HandWritten Numerals Recognition System

Amal Sufuih Ajrash
Computer Science Department- College of science for women-Baghdad University

Abstract

Recognition is one of the basic characteristics of human brain, and also for the living creatures. It is possible to recognize images, persons, or patterns according to their characteristics. This recognition could be done using eyes or dedicated proposed methods. There are numerous applications for pattern recognition such as recognition of printed or handwritten letters, for example reading post addresses automatically and reading documents or check reading in bank.

One of the challenges which faces researchers in character recognition field is the recognition of digits, which are written by hand. This paper describes a classification method for on-line handwritten digits and off-line handwritten digits in same time using Genetic Algorithm.

Genetic Algorithms (GAs), are search procedures that use the mechanics of natural selection and natural genetics, have been used in this paper to solve numbers recognition problem. The genetic algorithm treats numbers as a binary string of [6 x 10] pixels and by the process of mating and mutating; the input string is matched to the closest existing character in a database. The proposed method is tested on a sample of 500 digits written by 10 different persons and found to perform satisfactorily most of the time; this paper realized a high percentage of 85%.

Keywords: Handwritten numbers, Digits recognition, Genetic Algorithm, Off-Line recognition, On-Line recognition.

تمييز الأرقام المكتوبة يدويا باستخدام الخوارزمية الجينية

امال سفيح عجرش
قسم علم الحاسوب /كلية العلوم للبنات/جامعة بغداد

الخلاصة

تمييز الكتابة اليدوية هي مسألة صعبة بسبب الاختلافات الموجودة في صيغ الكتابة حتى للشخص نفسه ,لذلك يجب ان يكون هناك اهتمام كبير يؤخذ بنظر الاعتبار عند تصميم نظام تمييز.

هدف هذا البحث هو استخدام الخوارزميات الجينية في تمييز الارقام المكتوبه باليد ولكي نصل الى الحل الامثل يتم مطابقة الرقم المدخل إلى أقرب رقم موجود في قاعدة البيانات. تم اختبار الطريقة المقترحة على عينة من 500 رقما كتبه 10 أشخاص مختلفين وكانت النتائج مرضية معظم الوقت اذ وصلت الى نسبة تمييز 85٪ .

1. Introduction

Handwritten digit recognition problem can be seen as a subtask of the more general optical character recognition (OCR) problem. However, there are some applications (e.g. postal code and bank checks reading) that are restricted to recognizing digits but require very high accuracy and speed. While recognition of handwritten Latin digits has been extensively investigated using various techniques [1].

Handwriting recognition systems are either online or offline. Online recognition system is an automatic recognition system that provides one of the most natural ways for human beings to interact with computers without having to learn any typing skills. In offline recognition, systems input are a digital image of handwritten numbers [2]. This paper is concerned with the use of a genetic algorithm to find an optimum feature set for the classification of hand written digits.

In this paper we propose the use of Genetic Algorithms for solving handwritten number recognition problem. The basic idea of genetic algorithm comes from the fact that it can be used as an excellent means of combining various styles of writing a number and generating new styles. Closely observing the capability of human mind in the recognition of handwriting, we find that humans are able to recognize numbers even though they might be seeing that style for the first time. This is possible because of their power to visualize parts of the known styles into the unknown number. In this paper we try to depict the same power into the machines.

2. Genetic Algorithms: overview

The development of Genetic Algorithms (GAS) has borrowed many ideas from nature, that operate with any search problem require to encode the solutions (called phenotype) of this problem into another. Representation that takes a string form (called genotype or chromosome)[3].

Each chromosome (c) consists of many locations where each location is called a gene (G), such that C=G1G2……Gn . each gene (Gi) can take any value in a specified range , such as:
Gi {0,1,2,…,a,b,c,…}

These chromosomes are generated randomly, and they together form a community. All chromosomes in the community must be matched by scheme H.A. , scheme H is used to describe similarities between certain chromosomes ,which depended on the handle problem .for example <H>=001000 is a schema order all chromosomes must contain 6 genes, must contain “1” in the third position and the remaining position can be take any values on the range, e.g. the chromosome 001101 is matched by it, while 01010 is not.

Each chromosome in the community has an evaluation value (specified by the evaluation function of the problem under consideration)to be evaluated .When is operated on the community, new candidate solutions are introduced into the community by apply artificial genetic steps: Selection, Genetic Operators, and Replacement [4].

The genetic steps are explained in the following subsections:

2.1 Selection:

In the selection step two individuals from community are selected . Roulette Wheel Selection (RWS) is a search strategy, which searches exhaustively on the community to find two highest properties. Random selection is another way to select two random chromosomes [3,5]. These two chromosomes are considered as parents.

2.2 Genetic Operators:

They are two types: Crossover and Mutation:

Crossover: this is an extremely important component in each genetic algorithm. This operator selects one point randomly in each of the parent solutions and swaps the gene values after this point, thus generating two new children solutions.

There is large variation in the crossover operators which has been used by different experiments . For example, it’s possible to cross over more than one point [3].

Mutation: the gene value is altered with some fixed probability. It disperses the community throughout the search space, and so might be consider as an information gathering or exploration operation.

Replacement: the evaluation value for the new child is compared with the worst individual in the community. The fittest remains in the community and the other are displaced.

3. The Proposed Numerals Recognition System

Most available programs run on fixed formulations and analytical methods so the error in the analysis of the number is constant and there is no learning in the process. In the GA treats number as a binary string and by the process of mutating and applying simple genetic operators such as crossover and selection, the input string is matched to the closet existing numbers in a database.

The Algorithm

The general algorithm used to implement this application was[6] :

1. Input of number to be recognized (using a computer input device; “in this research a ***mouse*** or ***PDA*** as online input and ***scanner*** as off line input had been used”).
2. Coding of the input binary image as a string.
3. Match the input string with a preset vocabulary to find nearest numbers.
4. Mutate the given input string randomly by the closet neighbor approach to arrive at the initial population.
5. Run the GA on this population calculating the fitness with respect to the closet matched number.
6. Identify numbers.

3.1. Off-Line Typical Numerals Recognition System

The great variations in handwritten numbers make the recognition task hard to be automated. A handwritten number may appear differently from picture to picture due to the image transformations of size, orientation, or location. In addition, the diversity of writing styles results in vast variations in the appearance of numbers. A handwritten number presented in the image plane should be correctly recognized by the system in spite of these circumstances sequence stage [7]. The proposed system is to design recognition of handwritten numerals and the sequence stages are depicted in figure (1).

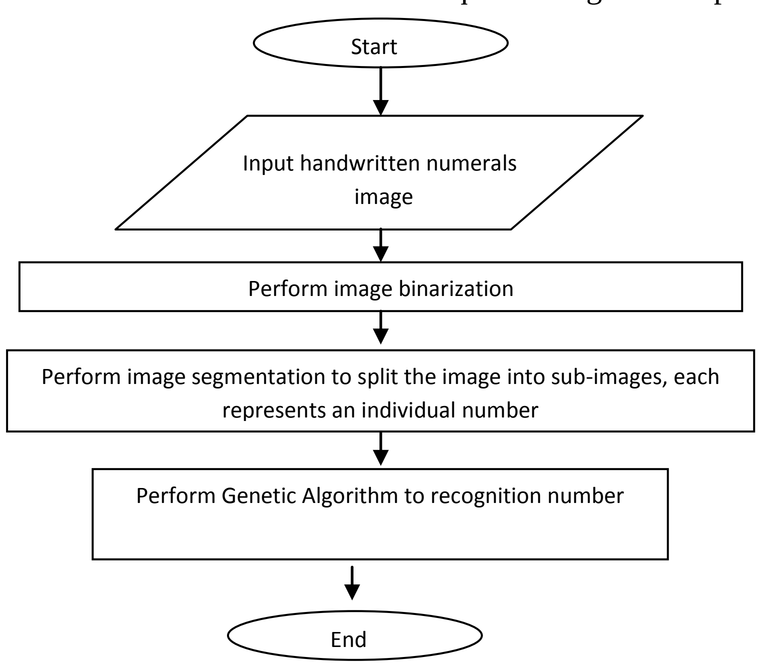
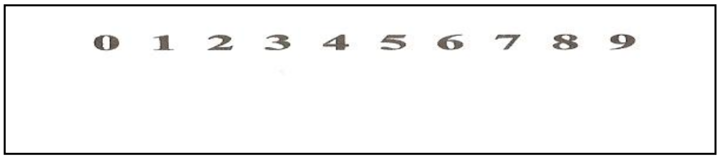


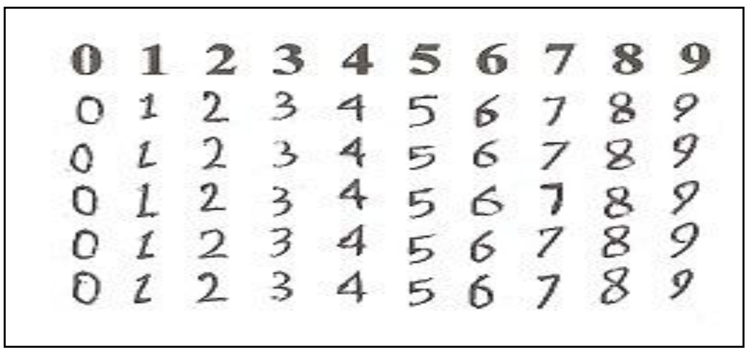
Figure (1) Typical off –line Number Recognition System

3.1.1 Input handwritten numerals image

The first step in the numerals handwritten recognition system the writing samples of each person are fed to the computer by using page scanner (300 DPI: Dots Per Inch). The Each sample then manipulated, separately, by denosing them firstly and then binarizing each isolated number separately. For English numbers adopted in this paper, we should have 10 numbers (from '0' to '9'), illustrated in figure 2.a . The features value of each isolated number can then be computed and stored in a reference database to be used in matching operation. The goal of this stage is to transform the contained of the document to a digital image which will be Bitmap format this document contains handwritten number.



a) Blank sheet of paper



b) Filled sheet of paper

Figure (2) Showing samples of blank and filled sheets

3.1.2 Perform image binarization

For processing or organization of samples by using computer, these patterns or images most be converted to suitable form to be saved and processed by digital computers.

The output is binary image black (1) and white (0) only (white is background and black are numbers), figure (3) shows the result of this stage.

0	0	0	0	0	0	0	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	1	0	0	0	0	1	0	0
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	1	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	1	1	1	1	0	0	0

Figure (3) binary image for number (3)

3.1.3 Segmentation

The term segmentation in image processing refers to mapping an image into waveform whose values are the sums of the values of the image points along particular directions [8]. In order to split the image into writing lines. In our present research, the parallel form projection is utilized in discrete image form, using intensity summing operation; i.e. horizontally and vertically, the number will be bounded by two summing zero values, respectively. Finally, the isolated numbers are surrounded by certain window's size which prepared for further manipulations. . In the simplest case (binary images) there are only two regions: foreground (number) region and a background region.

3.1.3.1 Line Segmentation

In this stage line segmentation algorithm applied on the text image in order to separate the text line into separated lines. Although, gray level images can be used, in general, the segmentation is performed on binarised version of the images. This is almost necessary when big amounts of pages are to be processed. Assuming the text skew corrected, projection profile cuts seems to be the most straightforward approach. In the this paper projection profiles are used for segmentation of lines and words.

Lines are extracted by thresholding the projection profile where the projection profile almost intuitively gives the lines of text that are formed by the image. If one imaging a simple vertical line to cross the entire image at the upper side of the projection profile, and then walk through that virtual line from the top until the bottom, two different areas will be crossed. One area will be *'empty'* (white) in the histogram, and the other area will be *'full'* (black).The transitions between the *"empty and full areas"* allow us to detect the top and bottom boundaries of each line in the text.

3.2. On-Line Typical Numerals Recognition System

This type of recognition deals with isolated or connected hand written numbers. In this processing, number interpretation supported by additional features of timing characteristics play important roles in simplifying recognition operation, in this system we use *Graphics Tablets and Light Pens* were the numbers are directly processed at the time of writing [8] [10].

3.3 Architecture of Genetic Algorithm

A Simple Genetic Algorithm (SGA) was used to arrive at the string matches. The difference between the mutation of the input string and the vocabulary strings was used to evaluate the fitness of a given numbers.

The population of these numbers was subjected to a tournament selection scheme and then crossed over and mutated to give rise to a new population. The GA was run for 100 generations and changing this parameter does not involve any change to the rest of the code. In this system the mutation is not background operator, so it will be discussed first before crossover [5] [6].

3.3.1 Mutation

Once the input string is stored in an array it is subjected to one of the three mutation order options with a mutation probability 1 (100%) [6]:

- ✓ Mutation_1 Change a single pixel in a character (1^{st} order mutation)
- ✓ Mutation_2 Change a two pixel in a character (2^{nd} order mutation)
- ✓ Mutation_3 Change a more than two pixels in a character (higher order mutation)

Further the mutation can be either cumulative (i.e. adding a pixel) or exclusive (i.e. moving a pixel). The mutation position is randomized.

3.3.2 Crossover

Once the mutation process is completed, a crossover operation is performed to obtain the next generation. A simple single point crossover scheme is used to generate the new generation.

Two strings are chosen at random from the population for the crossover and they undergo crossover and are stored in the new generation. The crossover took place if a randomly generated number was less than the crossover probability.

3.3.3 Selection

The selection is performed by tournament selection. The tournament size was set at two and the better of the two individuals survived. The individuals were selected at random from the population created by the crossover operation.

3.3.4 Fitness Function

A fitness function must be devised for each problem to be solved. Given a particular chromosome, the fitness function returns a single numerical “fitness”, or “figure of merit”, which is supposed to be proportional to the “utility” or “ability” of the individual, which that chromosome represents [9].

Fitness function can be as simple as having a human intuitively choose better solutions over worse solutions, or it can be an elaborate computer simulation or model that helps determine what is good. But the idea is that something must determine solution’s relative fitness to purpose, and whatever that the GA to guide the evaluation of future generation will use it [9].

A fitness function is assigned to each solution (chromosome) representing the abilities of an individual to “compete”. The individual with the optimal (or generally near optimal) fitness value is sought. The GA aims to use selective “breeding” of the solutions to produce “offspring” better than the parents by combining information from the chromosomes.

The GA maintains a population of n chromosomes (solutions) with associated fitness values. Parents are selected to mate, on the basis of their fitness, producing offspring via a reproductive plan. Consequently highly fit solutions are given more opportunities to reproduce, so that offspring inherit characteristics from each parent, Figure (4) show the recognition system when reading document through scanner, in first step segmentation the document into sub image (isolated number) then convert each of them into binary representation and input it into genetic algorithm that apply different process in each input to calculating the fitness with respect to the closet matched number.

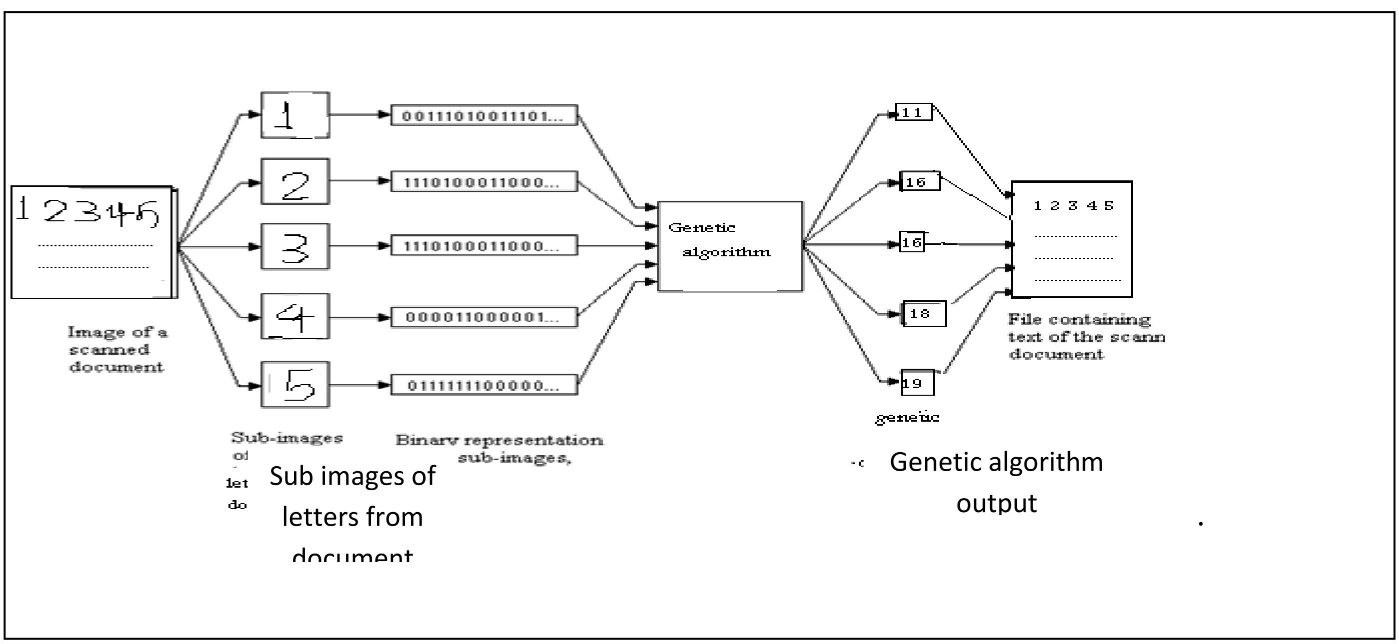


Figure (4) recognition system using a scanner as input devises.

We apply the system to recognize on-line where we should draw the number carefully which results in being recognized correctly. Figure (5) shows how the number **2** that is on-line hand drawn.

The direct application of GA to the vocabulary database, which contains excess of 10 numbers, would involve a very lengthy computational process. Running a convention pixel difference scheme to identify the closet matches narrows the solution space and thus reduces the load on the GA.

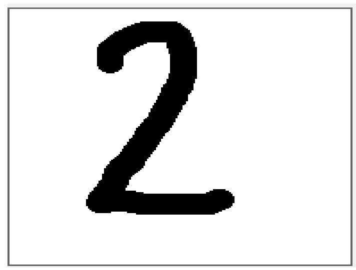


Figure (5) Handwritten Drawn Image

After converting the input character to a 60 – bit string it is compared to the vocabulary and the high approximate matches number from the vocabulary is displayed. This is assumed to be the solution space and the string that is sought seek should be identified here. At this Point there are two cases that could arise:

1. The best match is the correct match. This happens when the input string very closely matches the correct string in the vocabulary. This rarely happens when the character is bad or aberrant.
2. The best match is among the nearest number but not the closest match. This happens very frequently.

The population size is determined by the order of the mutation and the number of active pixels in the input character, see Eq. (1) It is governed by [9]:

Population _Size = Mutation _Order * Number of_ Active Pixels …..…….(1)

The rationale behind this is that population needs to be big enough to allow the input character to mutate and crossover to achieve considerable diversity so as to convergence towards the number in the vocabulary. After the initial population has been initialized, it is fed to the GA which runs for 500 generations . The best individual (the one with the high approximant), Figure (6) shows the recognition system when use the mouse to write on picture pad as input device.

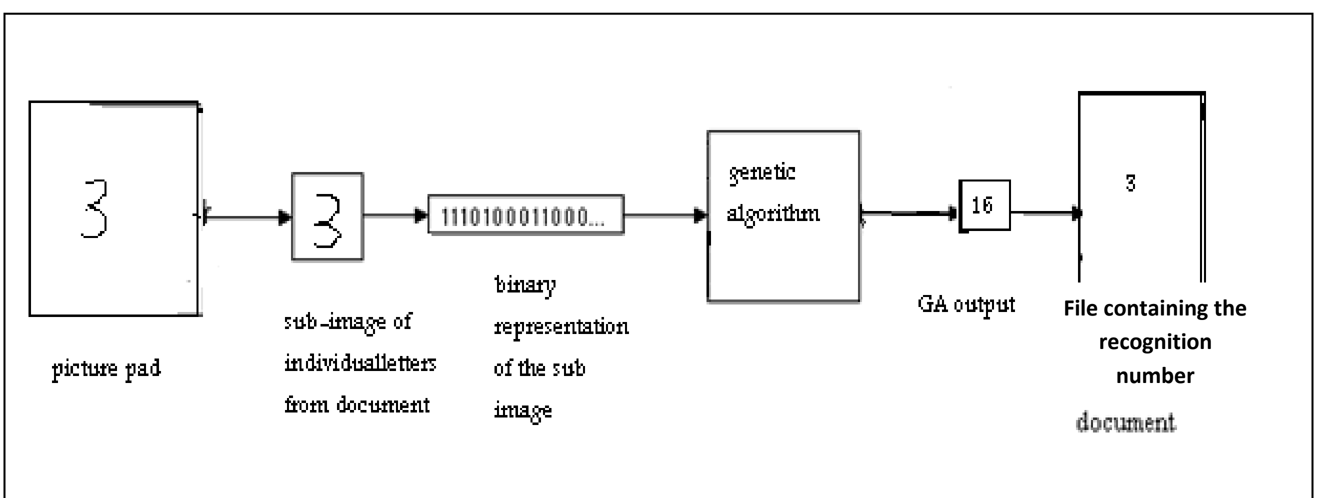


Figure (6) recognition system using mouse as input devise.

Table 1: Numerals matching after 100 generations. Error rate is location error in pixels, matching rate the maximum degree of match.

Number	Error rate	Matching rate
0	0.21	91%
1	0.21	93%
2	0.23	87%
3	0.24	89%
4	0.25	90%
5	0.24	84%
6	0.30	87%
7	0.29	82%
8	0.30	83%
9	0.30	83%

4. Conclusions

The implementation of our experimental work shows that, by making use of simple concepts of GAs in handwritten digit recognition, we can indeed achieve fairly good recognition results.

Further it was found to be a robust solution, as it required no special knowledge of how the recognition system works. Since there are relatively very few other methods to solve number recognition without relying on constrained formulation, using a GA system is an ideal application.

However, the system applied does not give a fairly good speed, because of the large number of GAs processes and the large size of database. This problem can be solved in future work.

5. Future Works

The application can work faster and more efficiently making some preprocessing to the number and by solving some of number problems such as: the scaling and rotating of the number in the image plane and the change of the number location. The scaling of the number in the image plane resulted from the change of character size; which can be solved by performing image normalization or by extracting from the number unique features, which are invariant to scaling. While the changes in the number orientation can be solved either by making normalization for elongated axis of number, or by using a vast amount of samples when the normalization of the elongated axis may not be properly define the orientation of a handwritten number.

Due to the relatively large time taken for recognition single number, such applications may not be very useful for real time analysis of number this can be solved by using another popular area, which is the parallelization of GAs, in order to decrease the processing time for a solution. A parallelization can be explicitly performed on the GAs (for example, parallelization on the genetic operation "crossover, mutation, and fitness calculation" over the population); or parallelization can perform by introducing changes to the architectural composition the way GAs function (for example, the population migration).

References

1. Sherif A. ‘ Comparing Arabic and Latin Handwritten Digits Recognition Problems‘, world Academy of Science, Engineering and Technology , Jun2009, Issue 30, p451.
2. El Emary Ibrahiem M.M. , Mustafa M.Hammad ,’On-Line Structural Approach for Recognizing Hand-Written Indian Numbers’ , ICGST-GVIP Journal, Volume(5), Issue (7), July2005.
3. Darrell Whitey , ‘ A Genetic Algorithm tutorial ‘ , statistics and computing , June 1994, Volume 4, pp 65-85
4. Parkins, A.D. and Nandi,A.K. (2004),’Genetic Programming techniques for hand written digit recognition’, Signal Processing, vol. 84, pp. 2345 – 2365 .
5. Ying-Hong Liao, and Chuen-Tsai Sun ‘An Educational Genetic Algorithms Learning Tool’, Member, IEEE.
6. Suresh A. ; ‘Development of a Pattern Recognition Program using Genetic Algorithm’ , IIIiGAL Report No.2000003, January 2000 .
7. A.Amin .D.Ziino and C. Sammut , ‘Recognition of hand printed Latin Characters Using Machine Learning’, Proc. 3rd Int. Conf. on Document analysis and Recognition, Canada , pp. 1098 - 1102 (1995).
8. Al-Emami S. and M.Usher ,’ On-line Recognition of Handwritten Arabic Characters’, IEEE Trans.Pattern Anal Mach .Intell. PAMI-12, 704-710 (1990).
9. Al-maliki S. , ’Character Recognition using Gentic Algorithms’, Ms.c. thesis, Baghdad university, college of science, 2004.
10. A.Alimi and O.Ghorbe. ‘The analysis in an On-line Recognition System of Arabic Handwritten Characters’ , Proc. 3rd Int. Conf. on Document Analysis and Recognition , Canada, pp. 890-893 (1995).