Probabilistic Artificial Neural Network for Recognizing the Arabic Handwritten Arabic Characters

Dr.Laheeb Mohammad ALZoubaidy
Associative Professor
Mosul University, College of Computer Sc. and Math., Dept of Computer Sciences
Email : lahmzub@yahoo.com
Mobile : 009647701618215
Phone : 0096460817369
Mail : Iraq – Mousl
Mosul University,
College of Computer
Sciences and Math.,
Dept of Computer Sciences

Mr.Bahaa Abdullah AlRifai
Lecturer
Al-Balqa'a Applied University, Dept. of Prince Abdall Bin Gazi for Science and Information Technology
Email : d_bahaa1@yahoo.com
Mobile : 00962795790307
Mail : Jordan – Amman
Jabel Amman - 11184
P.O. Box 840638

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Abstract

The objective of this paper is to present a new technique that assists in developing a recognition system to handle Arabic handwritten text. The proposed system is called Arabic Handwritten Optical Character Recognition (AHOCR). AHOCR is concerned with recognition of handwritten Alphanumeric Arabic characters. In the present work, extracted characters are represented by using Geometric Moment Invariant of order three the advantage of using moment invariant for pattern classification, as compared to the other methods of invariants with respect to its position, size and rotation. The proposed technique is divided into three major steps: the first step is concerned with digitization and preprocessing documents to create connecting components, detecting the skew of characters and correcting them. The second step deals with how to use geometric moment invariant features of the input Arabic characters to extract features. The third step focuses on description of an advanced system of classification using a Probabilistic Neural Networks structure which yields significant speed improvement . Our results indicate and clarify that proposed AHOCR achieves an excellent test accuracy of recognition rated up to 96% for Arabic text.

Keyword: Optical Characters Recognition (OCR), Arabic Handwritten Optical Character Recognition (AHOCR), Probabilistic Neural Network (PNN) , Geometric Moment Invariant (GMI).

1. Introduction

A computer technology sub-field which has potential to be useful in a plurality of settings is out to mate recognition of textual information. The field has been referred to generally as Optical Character Recognition (OCR). In general, an OCR machine reads machine printed/handwritten characters and tries to determine which character from a fixed set of the machine printed/handwritten characters is intended to be represented. The task of recognized characters can be broadly separated into two categories: the recognition of machine printed data and the recognition of handwritten data. Machine printed characters are uniform in size, position, and pitch for any given font. In contrast, handwritten characters are non-uniform; they can be written in many different styles and sizes by different writers and by the same writers therefare, the reading of machine printed writing is a much simpler task than reading handwriting and has been accomplished and marketed with considerable success[1,2].

Character recognition systems can contribute tremendously to the advancement of the automation process and can improve the interaction between man and machine in many applications, including office automation, check verification, and a large variety of banking, business and data entry applications. Very little research has gone into character recognition in Arabic due to the difficulty of the task and lack of researchers interested in this field, [Amin, 1997]. As the Arab world becomes increasingly computerized and mobile, and technology becomes increasingly ubiquitous, the need for a natural interface becomes apparent. Typing is not a natural user-friendly interface, leaving handwriting recognition as a viable alternative [1,3].

The work presented in this paper tries to construct **Arabic Handwritten Optical Character Recognition System [AHOCR]** to presents a new technique for the recognition of off-line handwritten Arabic characters using Geometric Moment Invariant to extract features, and neural networks (Probabilistic Neural Networks), pattern classification methods, and tries to demonstrate a frame work for giving good recognition accuracy rate for off-line handwritten Arabic characters. So our work tend to overlook the following phases: Studying the various techniques used in recognizing the handwritten Arabic characters, considering moment invariant (order 3) method, and neural networks (probabilistic neural net work) for studying this problem, developing a new recognition system technique to recognize handwritten Arabic characters problems in order to overcome the problems that exist in the current technique, and analyzing the recognized system from the proposed system with respect to the other recognized systems obtained from other techniques.

Finally, the proposed approach is trying to prove that using neural networks (Probabilistic Neural Network) for recognizing handwritten Arabic characters is better than other techniques by overcome all of the problems in the previous technique and suitable for all kind of problems in different fields. At the end, the system Arabic handwritten optical character recognition (AHOCR) development in the devices for Arabic character recognition processes many documents automatically. AHOCR aims to convert document images to symbolic for modification, storage, retrieval, reuse and transmission. It helps in the transition from book shelves and filing cabinets to the paperless world. Although there is no evidence yet of less paper, electronic document already abound. In this work, our system uses a new technique for the recognition of handwritten Arabic characters [3,4]. Achieving the previous objective requires presenting this paper which is organized in six sections. Section two deals with some of the related works done by other researchers. In section three, we describe the Optical Character Recognition system (OCR).

In section four, we present our proposed Arabic Handwritten Optical Character Recognition system
(AHOCR). Section five is concerned with the results and discussion and future works.

2. Related Works of Handwritten Arabic Character Recognition

Machine simulation of human reading has been the subject of intensive research for many decades. A large number of research are concerned with Latin, Chinese and Japanese characters; however, little work has been conducted on the automation of Arabic characters because of the complexity of its text. The main objective of this section is to present the state of Arabic character recognition research throughout the last two decades.

- **Hierarchical Rule Based Approach:** Sheik and Altaweel [5] assumed a reliable segmentation stage which divides letters into the four groups of position (initial, media, final and isolated). The recognition system depends on a hierarchical division by the number of strokes. One stroke letters were classified separately from two stroke letters and so on. Ratios between extreme and position of dots on comparison to the primary stroke were defined heuristically on the data set to produce a rule based classification.
- **Segmented Structural Analysis Approach** Al Emami and Usher [6] used a structural analysis method for selecting features of Arabic characters. The classifications use a decision tree. In preprocessing, some of the features extracted during the segmentation process were direction codes, slopes and the presence of dot flags, a new input needed to search three decision trees for the primary stroke, and also for the upper and lower dots. The system was trained on 10 writers with a set of 120 postal code words with a total of 13 characters. There was one tester who had a recognition rate of 86%.
- **Structural and Fuzzy Approach**: Amin and Bouslama [7] presented a hybrid system that combine structural and fuzzy techniques. Structural analysis discriminated between various letter classes to be recognized and fuzzy logic allowed for variability in people's handwriting within the same class. Sampling was done on the same class. Sampling was done on the input data points by comparing tangent angles at various points along the line. End points were kept automatically. The first point that had a tangent difference bigger than a threshold became the next sampled point. The authors chose basic shapes such as curves, loops, lines and dots as good feature for discrimination between letter classes. These were constructed using geometric and structural relationship between the sampled points. After fuzzifying the features, fuzzy "if _then rules" were created heuristically by the authors, following a study of the data set. These fuzzy rules could distinguish letters from combination of the fuzzy features and allowed for fuzzy membership to cover the variability in handwriting between authors.
- **Template Matching and Dynamic Programming Approach:** Alimi and Ghorbel [8] showed how to minimize errors in an offline recognition system for isolated Arabic characters using template matching and dynamic programming with assumed segmentation. The reference bank of prototypes was prepared after smoothing, normalization, and coding the data coordinates into a parametric representation of angles. When new data was presented to the system, the distance between the prototype and the new data string was minimized using dynamic programming. The number of prototypes was varied to see the affect on recognition rates. More prototypes give better accruing.
- **Artificial Neural Networks Classifiers:** Haraty and El-Zabadani [9] present a system for recognition of handwritten Arabic text using neural networks. Their work builds upon previous work that dealt with the vertical

segmentation of the written text. However, they faced some problems-like overlapping characters that share the same vertical space.

They tried to fix that problem by performing horizontal segmented, and the second one performs the horizontal segmentation. Both networks use a set of features that are extracted using a heuristic program. The system was tested and the rate of recognition obtained was 90%. This strongly supports the usefulness of proposed measures for handwritten Arabic text.
Artificial Neural Networks Classifiers have been presented in this paper for Haraty producing excellent results with a large database. The main contribution of an this research is the use of artificial neural network for Arabic characters recognition. Among the many applications that have been proposed for neural networks, character recognition has been one of the most successful, compared to other methods used in pattern recognition. The advantage of using a neural network for Arabic character recognition is that it can construct nonlinear decision boundaries between the different classes in a non-parametric fashion, and thereby offer a practical method for solving highly complex pattern classification problems. Furthermore, the distributed representation of the input's features in the network provides an increased fault tolerance in recognition; thus character classification can occur successfully when part of the input is broken off and not presented in the image, as well as when extra input signals are present as a result of noise. This is a very important characteristic for a recognition module in this application.

3. Optical Character Recognition System

The goal of optical character recognition (OCR) is to classify optical patterns (often contained in a digital image) corresponding to alphanumeric or other characters. The process of OCR involves several steps including: segmentation, feature extraction and classification.

First, for the classification process, there are two steps in building a classifier: training and testing. These steps can be broken down further into sub-steps as shown in Figure 1 [10].

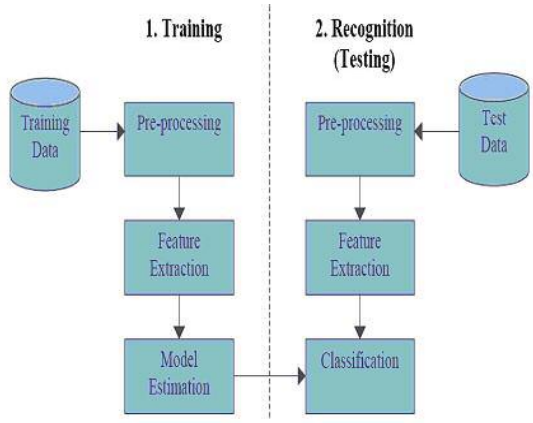

Figure 1: The Pattern Classification Process

From Figure 1, we see that the training phase is structured from three steps given by pre-processing, feature extraction and model estimation. On the other hand, for the testing phase, this phase contains also three sub phases: pre-processing, feature extraction and classification.
Second, for the OCR-Preprocessing process; preprocessing is primarily used to reduce variations of characters. In OCR systems, preprocessing includes the connection of segmentation and normalization as shown in Figure 2. Preprocessing receives a first binary image of a plurality of characters. Preprocessing generally consists of a series of image to image transformations. The preprocessing steps often performed in OCR are: scanning, binarization, noise removal, segmentation and normalization [11].

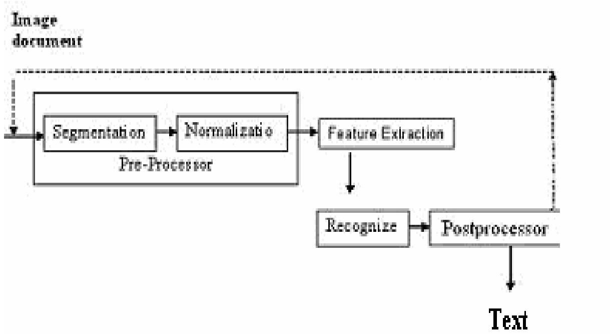

Figure 2: A Flow Diagram for Optical Character Recognition System

Third, with regard to feature extraction, this step is the key issue of character recognition. Feature extraction abstracts high level information about individual patterns to facilate recognition. A wide variety of approaches have been proposed to capture the distinctive feature of machine characters. These approaches fall into one of two categories: (1) global analysis which contains techniques such as moments and mathematical transforms. (2) Structural analysis in which efforts are made at capturing the essential shape features of characters generally from their skeletons of contours.

Fourth, with regard to recognizer (classifier), there are three categories of character classifiers: neural network approach, statistical approach and structural approach.

Fifth, the final phase of OCR, which is post-processor. The post-processor is designed to supplement the recognition process to improve the accuracy of the process. The postprocessor examines the bitmap generated by the recognizer and makes a determination as to the validity of the selection made by the recognizer. In one embodiment, gross structural feature such as character strokes and contours contained in the bitmap, fed to the post-processor by the recognizer are used for this purpose. The post-processor uses various techniques to distinguish one character from another. For example, the geometry/topology of an image (e.g bitmap) can be used to distinguish characters represented by the image. Geometric/topological features include (i) loops such that appear in the handwritten letters هـ، و، ق،ف. (ii) Straight lines which appear in such handwritten letters as أ. (iii) endpoints, and (iv) intersections.

4.Arabic Handwritten Character Recognition System (AHOCR)

Handwritten Arabic character recognition system (AHOCR) aims to convert image documents to text.

In AHOCR, after moving the document from a storage location to a digital scanner, each image document scanned at 300 dpi with the output formatted image as a (windows bitmap (bmp), joint photographic expert group (jpeg)) and adequate results are obtained with this quality, the scanner generates image document or a selected position of the image document, the scanner then applies the image to a recognition system according to the invention. The AHOCR recognition system as shown in Figure 3 includes a Geometric Moments Invariant (GMI) for feature extraction and Probabilistic Neural Network (PNN) for recognition. Recognizer can process the image received from the scanner to determine all of the character written on the document that was scanned. In general, the recognition system generates data representative of each character on the document and passes that data as output to a buffer memory. The central computer typically controls and/or initiates other aspects of the operations such as storage, retrieval, reuse and transmission. It helps the transition from bookshelves and filing cabinets to go paperless. AHOCR perform the following operations:

4.1 <u>Thresholding Operation of AHOCR</u>

The task of thresholding is to extract the foreground (ink, writing) from the background (paper), [3]. The *histogram* method is used for thresholding, the task of determining the threshold gray-scale value (above which the gray-scale value is assigned to white and below which it is assigned to black).

4.2 <u>Noise Removal Operation of AHOCR</u>

It is necessary to perform several document analysis operations prior to recognizing text in scanned documents. One of the common operations performed prior to recognition are noise removal, the extraction of the foreground textual matter by removing, say, textured background, salt and pepper noise and interfering strokes,[10]. Smoothing operations (*Neighborhood Averaging*) is used to eliminate the artifacts introduced during .image capture. Thresholds on minimum component area and dimensions are used to discard small connected components corresponding to salt and pepper noise during the process of chain code generation.

4.3 <u>Segment Operation of AHOCR</u>

Once the image has been converted to a useful representation, the writing must be separated into individual digits or segments, this process is known as ***segmentation***. This is accomplished by examining the ***horizontal histogram*** profile at a small range of skew angles. Line separation is usually followed by a procedure that separates the text line into words and characters. It focus on identifying ***physical gaps*** using only the components.

Word segmentation followed by the techniques applied for segmenting handwritten Arabic words into individual characters, this is implicit segmentation (***straight segmentation***): in this technique, words are segmented directly into letters. This type of segmentation is usually designed with rules that attempt to identify all the character's segmentation points. In all Arabic characters, the width at a connection point is much less than the width of the beginning character. This property is essential in applying the baseline segmentation technique, [4 .6], and this strategy is used to solve the overlap between characters, which is a common in the Arabic handwritten characters.

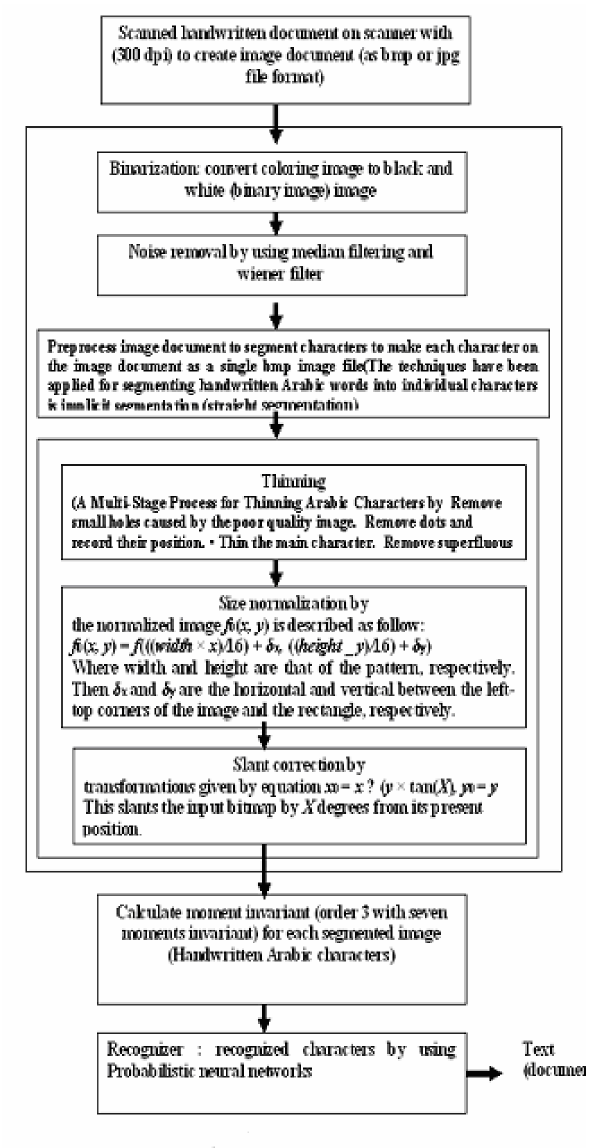

Figure 3: Operation Done on Image Document By AHOCR

4.4 Character Feature Extraction Operation of AHOCR

The key issue of **AHOCR** is feature extraction; the feature extraction stage in **AHOCR** decomposes a normalized image of the character into numbers of features. This approach generally falls into a global analysis technique using **geometric moments invariant**. It receives a binary image array (16×16 pixels) from the segmentation process creating a feature extractor for it by calculating moment invariant.

Table 1: Geometric Moments Invariant for Handwritten Arabic Character (ع) Represent Input Data to Probabilistic Neural Networks

Geometric Moments Invariant	*Value*
First invariant moment	**1.014080**
Second invariant moment	**0.471489**
Third invariant moment	**0.234804**
Fourth invariant moment	**0.020425**
Fifth invariant moment	**-0.001218**
Sex invariant moment	**-0.013615**
Seventh invariant moment	**0.000241**

A brief summary of the features and their sizes is given in table 1. One of the fundamental issues in the design of an image recognition system is related to the selection of appropriate numerical features in order to achieve high recognition performance. Furthermore the geometric moment invariant used in **AHOCR** as a feature extractor is to extract an object invariant with respect to its position, size, and orientation, [12].

Moments and function of moments have been utilized as the pattern feature in a number of applications to achieve invariant recognition of two - dimensional image patterns. Moments Invariant were first introduced in 1961, based on a method of algebra invariants. Using non-linear combination of regular moments which are referred to as (GM), a set of moments invariant were derived. It is a desirable property of being invariant under image translation, scaling and rotation. This type of moment is best fit to recognize the Arabic character,[12].

In this study, the GM technique, with its set of moments invariant, has been used because of its characteristic of being invariant against translation, scaling and rotation and its attributes of each formula of its set. It is non-linear correlation for the second and third moments. This set of invariant which can be used with the binary value and real value, depends on the problem. In the recognition of character (Arabic, English,... etc) this with binary values has been used.

4.4.1 Moments Invariant for Arabic Character of AHOCR

In this study we will build a database for moments invariant (order 3) of 141 patterns (28 Arabic characters in four positions (isolated, at beginning, at the end, at the middle of the word) , numeral characters (0 - 9) and some special characters (+ , - , * , / , = , ! [,] , . , : , ?).

The database as shown in Figure 4 had a total of 141 patterns. One of the aims of AHOCR was to test the usefulness of the set of described features in classifying Arabic characters. There are several advantages of using moment invariant for pattern classification as compared to other methods, the major competition comes from those features to be extracted by using moment invariants is invariant with respect to its position and size.

In **AHOCR**, each character on the image document is a single image file, preprocessing step in which original character image is transformed into a binary image by converting colored images to black and white images, Then, noise removal is done. After that, the Arabic character is thinned sized and normalization and slant correction operations are done on each patterns. The Final operation is to calculate invariant moment for each Arabic character (pattern) and then store it into the database.

4.5 Probabilistic Neural Networks Classifier of AHOCR

In AHOCR, the recognizer, according to the invention, receives the output of the feature extractor (moments invariant, order 3, seven moments invariant) as its input. The recognizer module processes images to generate a "best guess" as to the identity of the character represented by the input bitmap and produces an output bitmap of that best-guess character. The recognizer is a Probabilistic Neural Network-based. Referring to Figure 5, in one embodiment, the recognizer includes a fully-connected, three-layer neural network which accepts seven continuous moments invariant values of image character.

As indicated by Figure 5 the disclosed embodiment of the neural network includes an input layer Radial basis layer, and a Competitive layer. The input layer includes seven units, one for every seven moment invariant in an input bitmap. (Units are also known as "neurons"). The competitive layer has 142 units whose activations vary from 1 to 0. Each unit in the competitive (output) layer represents a different one of the 141 possible Arabic characters and the last unit for rejection result. As a result of the recognition process, a bitmap of the characters corresponding to the output unit with the highest activation is produced as the output bitmap by the neural network-based recognizer. For Probabilistic Neural Networks creates a two layer network.

• The first layer has Radial basis transfer function neurons, and it calculates its weighted inputs with Euclidean distance weight function, and its network input with Product network input function.

• The second layer has Competitive transfer function neurons, and calculates its weighted input with Dot product weight function and its net inputs with SUM. Only the first layer has biases.

Output result, see table (2) is (1,69), 69 mean the node that represent Arabic character (ع).

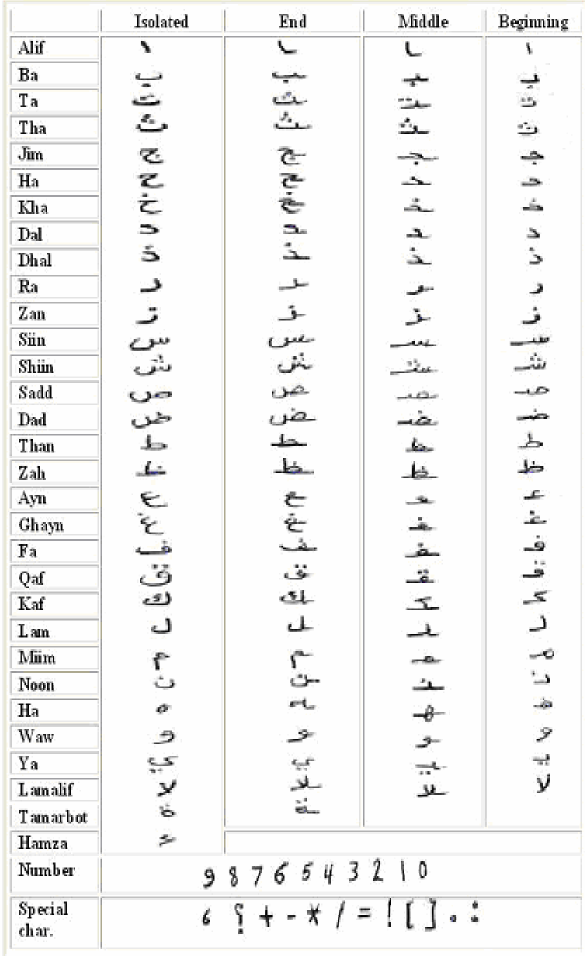

Figure 4: Database Arabic Characters and Their Four Forms at Different Positions in the Word

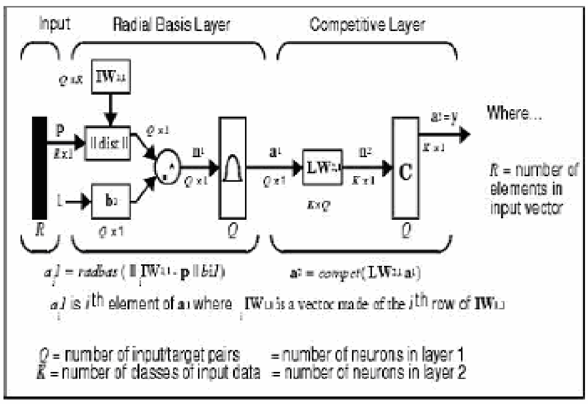

Figure 5: Probabilistic Neural Networks Architecture

Table 2: Output Layer in Probabilistic Neural Network and the Result after Recognize Handwritten Arabic Character (ع)

Output layer	Classifier value
(1,1)	0
(1,2)	0
.	0
(1,69)	1
.	0
(1,141)	0
(1,142)	0

5.Experimental Results of AHOCR for Handwritten Arabic Text

Our experiments were conducted on the Arabic handwriting of 25 independent writers document shown in Figure 6. These documents were then processed. The experiments were done on 3 disjoint data sets given by:

1.Training (37800)= 20 volunteers x 5 iterations x 378 characters
2.Validation (3780)= 10 volunteers x 378 characters
3.Test (764) (5 volunteers with different number of characters in each document).

The Validation set was composed of characters that were written by the same authors that were totally observed in the training process. The test set was written by 5 authors that were totally unobserved in the training process. There are two procedures done in our experiments: training and was testing. The trial trained on the validation

The experiment was to simply train the probabilistic neural network architectures on the training set and test on all three sets. The results became the baseline for letter optimization. The baseline for recognition accuracy was defined as the average accuracy of the validation and test set of the best PNN architecture.

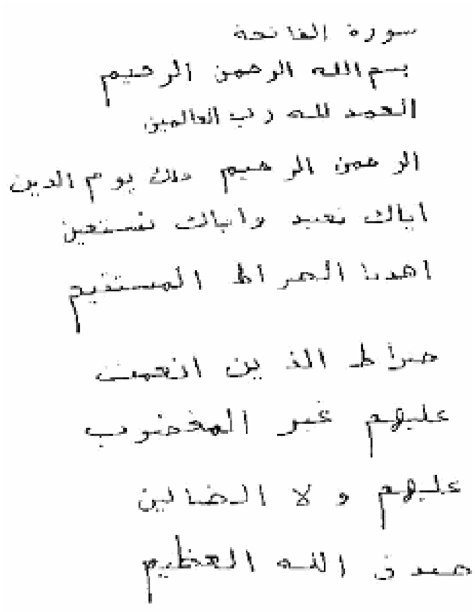

Figure 6: Arabic Handwritten Document Written by First Test Writer (21).

Probabilistic Neural Network (PNN) has 7 input nodes in its input layer and 142 nodes in its output layer architecture. For this architecture, there are 7 nodes in the input layer a node for each of the seven moment value of input data (image character) and described in table 1, 142 output nodes (141 for Arabic characters, last node for reject result). In the output layer, we take the advantage of the fact that final values range from 0 to 1. Given this, we can interpret each output of a node in the output layer as a confidence level for each possible output. So, each node in the output layer represents a possible Arabic character being recognized. The output layer is set to reorganize 142 possible outputs:(أ-ي), (0-9), (+, -, *, 1, =, !, ., ;, ?) and not recognized. Running our algorithm with a learning rate of η=0.9, we found that choosing an error goal for probabilistic architecture during the 8000 epochs probabilistic training time will improve: the accuracy across training, validation and test, (see tables 3& 4). The best probabilistic for recognition accuracy is the probabilistic three layers neural

Networks architecture. For training, it recorded a recognition accuracy rate of 99%. For validation, it had recognition accuracy rate of 98%. For test, it had recognition accuracy rate of 96%, and the average recognition accuracy rate is 97%.

Looking at a breakdown of the test set results, see tables (3,4) , we notice that five test writers had a good accuracy rate as shown in Figure 7.

Train recognition	Validation recognition	Test recognition	Average recognition
99%	98%	96%	97%

Table 3: Recognition Accuracy Result for Text Arabic Character

Writer	Error rate	Accuracy rate	Average test accuracy rate
21	4%	96%	96%
22	5%	95%	
23	3%	97%	
24	3%	97%	
25	5%	95%	

Table 4: Five Test Writers and Recognition Accuracy Rate for Them

سورة الفاتحة
بسم الله الرحمن الرحيم
الحمد لله رب العالم~~
الرحمن الرحيم ، مل~ يوم الدين
ايا~ نعبد وا~ ا ~ نستعين
اهدنا الصرا~ المستقيم
صراط الذين انعمت
عليهم غير المغضوب
عليهم و لا الضالين
صدق الله العظيم

Figure 7: Text Document as a Result of AHOCR for Arabic Handwritten Image Document As Seen in Figure 6

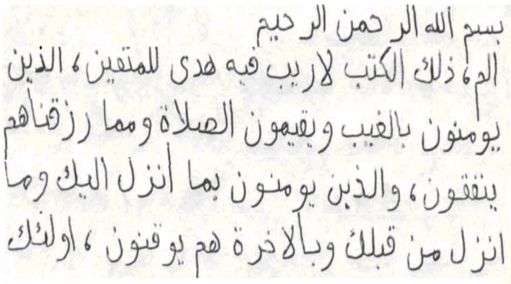
بسم الله الرحمن الرحيم
الم، ذلك الكتب لاريب فيه هدى للمتقين، الذين
يومنون بالغيب ويقيمون الصلاة ومما رزقناهم
ينفقون، والذين يومنون بما انزل اليك وما
انزل من قبلك وبالاخرة هم يوقنون، اولئك

Figure 8: Arabic Handwritten Document

6 <u>Comparing AHOCR with Previous Systems</u>

Table (5) summarized previous approaches in Arabic handwritten character recognition. Since none of these systems were applied on the same data set, and many of these systems were not tested on independent and extensive test sets, and most of them built to recognized Arabic characters, it is not a fair match to compare how these systems did against each other as well as our system. However, to give a rough estimate of relative performance, we have included this table for completeness.

Approach	Segmentation	Writers	Sensitive to noise	Classes	Data set	Recognition Accuracy
Hierarchical Rule-based	NO	?	YES	60	1200	100 %
Segmented Structural Analysis	YES	1	YES	13	120 postal code	86%
Structural / Fuzzy	NO	?	YES	28	?	?
Template / Dynamic	NO	1	YES	9 proto-types	9	96%
K-nearest Neighbor	NO	7	YES	28	60	84%
Neural Network Approach for farah	YES	100	NO	28	2400	93%
Neural Network Approach for haraty	YES	10	NO	28	1000	90%
Neural Network Approach for Naili	YES	handwritten Arabic words collected at the depar -tment of Electronics; university of Annaba	NO	48	5000	95%
IFN/ENIT database	YES	411	NO	10-class	964 towns name	94%
AHOCR with isolated Arabic character	YES	25	NO	141	15933	97%
AHOCR with Arabic document	YES	25	NO	141	42344	96%

Table 5: Summary of Previous Approaches in Handwritten Arabic Characters with HACRS

6. Conclusion and future works

AHOCR is optical handwritten Arabic character recognition (OCR) system capable of producing a fully editable electronic document with current accuracy is 96% for Arabic handwritten document recognition, after running AHOCR system and experimentation on total of 42344 Arabic characters for Arabic text. These characters were then process the experiments on 3 disjoint data sets: the training data set, validation data set, and the test data set text using Arabic characters. We conclude the following assure points.

- Moment- invariant features for handwritten characters are tuned to produce relevant features for Arabic recognition from data coordinates while reducing the input space.
- Probabilistic networks are tuned to recognize the 141 character classes in an easy and powerful recognizable way.
- Accurate recognition rate for **AHOCR** (Arabic text) is 99% for training data set, 98% for Validation data set, 96 % for test data set, and average recognition rate is 97%. The accurate recognition rate for **AHOCR** is good rate and best results when we compare theses rates with the accurate recognition rate of previous researches and systems of OCR, see table (5).

Arabic handwritten recognition is a difficult problem but our hope is that the AHOCR system will be a step towards a neural network approach to robustly solve it. Now, it remains for further research to build on this foundation and work towards automatic recognition of Arabic document handwritten character, recognized Arabic motions.

References:

[1] A.Amin, "Recognition of printed Arabic text based on Global Features and Decision tree learning techniques", Pattern recognition, Vol.33, No.8, 2000, pp.1309-1323.

[2] Amondon. R, and Srihari, "On-line and off-line handwriting recognition: A comparative study", IEEE transaction on pattern analysis and machine intelligence, Vol.22, No.1, 2000, pp. 63-84.

[3] A. Amin and K.Mandana, "Automatic recognition of printed Arabic text using neural network classifier", IEEE transaction on pattern analysis and machine intelligence, Vol. 20, No.1, 1999.

[4] A. Amin and S. Singh, "Neural network recognition of hand printed characters", neural computing and applications, Vol.8, No.1, 1999, pp. 76-76.

[5] T. Klassen, "Towards neural network recognition of handwritten Arabic letters", master thesies, Dalousie university, Halifax, U.S.A, 2001.

[6] S, Al Emani and M. Usher, "off-line recognition of analysis and machine intelligence", Vol. 12, No.7, 1990, pp. 704-710.

[7] F. Bouslama and A.Amin, "Pen-based recognition system of Arabic character utilizing structural and fuzzy techniques", second international conference on knowledge- based intelligent electronic systems, 21-23 April 1998, Adelaide, Australia. Jain , 1998, pp. 76-85.

[8] A. Alimi and O. Ghorbel, "The analysis of error in an off-line recognition system of Arabic handwritten characters", Proceeding of ICDAR, Montreal, Canada, 1995, pp.890-893.

[9] R.A Harty and H.M El-Zabadani, "An offline Arabic handwriting recognition system", international journal of computers and applications, 2005.

[10] R.A Farah,. , Khadir, M.T. and M. Sellaim, "Artificial neural network fusion: Application to Arabic words recognition", ESANN 2005 proceeding, European symposium on artificial neural networks, bruges (Belgium), April 2005, pp. 27-29.

[11] X. Yihong and G.Nagy, "Prototype extraction and adaptive OCR", IEEE transaction on Pattern analysis and machine intelligence, Vol. 21, No.12, 1999.

[12] Y.Yanjun, " Reforming the theory of invariant moments for pattern recognition". Pattern Recognition, Vol. 25, No. 7, 1992, pp: 723-730.