organization of the elements is guided by some factors described as Gestalt laws principles corresponding to:

- *Similarity*: where we tend to group objects with similar properties (color, shape, texture).
- *Figure-ground*: The Figure-Ground phenomenon captures the idea that in perceiving a visual field, some objects take a prominent role while others recede into the background. Your mind can perceive them as two distinct shapes but only focus on one or the other.
- *Proximity*: where we tend to assemble nearby objects, and objects that are near each other seem to be grouped together.
- *Continuity*: predicts the preference for continuous figures. For example, we have a tendency to assign objects to an entity that is defined by smooth lines or curves.
- *Closure*: the principle of closure applies when we tend to see complete figures even when parts of information are missing. Our minds react to patterns that are familiar, even though we often receive incomplete information. Humans are so familiarized to see closure that we sometimes close things that are not. Objects are grouped together if they seem to complete some entity.
- *Symmetry*: symmetrical images are perceived collectively, even in spite of distance.

These laws of perceptual organization tend to encourage the emergence of perceptual forms and to promote the grouping of those forms [15].

In 1950, we mark the apparition of the Ecological theory or Gibson's theory of direct perception founded by James Gibson. He referred to his theory as an ecological approach, he believed that perception was direct, by which he meant that perception is not mediated by a process of inference, and precepts are not constructed from sensations. He emphasised relations in the environment. All necessary information to perception are presented into environment. It is determined by observatory moving. Gibson (1976) says: "*… perceiving is an act, not a response, an act of attention, not a triggered impression, an achievement, not a reflex*" [15, 24]. The following theory is the computational one, illustrated by the study of David Marr in 1982; he says "*Vision is a process that produced from images of external world a description that is useful to the viewer and not cluttered with irrelevant information*". Perception proceeds as an information-processing system organized into successive stages: the primal sketch, the $2^{1/2}$D sketch and the 3-D model representation [15]. As a development of Marr's approach, we have the Recognition By Components (RBC) approach or a: Biederman one. This theory treats visual form recognition of objects in the real world. It involves 3-D representations of objects parts, these components of objects are called geons (geometrics Ions), and so an object is a combination of geons. In this theory, an object is still recognized even some parts are deleted, missed or hidden [9]. Reviewing these different theories of visual perception, we note that all of them treat images, objects and forms. So, we proceed to propose a new perceptual theory for handwriting as detailed in section 3.

To analyse handwriting, we survey reading/writing models. Reading a word is recognizing it, so word recognition implies the process of visual information, and its representation at the linguistic level. Psychologists call lexical access the process by which humans associate the image of the word with its meaning. Most lexical access models take into account the orthographic (the way the word is written) and the phonological aspects (the way the word is pronounced) of the word [10]. Many experiences were made in order to understand the way that human can read and write handwriting. For example, McClelland notices that learning information concerning a word or another object is the result of the memory traces led by the different and individual experiences that man had. He calls this "*enumeration of the specific experiences*". This enumeration seems to be expensive and require a mass of data and a high capacity memory as well as a means of researches and accesses to these data.

Other experiences were made to show that the necessary time for reading one word is 500 milliseconds. The questions are: what's happened during this half second and how the perceptual visual system recognizes the word? And how can we recognize a set of letters such as a familiar form [35]?

Several reading and writing models have been developed in order to understand the handwritten recognition processes. The first one is the Pandemonium model by Selfridge in 1959. This model is hierarchically composed of detectors named "demon" which function in parallel way [33,26]. In 1969, the Logogen model by Morton, it associates at every Logogen a threshold indicating the necessary activation level to recognize the word partner [10]. McClelland and Rumelhart present the interactive activation model in 1981, in this model, a connexion's architecture of three layers hierarchically organized was used (primitive, letters and words). They present the word superiority effects: the necessary time needed to recognize one letter in a word is less than a time needed to recognize letter in isolation position [10, 35].

In 2001, we note the apparition of the Beta-elliptic model for on-line handwriting generation (as detailed in section 3.3) [4, 5, 6, 7]. Using the Beta-elliptic model, an on-line script is characterized by Beta-elliptic parameters and segmented into different strokes. These strokes are modelling with elliptic arcs and classified into elementary perceptual codes as detailed in the following section. Reviewing the literature of the developed perceptual models based on reading writing models such as McClelland and Rumelhart, little research has been done for the on-line handwriting scripts. These models are used for the offline handwriting style expected the Beta-elliptic model. The majority of the developed models treat the off-line case of handwriting. We note some of these models: Snoussi S. [44], Pinales J.R. [33], Miled H. [26], Côté M. [10], Lecolinet E. [19].

For on-line handwriting, we mark few models such as Oudot L. model which propose an on-line texts recognition system based on the activation verification model [32], FOHDEL a fuzzy handwriting description language or the syntactic description of handwritten patterns [23], the perceptual model of on-line handwriting drawing, where the proposed method for segmentation for cursive letters and words is based on the detection of a set of perceptual anchorage points and structures [3], FOHRES model which present a fuzzy online handwriting recognition system based on the advantages of fuzzy sets theory for the classification of handwritten in different stages of processing [23].

So, reviewing these models, we note that the same fundamental problem in handwriting analysis is its segmentation into features. This problem is related to natural form of the generated handwriting with different styles. Consequently, we are interested to improve this research filed by proposing PerTOHS theory and an encoding system for the on-line handwriting case.

3. PerTOHS : A new perceptual theory for on-line handwriting segmentation

PerTOHS is the abbreviation of **Per**ceptual **T**heory for **O**n-line **H**andwriting **S**egmentation.

3.1 PerTOHS: the proposed theory

Our perceptual theory for handwriting is based on the following assumptions:

- All we perceive is a form;
- Form is a principal criterion to identify what we see;
- Recognition of form is made even if some of their parts are missing;
- Handwriting and objects are different forms;
- Handwriting is obtained by hand movement creating forms;
- Handwriting is a visual scene perceived in order to decode the contained message.

The perception of form begin with the identification of some primitive features, when primitive features are identified, our perceptive system tries to group them in appropriate form in order to obtain a comprehensible visual scene. So, as a basic hypothesis for our study, handwriting is also a special form.

All presented theory treats the cases of forms and images, any one theory interest on handwriting that is why we propose a new theory for handwriting. Based on the hypothesis that handwriting is considered as a form, we propose a perceptual theory for handwriting segmentation inspired from the presented ones in section 2. As defined in the first part, handwriting is a graphical mark on a paper or other, and it is composed from perceptual codes grouped together in order to obtain a recognizable script even some information are missing.

In order to study handwriting, to analyse, to understand the phenomena of reading/writing and to make ergonomic communication between human beings and machines, we are interested to the on-line handwriting case, where the human writes on a special digital tablet, and he follows his own script on the screen of computer. So, our proposed theory is inspired from some visual perceptual theories of and reading/writing model. PerTOHS theory is based on the combination of the Gestalt theory [15], the recognition by components (RBC) approach [9] and the Beta-elliptic model [4, 5, 6, 7] for the generation of handwriting script. So, we use the principals of the Gestalt theory [15] (similarity, proximity and continuity), and the basic idea of the RBC approach which consists that an object is composed from different geons and is still recognized even some parts are missing or hidden.

To understand the complex system of information processing such as handwriting recognition, it is necessary to divide the problem in three layers: sensation, perception and recognition. The first stage concerns the sensation of the script; perceiving the visual shape which perceives the 2-D display of the handwriting as an image [24]. Our contribution is in the second stage of perception; this stage of perception concerns the detection of some perceptual codes composing handwriting. To segment one script, we detect global perceptual codes composed of sets of elementary perceptual ones. This stage of perception is divided into two layers: in the first one, we detect the elementary perceptual codes (EPCs), and in the second one we detect the global ones (GPCs). In the stage of recognition, the set of perceptual codes detected must be gathered in the brain in order to recognize the script.

3.2 PerTOHS and perceptual codes

Handwriting is defined as a sequence of perceptual codes: global and elementary ones. Note that global perceptual codes (GPCs) are also a sequence of elementary ones. In this section, we detail all these perceptual codes with some examples.

To introduce these perceptual codes, if we use for example these three GPCs (a *Right half opening occlusion* ⊂ , a *Shaft* | , a *Valley* —) different forms of letters can be obtained such as the letters **"d"** , **"q"** , or the Arabic letters **"ح"**, **"ـع"**, **" hamza"** . For example, the GPC "*Right half opening occlusion*" can be obtained by this sample of different EPCs combinations (*Valley, Valley, Left oblique shaft, Shaft, Right oblique shaft, Valley, Valley*). Gathering these different EPCs (*Shaft, Shaft, Left oblique shaft, Shaft, Shaft, Shaft*) the GPC "*Shaft*" is obtained. We remark that handwriting is a sequence of perceptual codes in a definite arrangement, and from the same set of GPCs we can obtain different handwriting scripts.

Reviewing the reading models such as: the Pandemonium [26, 33, 35], we remark that there are common basic features necessary to read, to write and to recognize handwriting. We try to approximate these basic features by perceptual codes, elementary and global ones. The elementary perceptual codes are illustrated in Table 1 [28 ,30 ,31].

Table 1: The elementary perceptual codes.

Elementary Perceptual Code (EPC)	Abbreviation	Shape
EPC_1: Valley	Valley	—
EPC_2: Left oblique shaft	L-o-s	/
EPC_3: Shaft	Shaft	|
EPC_4: Right oblique shaft	R-o-s	\

Global perceptual codes (GPCs) are obtained by the combination of elementary ones. Analysing handwriting we obtain different GPCs, classified with their form into two classes: simple and complex one. Table 2 presents the different GPCs, their classification, abbreviation and the corresponding shape, [28 ,30].

Table 2: The global perceptual codes for handwriting: GPCs.

	N°	Global Perceptual Code	Abbreviation	Shape
Simple GPC	1	Valley	Valley	—
	2	Left oblique shaft	L-O-S	/
	3	Shaft	Shaft	|
	4	Right oblique shaft	R-O-S	\
Complex GPC	5	Right half occlusion	R-H-O	⊂
	6	Left half occlusion	L-H-O	⊃
	7	Up half occlusion	U-H-O	∪
	8	Down half occlusion	D-H-O	∩
	9	Occlusion	OCC	o
	10	Ain	AIN	ع

Handwriting is defined as a form of object, and based on the following assumption: perception starts with the identification of basic features that are gathered into more complex objects, until we identify an object. So, handwriting is a combination of basic features called perceptual codes. As a consequence of the combination of elementary perceptual codes, we obtain the global ones, until we identify a form of handwriting [30]. Handwriting is described by the Eq. 1:

Handwriting = {GPC_{1i}, GPC_{2i}, …, GPC_{ki}, … ,GPC_{ni}} (1)

With n: the total number of GPCs composing handwriting and i: {1, : , 10} corresponding to GPC (see Table 2). As mentioned that GPC is a sequence of EPCs, so a GPC is described by Eq. 2:

GPC = {EPC_{1j}, EPC_{2j}, …, EPC_{ij}, … ,EPC_{mj}} (2)

With m: the total number of strokes identified in the script by the Beta-elliptic model and j: {1, 2, 3, 4} corresponding to EPC (see Table 1).

3.3 The PerTOHS architecture

Handwriting segmentation is an important step for handwriting analysis, we present a new approach for on-line handwriting segmentation with perceptual codes. In our proposed architecture, the input is an on-line script which is divided into elliptic arcs by the means of the Beta-elliptic model, and then we proceed by the detection of the different perceptual codes in the segmentation stage. To validate this new theory, we propose the following PerTOHS architecture by adding the perceptual encoding system as illustrated in the Figure 2.

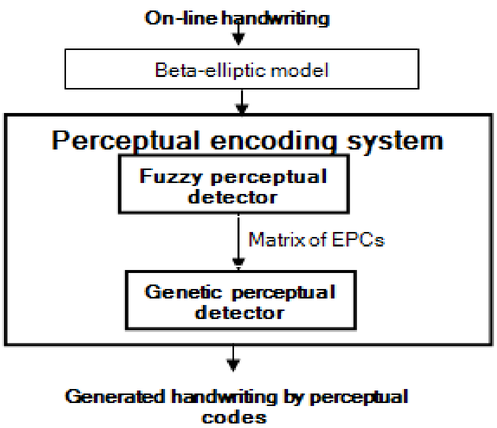

Fig. 2 The architecture of PerTOHS theory.

As presented in Figure 2, our architecture is based on the Beta-elliptic model [4, 5, 6, 7]. This model considers that handwriting movement, like any other highly skilled motor process which, is partially programmed in advance. It also supposes that 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. It is based on the Beta equation that describes the velocity profile in the kinematic domain and the elliptic equation that characterizes the shape of a simple movement. The Beta function is defined as follows in Eq. 3.

$$\beta(t,p,q,t_0,t_1) = \begin{cases} \left(\dfrac{t-t_0}{t_c-t_0}\right)^p \left(\dfrac{t_1-t}{t_1-t_c}\right)^q & \text{If } t \in \,]t_0, t_1[\\ 0 & \text{If not} \end{cases} \quad (3)$$

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

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

The curvilinear velocity is described by Eq. 4:

$$V(t) = \left((dx/dt)^2 + (dy/dt)^2\right)^{1/2} \quad (4)$$

The Beta-parameters are: t_c, $\Delta = t_1 - t_c$, p, q, H: Beta amplitude.

The different elliptic parameters correspond to: 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 equation n°5, 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.

$$\boldsymbol{\theta} = \mathbf{atan}\left(\frac{y_1 - y_0}{x_1 - x_0}\right) \quad (5)$$

Using the Beta-elliptic model, an on-line handwriting script is segmented into different elliptic strokes, and each one has the following beta-elliptic parameters: t_c, $\Delta = t_1 - t_0$, p, q, H, x_0, y_0, a, b, θ.

3.3.1 Fuzzy logic for the detection of elementary perceptual codes

Because of the different constraints which are involved in the writing process, the analysis of handwriting shows different properties such as style, speed, position, size, orientation, lack of information… These characteristics affect the generated form of cursive script and make difficult its treatment and analysis. The proposed method starts with the segmentation of the on-line script into a sequence of elliptic strokes based on the Beta-elliptic model for the generation of complex handwriting scripts.

The main idea of this section is to associate to each elliptic stroke obtained an EPC with a certain membership degree [28, 30, 31]. To resolve the problems of fuzzy perception and the uncertainty of assessed EPC, we opt to use fuzzy logic representation [14, 41]. This implies that for each stroke, a certain belongingness degree will be allowed. By means of the fuzzy perceptual detectors, each stroke of the segmented on-line script is codified into EPCs with different membership degrees [28, 31]. In constraint to Freeman's chain coding as presented in Figure 3(a), we don't use only eight directions, but the whole region contains a set of directions as shown in Figure 3(b).

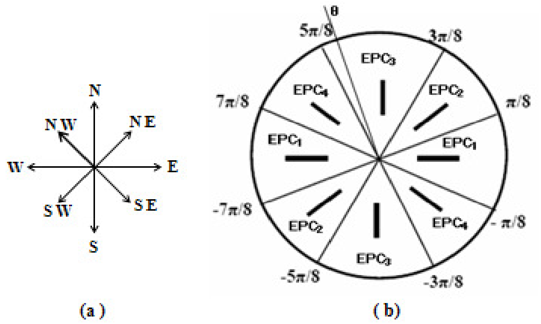

Fig. 3 Deviation direction: (a): Freeman's chain code, (b) : The proposed deviation angles regions and EPCs on the trigonometric circle.

Between two successive regions of θ and on their limits, we consider an overlapped interval values (noted: **cst**) where we have a problem of indecision of the corresponding EPC, so we must resolve this fuzzy perceptual problem. For the example of the **θ** depicted in Figure 3 (b), we have a certain vagueness on the decision of the corresponding EPC. The The EPC related to the elliptic stroke of presented **θ** may be the EPC_3 (*Shaft*) or the EPC_4 (*R-o-s*) ? To resolve this perceptual problem and the uncertainty of assessed EPC, we go for to use fuzzy logic theory [2, 23, 28, 30, 3 allow at each EPC a certain membership degrees.

the deviation angle extracted by the Beta-elliptic model, we evaluate the fuzzy membership degrees of the different strokes of on-line handwriting. Figure 4 presents some examples of fuzzy perception problems.

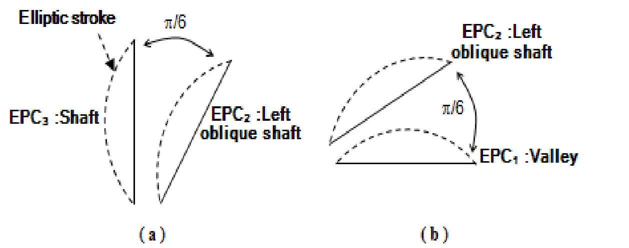

Fig. 4 Example of fuzzy perception problems: (a) : Shaft or Left oblique shaft, (b) : Valley or Left oblique shaft.

For the same example of an on-line handwriting and testing with different values of **cst** such as $\pi/8$, $\pi/12$, $\pi/16$; we notice the differentiability of the obtained membership degrees values of EPCs. After comparisons between these different obtained values, we opt to use **cst** equal to $\pi/16$ which offer the appropriate obtained values and the best corresponding EPCs on the trigonometric circle. In the following figure, we present an example of perceptual problem decision on the belongings of θ presented on Figure 5.

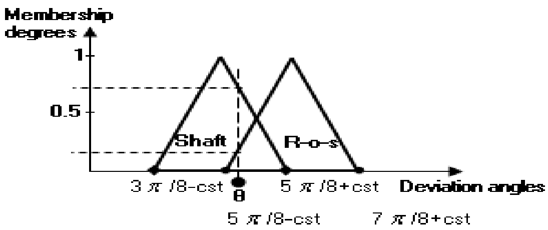

Fig. 5 Example of perceptual problem decision using fuzzy logic.

Using the concepts of fuzzy logic, it correspond to the EPC_3 (*Shaft*) with 67% of membership degrees and to the EPC_4 (*R-o-s*) with 33 % of membership degrees. Note that θ is equal to $(4.83/8)\pi$.

By means of the fuzzy perceptual system, each elliptic stroke of the segmented on-line script is codified into EPCs with different membership degrees. The input of the fuzzy perceptual system is the deviation angle **θ** of generated elliptic stroke, and the outputs are a list of membership degrees of the corresponding EPCs [30, 31]. To evaluate the fuzzy membership degrees of the different strokes, the deviation angle extracted by the Beta-elliptic model is required. The linguistic values associated to the deviation angles are represented in the regions of the trigonometric circle and illustrated in Table 3.

Table 3: The fuzzy sub-sets and the associated linguistic values.

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

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 each 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 [28, 31].

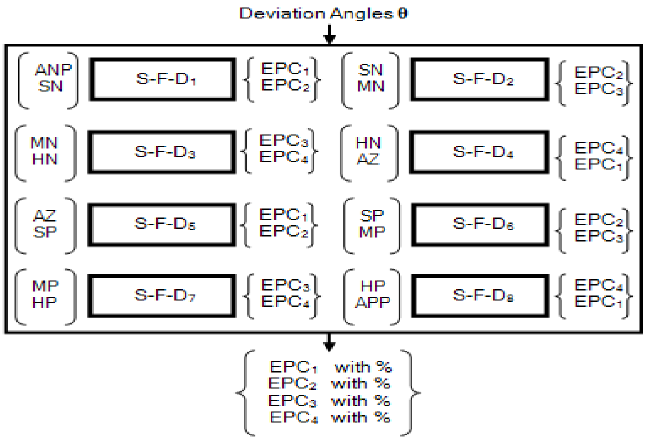

Fig. 6 The detailed architecture of the fuzzy perceptual detector.

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.

The generated fuzzy rules can be written in the following form:

- **if** (θ is ANP or θ is AZ or θ is APP) **then** EPC is Valley.
- **if** (θ is SN or θ is SP) **then** EPC is L-o-s.
- **if** (θ is MN or θ is MP) **then** EPC is Shaft.
- **if** (θ is HN or θ is HP) **then** EPC is R-o-s.

As a result, using the fuzzy perceptual detector, an on-line handwriting will be characterized by a matrix of different membership degrees of all EPCs.

3.3.2 Genetic algorithms for the detection of global perceptual codes (GPCs)

a- Genetic algorithms properties

As defining, handwriting is a sequence of perceptual codes, and by perceptual organization of elementary ones, we obtain global ones. GPC detection is considered as a tool for reduction data. As mentioned in equation 2, a GPC is obtained by combining different elementary perceptual codes, note that the same GPC can be obtained by different EPCs sets [28]. To detect GPCs, some constraints are mentioned such as: many possible combinations of EPCs that can form the GPCs, the existence of large variability of combination possibilities concerning either the number or the type of EPCs that form an appropriate GPC, the variance of GPCs length vector. Consequently, a large set of GPCs features is assumed to be available in order to identify the corresponding GPCs of the initial handwriting. For these reasons, this problem of the tolerable choice can consequently be regarded as a problem of optimization. So, we opt to use genetic algorithms (GAs) as a tool to find an optimal subset of GPCs. GAs are adaptive methods used to solve search, optimisation and non-linear problems. GA starts with an identification of the population which composed from a set of solutions. These solu composed by chromosomes. After evaluating each chromosome using a fitness function, we use to update population these three different operators: selection, crossover and mutation. A generation corresponds to an iteration of these three previous operators. This process is repeated until a termination criterion is not satisfied which correspond to a reaching a predefined time limit or number of generations or population convergence [16, 17, 25, 28, 36, 46]. Figure 7 illustrates the architecture of the proposed global perceptual codes detectors using genetic algorithms. For each GPC a genetic algorithm is developed, which treats a matrix of elementary perceptual codes and generates a set of GPC forming the initial script. The detected GPCs may contain redundancies (GPCs that have the same location in the script with different fitness values) or overlapping between some GPCs. To resolve theses problems a refinement stage is added in order to obtain all GPCs of the script.

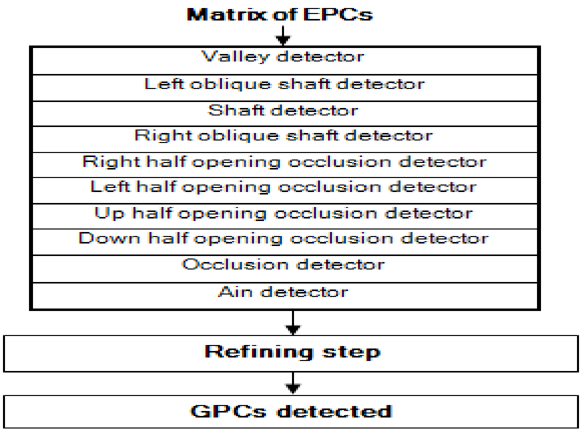

Fig. 7 The architecture of the genetic perceptual system.

To each GPCs presented in Table 2, we associate a genetic algorithm detector with the following properties:

- *Chromosome representation :* unlike the traditional genetic algorithms (GAs) that use binary bit strings to encode a chromosome.

The chromosome corresponds to GPC which is a set of EPCs with their different membership degrees as shown in Eq 6. and corresponded at each row of the initial population presented in Table 4.

Chromosome = {membership degrees of EPCs} = {gene} (6)

A membership degree of an EPC is a gene.

- *Initialization of the population:* the initial population is generated randomly with size corresponding to 100 chromosomes in rows and **n** in columns. The size of each chromosome varies from **12** to **n**: 12 is the minimum size of a GPC and **n** is the maximum number of EPC forming the original handwriting. In process of the generation of the initial population, if there are chromosomes whose size is less than **n** we complete it by a set of zero. The cells correspond to genes which indicate the membership degrees of a EPCs. Table 4 presents an example of an initial population.

Table 4: Example of the initial population.

Valley	L-o-s	shaft	R-o-s		Valley	L-o-s	shaft	R-o-s
...	...	...	...	...	...	...	...	...
7,58	92,42	0,00	0,00	...	62,38	0,00	0,00	37,63
18,17	81,83	0,00	0,00	...	93,52	6,49	0,00	0,00
24,80	75,20	0,00	0,00	...	24,32	75,69	0,00	0,00
82,47	0,00	0,00	17,54	...	56,61	0,00	0,00	43,39
59,07	40,93	0,00	0,00	...	94,88	0,00	0,00	5,12
11,25	**0,00**	**0,00**	**88,75**	...	**54,94**	**0,00**	**0,00**	**45,06**
49,85	50,15	0,00	0,00	...	50,36	49,64	0,00	0,00
94,78	0,00	0,00	5,22	...	37,77	62,23	0,00	0,00
...	...	...	...	...	...	...	...	...

For the row with grey background from the Table 4, the first quadruplet correspond to the EPC "*R-o-s*" with membership degrees equal to 88,75% and the final one correspond to the EPC "*Valley*" with 54,94%.

- *The fitness function*: is one of the important steps in GA, which evaluate the quality of each chromosome in a population. It is defined as the percentage of correspondence between the chromosome and a part of handwriting script based on the comparison between the genes of the chromosome and the membership degrees of EPCs composing the initial script. Note that, these comparisons are made by quadruplet, where we try to find in the same position a gene with values up to 50% corresponding to a membership degree in the EPCs matrix. If this search is not marked, we go to the next quadruplet, until we find a correspondence in order to begin the evaluation of the fitness function values. If there are at least two successive quadruplets of genes of the required GPC that have no correspondence in the matrix of EPCs, we have to stop the research process. If the number of genes with found is greater than or equal to 12 (three successive quadruplets corresponding to the smallest size of GPC), we retain the initial and final position of the GPC in the matrix of EPCs.

Eq.7 describes the fitness function.

$$f = \frac{\sum_{i=1}^{n} (G\_EPC)}{n / 4} \quad (7)$$

With:

n: the length of the chromosome from the initial population divided by 4 corresponding to the number of EPCs.

G_EPC: a gene from a chromosome corresponding to an EPC from the script with membership degrees up to 50 %.

Figure 9 presents an example of calculation of a fitness function, and a detailed example of the used fitness function is given. In this example, we try to search the existence for the chromosomes corresponding to GPCs: *Shaft* and *Valley* on a given example of EPCs matrix for an on-line script. We begin by a comparison on genes of the first quadruplet and the first quadruplet from the EPCs matrix.

For the GPC "*Shaft*", the correspondence between values on the first quadruplet is founded, so we retain the initial position (**Ip**=1). We continue with this process, but we don't find correspondence even in the second and in the third quadruplet. The fitness function value is equal to 32,62% as presented follow:

$$f(GPC\_Shaft) = \frac{97{,}86}{12/4} = 32{,}62\%$$

For the GPC "*Valley*", the correspondence between values on the first quadruplet is founded, so we retain the initial position (**Ip**=5). We continue with this process, we find correspondence in the second and in the third quadruplet. In the fourth quadruplet, there is not correspondence, so we retain the final position (**Fp**=20)

The fitness function value is equal to 61,92% as calculated follow:

$$f(GPC\_Valley) = \frac{(83{,}10 + 99{,}41 + 65{,}15)}{16/4} = 61{,}92\%$$

So the retained GPC in Figure 8 is a "*Valley*" with a fitness function value equal to 61,92%, which begin from the initial position **Ip** = 5 and finish in the final posit 20.

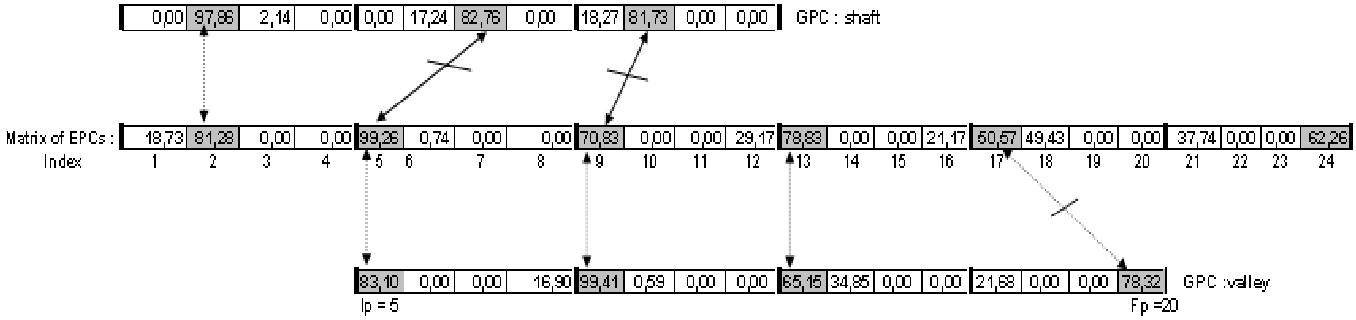

Fig. 8 Example of the fitness function evaluation for the GPCs "Shaft" and "Valley".

• *Selection*: Selection in genetic algorithms aims to give a higher probability for reproduction to better individuals in a population where the principle of "survival of the fittest" is applied. Here, we keep the best parent (based on the fitness value) from the current population as one of the candidates in the next generation. For the other candidates, the roulette selection scheme is used. The individuals selected will then go through crossover and mutation.

• *Crossover*: the essence of any crossover operator is to exchange the components of two parents to form new child. In our experiments, it was found that a crossover probability Pc=0.6, or higher which produce good results. Single-point crossover is realized by cutting the chromosomes at a randomly chosen position and then substitutes the segments between the two parents.

• *Mutation*: Mutation is a genetic operator that alters one gene values in a chromosome from its initial form, which give a new gene values to be added to the population. With these new gene values, the genetic algorithm may be able to arrive at better solution than was previously possible.

b- Extraction criteria's for simple GPCs

The class of simple GPCs is composed from: *Valley, Left oblique shaft, shaft* and *Right oblique shaft*. For their detection, we use the same criteria's. We opt to search for consecutive set of EPCs corresponding to the same GPCs to be detected. For example a GPC "*Valley*" is a sequence of EPCs "*Valley*" with various lengths (minimum 3 consecutives EPCs *Valley*) or a sequence of EPCs "*Valley*" with certain vagueness in handwriting process in which we authorised the presence of the EPC "*Left oblique shaft*" or the EPC "*Right oblique shaft*" in its middle. If the length of the searched GPC is equal or greater than 12, we retain this GPC with initial and final position in the EPCs matrix of the script and the fitness function value.
The following table presents an example of the GPC "Left oblique shaft" and its composed EPCs.

Global Perceptual Code (GPC)	Shape	Examples of combination of EPCs
Left oblique shaft	/	

Table 5: Some examples of the GPC "Left oblique shaft" elaborated from different EPCs.

c- Refinement
To obtain optimal GPCs of the initial script, and after the detection of the different GPCs composing the initial script, we proceed by the refining step. This step is based on the comparison of initial and final position of each obtained GPC and the fitness function value [28].
In this step we generally proceed by:
Refinement in the same GPC: we retain all possible positions of this GPC in the initial matrix of the script. Some presented cases appear:

- If two GPCs have the same initial and final position in the script, we retain the GPC with higher fitness value,
- If two GPCs have the same initial position in the script, we choice the GPC with maximum final position.

Refinement by class of GPCs (Complex and Simple GPCs) : We proceed by an internal refinement in the each class of GPCs. The different tests were made on the initial and final positions of each GPCs.
Refinement in obtained results of GPCs: in this case, we go on:

• Maintaining all complex GPCs, if the simple ones do not appear in the script,
• Retaining all simple GPCs, if the complex ones do not exist in the script,
• Keeping all simple GPCs presented before or after complex ones,
• The elimination of complex GPC which are overlapped each others (respectively: simple GPCs),
• Exclusion of the simple GPCs appeared in the complex ones.

4. Application to on-line handwriting segmentation

In order to test the performance of our proposed theory, we are interested in on-line handwriting segmentation on MAYASTROUN and IRONOFF databases.

4.1 MAYASTROUN database

In order to test the validity of our proposed theory for on-line handwriting segmentation, we have developed MAYASTROUN database. In its first version it contains 400 letters, 300 digits, 200 words and 200 Arabic texts [29] acquired by 15 writers. Using a digital tablet, we obtain an output large file contains three columns: the two first columns indicates the coordinates of the stylus, and the third one indicate pen ups (0) or pen downs (1) of the stylus.
The following example considers the word "CPE" as shown in Figure 10(a). This word is composed by six strokes. Each stroke is characterized by ten beta-elliptic parameters (B-E parameters), and by four membership degrees of E

the sizes of corresponding matrix, see Table 5. The word "EPC" is generated by elliptic strokes and elementary perceptual codes as illustrated in Figure 10 (b) (c)**.** As a result for the GPCs detector we obtain the following GPCs: *Right half opening occlusion (R-H-O), Shaft (Shaft), Left half opening occlusion (L-H-O), Shaft (Shaft), Valley (Valley), Valley (Valley), Valley (Valley).* The Figure 10 (d) shows these retained GPCs. For this example and according to Table 2, the GPC matrix is as follow: 5,3,6,3,1,1,1.

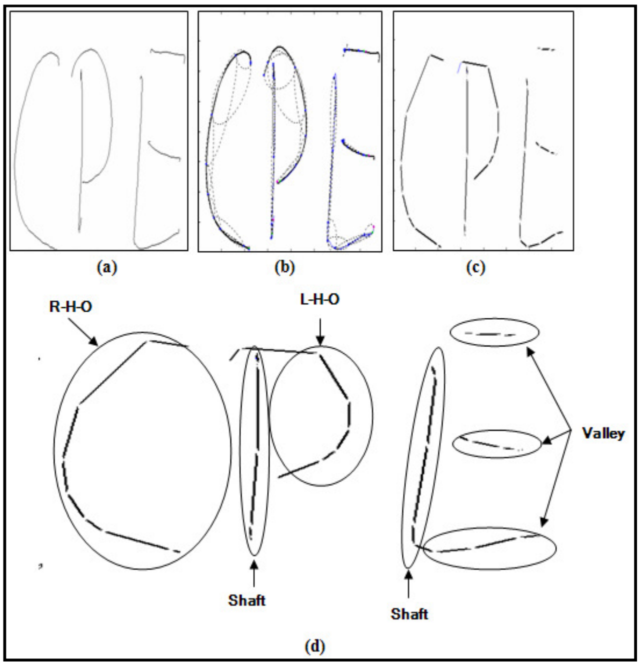

Fig. 10 Modelling of the word "CPE" from MAYASTROUN database (a): the word "CPE", (b) : the word "CPE", generated by elliptic strokes, (c): generated by elementary perceptual codes, (d): detected and retained GPCs.

In addition to results presented in [29], other experiments are made on samples from MAYASTROUN database: such as digits, words, show successful segmentation results by perceptual codes. This database, and in its actual version it contains up to 67000 samples [45], which offer opportunities for research community validate new systems and algorithms.

4.2 IRONOFF database

We also evaluate our proposed theory on IRONOFF database [38]. We are interested on letters.
Figure 11 (a) presents the letter "A" written by two strokes. Figure 11 (b) (c) presents this letter in generated form by elliptic strokes and by elementary perceptual codes**.** Table 5, presents also the matrix sizes of the B-E parameters, EPCs and GPCs.
The obtained and retained result GPCs is depicted in Figure 11(d). The corresponding detected and retained GPCs are: *Shaft (Shaft), Shaft (Shaft), Valley (Valley).* The corresponding GPCs matrix is: 3, 3, 1.
Figure 12 (a) presents the letter "N" written by one stroke. Figure 12 (b) (c) presents this letter in generated form by elliptic strokes and by elementary perceptual codes. The detected GPCs are Shaft (Shaft), Right oblique shaft (R-o-s), Up half opening occlusion (U-H-O) and Left oblique shaft (L-O-S). The obtained result after refining step is: *Shaft (Shaft)* and *Up half opening occlusion (U-H-O)*.
We note the elimination of the GPCs "Right oblique shaft, Left oblique shaft" which is overlapped by the GPC Up half opening occlusion. The Figure 12 (d) (e) shows these results. For this example and according to Table 2, the GPC matrix is as follow: 3, 7.

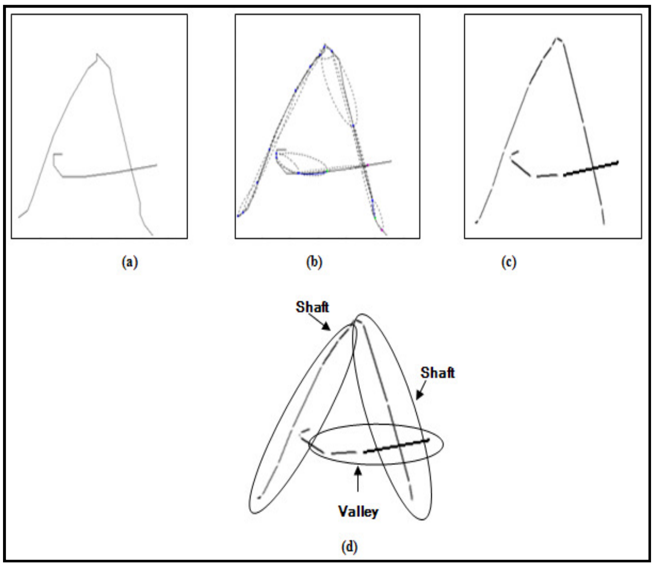

Fig. 11 Modelling of the letter " A " from IRONOFF database: (a): the original letter "A" , (b) : the letter "A" generated by elliptic strokes,(c): generated by elementary perceptual codes, (d): detected and retained GPCs.

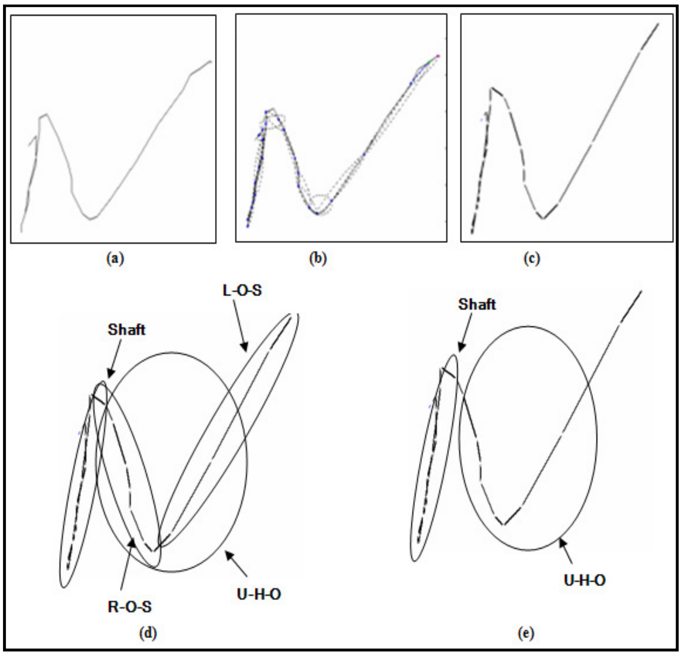

Fig. 12 Modelling of the letter "N" from IRONOFF database, (a): the letter "N", (b): the letter "N" generated by elliptic strokes, (c): generated by elementary perceptual codes, (d): detected GPCs, (e): refined and retained GPCs.

4.3 Discussion

Using different examples from these databases offers the opportunities to validate our proposed theory. The obtained results show successful representation of handwriting by perceptual codes. Experiments are made on different samples from these databases, which are varied in the acquired lexicon, the type of scripts.
These presented experiments show successful segmentation of on-line handwriting, and an important reduction in the initial acquired data in noted. As input of our system, we have a large file from a digital tablet for handwriting, using our proposed theory, as output the handwriting is characterized by a simple GPC matrix.

To calculate the **D**ata **R**eduction **R**ate (**DRR**) we use the following equation:

$$DRR = \left(\frac{\text{Number of lines from Initial data} - \text{Number of lines from GPCs Matrix}}{\text{Number of lines from Initial data}}\right) * 100$$

The **DRR** from presented examples is around 94%. Table 5 presents the data reduction marked from the presented examples.

Table 5: Data reduction from the presented examples.

Example	Word "CPE"	Letter "A"	Letter "N"
Matrix size of initial data	[602,3]	[28,3]	[31,3]
Matrix size of B-E parameters	[14,60]	[12,20]	[24,10]
Matrix size of EPCs	[14,24]	[12,8]	[24,4]
Matrix size of GPCs	[7,6]	[2,2]	[2,1]
DRR	98%	92%	93%

Figure 12, presents data reduction marked from the presented examples.

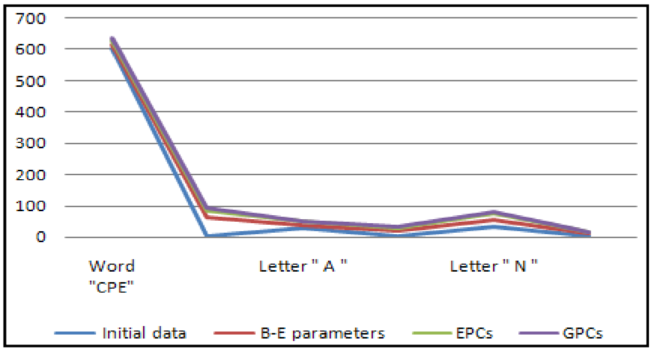

Fig. 12 Data reduction for the cited examples.

5. Conclusions

In this paper, we present PerTOHS theory for on-line handwriting segmentation inspired from the human perceptual system, based on the fact that handwriting is composed by a sequence of basic features approximated by perceptual codes. The elementary perceptual codes *EPCs* correspond to: *Valley, Left oblique shaft, Shaft, Right oblique shaft*. The *GPCs* are :*Valley, Left oblique shaft, Shaft, Right oblique shaft, Occlusion, Left half opening occlusion, Right half opening occlusion, Up half opening occlusion, Down half opening occlusion, Ain*. We have reviewed the filed of handwriting, theories of visual perception and reading/writing models, which are also on the base of our proposed theory. We detail the PerTOHS theory and its architecture based on the Beta-elliptic model for the generation of handwriting script and the perceptual encoding system for perceptual codes detection. We use the fuzzy set theory to detect EPCs and genetic algorithms to detect GPCs. We validate PerTOHS theory on on-line handwriting segmentaion and reccognition. We use MAYASTROUN database containing digits, letters, words in Arabic and Western language, Arabic texts, and IRONOFF database. The encouraging achieved results are similar to those produced by the human perceptual system during writing process and helpful for the analysis and the segmentation handwriting problems and allow an important reduction for the initial acquired information. A promising data reduction rate around 96% is obtained. Our perspectives are: using the generated GPCs as input for an on-line multilingual handwriting recognition system, and the development of an interactive user interface for handwriting learning using perceptual codes.

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References

[1] Alimi A.M, “Evolutionary Computation for the Recognition of On-Line Cursive Handwriting”. IETE Journal of Research, Special Issue on "Evolutionary Computation in Engineering Sciences” edited by S.K. Pal et al., vol. 48, no. 5, pp. 385-396, 2002.

[2] Alimi A.M., “Neuro-fuzzy approach to recognize Arabic handwritten characters”, Proceedings of the IEEE International Conference on Neural Networks, ICNN, Vol 3, pp. 1397-1400 , 1997.

[3] Anquetil E., Lorette G., ‘‘Perceptual model of handwriting drawing application to the handwriting segmentation problem’’, Proc.Int.Conf., International Conference on Document Analysis and Recognition, Germany, pp. 112-117, 1997.

[4] Bezine H., Alimi A.M and Sherkat N., “ Generation and analysis of handwriting scriot with Beta-elliptic model”, IWFHR 2004.

[5] Bezine H., Alimi A.M, Derbel N., ‘‘An explanation of the feature of a handwriting trajectory movement controlled by a Bêta-Elliptic Model’’, Proc.Int.Conf., ICDAR, Edinburgh UK, pp. 1228-1232, 2003.

[6] Bezine H., Alimi A.M and Derbel N.,"A Developmental Theory of the Relation Between Geometry and Kinematics in Handwriting", Proc. Int. Conf. SMC’02, Hammamet, Tunisia, Oct., pp.315-320, 2002.

[7] Bezine H., Kefi M., Alimi A.M, “On the Beta-elliptic model for the control of the human arm movement”, IJPRAI, vol 21, n°1, 2007.

[8] Bezine H., Njah S., Alimi A.M., “ Identification des fonts arabes anciennes par réseaux de neurones”, Atelier sur la Numérisation de l’Ecrit Ancien et des GRAndes Masses de données, Fribourg, Swiss 2006.

[9] Biederman I., “Recognition-by-Components: A Theory of human image understanding”, Psychological review 94 (2),pp 115-147, 1987.

[10] Côté M., Lecolinet E., Cheriet M., Suen C.Y., “ Automatic reading of cursive scripts using a reading model and perceptual concepts, The PERCEPTO system”, IJDAR, vol 1, pp. 3-17, 1998.

[11] Daifallah K., Zarka N., Jamous H., “ Recognition-based Segmentation Algorithm for On-line Arabic Handwriting”, International Conference on Document Analysis and Recognition, Spain, pp. 886-890, 2009.

[12] El Abed H., Märgner V., “Comparison of Different Preprocessing and Feature Extraction Methods for Offline Recognition of Handwritten Arabic Words”, International Conference on Document Analysis and Recognition, Brazil, pp. 974-978, 2007.

[13] Elarian Y., Al-Muhtaseb H., and Ghouti L.B19 “Arabic Handwriting Synthesis”, FAHR 1st International Workshop on Frontiers in Arabic Handwriting Recognition, in conjunction with ICPR 2010, Istanbul, Turkey, pp. 15-20, 2010.

[14] Gagné C., Parizeau M., “Genetic engineering of hierarchical fuzzy regional representations for handwritten character recognition”, International Journal on Document Analysis and Recognition, vol 8 n°4, pp. 223-231, 2006.

[15] Gorden I.E, “Theories of visual perception”, Third edition, Psychology press, ISBN 1-84169-383-9, 2004.

[16] Hamdani T.M., Alimi A.M., Karray F. , “Distributed genetic algorithm with bi-coded chromosomes and a new evaluation function for features selection”, IEEE Congress on Evolutionary Computation,CEC, pp. 581-588, 2006.

[17] Kallel I, Jmaiel M., Alimi A.M., “A multi-agent approach for genetic algorithm implementation”, Proceedings of the IEEE International Conference on systems, Man and Cybernet pp.358-363, 2002.

[18] Kherallah M., Njah S., Alimi A.M, Derbel N., "Recognition of on-line handwritten digits by neural networks using circular and beta approaches". Proc.Int. Conf. IEEE International Conference on Systems, Man and Cybernatics, Hammamet, Tunisie, 2002.
[19] Lecolinet E., "Cursive script recognition by backward matching", In: Advances in Handwriting and Drawing: A Multidisciplinary Approach, pp.117-135, Europia, Paris, 1994.
[20] Lorette G., "Handwriting recognition or reading? What is the situation at the dawn of the 3rd millennium?", International Journal on Document Analysis and Recognition, vol 2, pp. 2-12, 1999.
[21] Louloudis G., Gatos B., Pratikakis I., Halatsis C. "Text line and word segmentation of handwritten documents", Pattern recognition letters, vol 42, pp. 3169-3183, 2009.
[22] Malaviya A., Peters L, "Fuzzy handwriting description language: FOHDEL", Pattern Recognition, vol 33, pp. 119-131, 2000.
[23] Malaviya A., Peters L., Camposano R., "A Fuzzy Online Handwriting Recognition System: FOHRES", Proc.Int.Conf., on fuzzy theory and technology, Durham NC USA, pp. 1-15, 1993.
[24] Marr D., "VISION: A computational Investigation into human representation and processing of visual information''. W.H Freeman and company, San Francisco, ISBN 0-7167-1284-9, 8-41, 1982.
[25] Menier G., Lorette G., Gentric P., " A Genetic algorithm for on-line cursive handwriting recognition", Pattern Recognition, Vol. 2 , p 522 – 525, 1994.
[26] Miled H., "Stratégies de résolution en reconnaissance de l'écriture semi-cursive : Applications aux manuscrits arabes", PHD, University of Rouen, 1998.
[27] Njah S., "Reconnaissance en ligne des chiffres manuscrits par réseaux de neurones en utilisant l'approche " bêta-circulaire", Master thesis, University of Sfax, 2003.
[28] Njah S., Bezine H. and Alimi A.M., "A fuzzy-genetic system for segmentation of on-line handwriting: application to ADAB Database", IEEE Symposium Series on Computational Intelligence, 5th IEEE International Workshop on Genetic and Evolutionary Fuzzy Systems, Paris-France, pp.95-102, 2011.
[29] Njah S., Bezine H. and Alimi A.M., " On-line Arabic Handwriting Segmentation via Perceptual Codes: Application to MAYASTROUN database", IEEE 8th International Multi-Conference on Systems, Signals & Devices, Sousse-Tunisia, 2011.
[30] Njah S., Bezine H. and Alimi A.M., " A new encoding system: Application to on-line Arabic handwriting", International Conference on Frontiers in Handwriting Recognition, Kolkata-India, pp. 451-456, 2010.
[31] Njah S., Bezine H., Alimi A.M, "A new approach for the extraction of handwriting perceptual codes using fuzzy logic", International Conference on Frontiers in Handwriting Recognition, Canada, pp. 302-307, 2008.
[32] Oudot L., Prevost L., Maurice M., "Un modèle d'activation vérification pour la lecture de textes manuscrits dynamiques''. In: Proc.Int.Conf., CIFED, 117-122, France, 2004.
[33] Pinales J.R, "Reconnaissance hors-ligne de l'écriture cursive par l'utilisation de modèles perceptifs et neuronaux'', PHD, University of Paris, 2002.
[34] Plamondon R., Srihari S.N., "On-line and off-line handwriting recognition: A comprehensive survey", IEEE Trans. Pattern Anal. Machine Intell, vol 22, pp; 63–84, 2000.
[35] Rumelhart D.E, McCleland J.L., "Parallel distributed processing, explorations in the microstructure of cognition", In: Psychological and biological models, The MIT press, London, ISBN 0-262-13218-4, 432-443, 1986.
[36] Sharapov R.R, "Genetic algorithms: Basic ideas, Variants and Analysis", Vision systems: segmentation and pattern recognition, pp. 407-422, 2007.
[37] Sternby J., Morwing J., Anderson J., Friberg C., "On-line Arabic handwriting recognition with templates", Pattern Recognition, vol 42, pp. 3278-3286, 2009.
[38] Viard-Gaudin C., and Lallican P M., and Knerr S., Binter P., "The ireste On/Off (IRONOFF) Dual Handwriting database", International Conference on Document Analysis and Recognition, 1999.
[39] Vincent N., Seropian A., Stamon G., "Synthesis for handwriting analysis". Pattern Recognition Letters, vol 26, pp 267–275, 2005.
[40] Wshah S., Shi Z., Govindaraju V., " Segmentation of Arabic handwriting based on both contour and skeleton degmentation", International Conference on Document Analysis and Recognition, Spain, pp. 793-797, 2009.
[41] Zadeh L.A, "Fuzzy sets", Information and control, vol 8, pp. 338-353, 1965.
[42] Bunke H., "Recognition of Cursive Roman Handwriting - Past, Present and Future", Proceeding of 7th International Conference on Document Analysis and Recognition, pp. 448-461, 2003.
[43] Sadri J., Suen Y.S., Bui T.D., "A genetic framework using contextual knowledge for segmentation and recognition of handwritten numeral strings", Pattern Recognition, vol 40, pp. 898-919, 2007.
[44] Snoussi S., Belaud A., Choisy C., Amiri H., "Modèle perceptif neuronal à vision globale-locale pour la reconnaissance de mots manuscrits arabes" , Proc.Int.conf., CIFED, Tunisia, pp. 1-14, 2002.
[45] Njah S., Bezine H. Ben Nouma B., and Alimi A.M., "MAYASTROUN- A Multilanguage Handwriting Database", International Conference on Frontiers in Handwriting Recognition, Bari-italy, 2012.
[46] Kala R., Vazirani H., Shukla A., Tiwari R., " Offline Handwriting Recognition using Genetic Algorithm ", International Journal of Computer Science Issues, vol. 7, Issue 2, No 1, pp. 16-25, 2010.
[47] Muthumani .I, Uma Kumari C.R, "Online Character Recognition of Handwritten Cursive Script", IJCSI International Journal of Computer Science Issues, vol. 9, Issue 3, No 2, pp 352-354, 2012.

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