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Arabic Character Recognition Based on Moments Method

A Thesis

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of Science in
Computer science**

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((هذا من فضل ربي ليبلونني ء اشكر أم اكفر ومن
شكر فانما يشكر لنفسه ومن كفر فان ربي غني
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صدق الله العلي العظيم

القرآن الكريم – سورة النمل ، آية ٤٠

الاهداء

الى العراق.....وطني الاوحد.
الى كل من ساهم بشرف في بنائه.
الى من ربياني صغيرا ورعياني كبيرا
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النرجس العطرة
عائــــــــــــلي.....

اهدي ثمرة جهدي المتواضع

رغد

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Raghad

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Abstract

Pattern recognition is an essential part of any high-level image analysis systems.

Arabic language has four forms for each letter depending on the position of the letter in each word. These are initial, medial, final and isolated. This research concerned with recognizing an isolated Arabic Characters using Hu's seven moments concept.

Moments and functions of moments have been extensively employed as invariant global features of images in characters recognition.

Character recognition performed by two stages; first is the training stage and the second is testing stage, these involves several major functions starting from the input character until deciding the recognition of character.

These functions are preprocessing, feature extraction and characters matching. Preprocessing function includes; image acquisition, noise removal using median filter, image binarization and characters segmentation.

The characters matching include the computation of the Euclidean distance between testing and training characters.

Recognition system has been performed on the printed Arabic characters and the percentage accuracy for recognize 65 printed characters was 96.92307% While in hand written characters the recognition percentage is decreased, due to irregularities appears in the handwritten characters.



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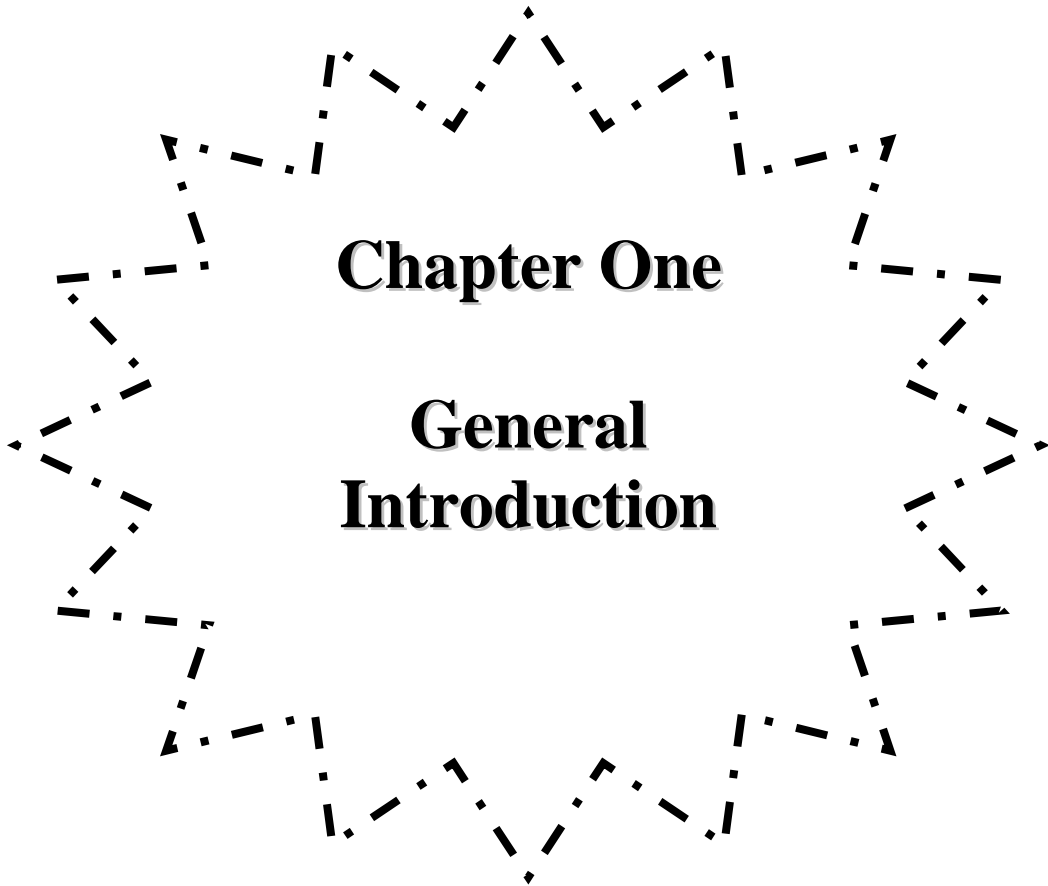
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List of Abbreviations

RMS	Root Mean Square
OCR	Optical Character Recognition
DCG	Definite Clause Grammar
ACR	Automatic Character Recognition
DPI	Dot Per Inch
BPP	Bits Per Pixel



Chapter One

General Introduction

Chapter One

General Introduction

1.1 Introduction

One of the most frequent tasks in computer vision and image processing is the recognition of an image or an object in the image. Among these tasks, Optical Character Recognition (OCR).

Various OCR algorithms have been found to achieve better performances. These algorithms include template matching, image signatures, image geometric features, and shape-based image invariants. Among these algorithms, the shape-based image invariants are of particular interests as they have the invariance property which can improve the recognition performance even the images have undergone various image transformations such as translation, scaling and rotation. There are two types of shape-based image invariants: boundary-based and region-based [Zha02]. The boundary-based image invariants focus on the properties contained in the image's contour. The most common boundary-based image invariants include Fourier descriptors. The region-based image invariants take the whole image area as the research object. Region-based image invariants include various moment-based invariants such as Hu's seven moment invariants.

The aim of the present work is to make computers able to recognize optical symbols without human intervention. This is accomplished by searching a match between the features extracted from the given symbol's image and the library of image models. Ideally, features should be distinct for different symbol images so that the computer can extract the correct model from the library without confusion. Meanwhile, also it is wanted the features to be robust enough so that they will not be affected by viewing transformations, noises, resolution variations and other factors.

1.2 Historical Review

Historically, the Automatic Character Recognition (ACR) systems have evolved in three ages. *The early age expanded through the interval 1900-1980:* The ACR studies were started by the Russian scientist Tyurin in 1900 [Gov90]. The first modern character recognizers appeared in the middle of the 1940s with the development of the digital computers. In this time early work on the automatic recognition of characters has been concentrated either upon printed text or upon small set of handwritten text or symbols. Successful but constrained algorithms had been implemented mostly for Latin characters and numerals. Besides, some studies are published on Japanese, Chinese, Hebrew, Indian, Cyrillic, Greek and Arabic (characters and numerals) in both printed and handwritten cases are also done [Adi91]. In 1950 the commercial character recognizers appeared with introducing electronic tablets capturing the x-y coordinate data of pen-tip movement this innovation enabled the researchers to work on the on-line handwritten recognition [Sue80].

The middle age was during the decade 1980-1990: The studies until 1980 suffered from the lack of advanced Algorithms, powerful hardware and optical devices. With the explosion on the computer hardware and software technology, the previously developed methodologies found a very fertile environment for rapid growth in many application areas as well as ACR system development [Boz89].

The last age begin after 1990 Advancements: There is a renewed interest in the character recognition field was found, which involves the recognition of both printed and handwritten characters. Nowadays, it is not only we now have more compact and powerful computers and more accurate electronic equipment such as scanner, camera, electronic tablet etc., but, it was have better recognition algorithms which utilize advanced methodologies such as neural networks, hidden markov models or fuzzy set reasoning. But, still there is a long way to go

in order to reach the ultimate goal of machine simulation of fluent human reading.

Since the past few decades a number of researchers have investigated the problem of handwritten digit (character) recognition and many methods have been developed. However, no system to date has achieved the goal of system acceptability. Researchers in this field have proposed different approaches, such as statistical, structural, and moments based approaches [**Cas95**].

In 1987 N. Ula [**Ula87**] used a table look-up for the recognition of isolated handwritten Arabic characters. In this approach, the character is placed in a frame, which is divided into six rectangles and a contour tracing algorithm is used for coding the contour as a set of directional vectors by using a Freeman code. However, this information is not sufficient to determine Arabic characters. Therefore, extra information related to the number of the secondary parts and their position was added. If there is no match, the system will add the feature vector to the table and consider that character as a new entry).

In 1990 S. Dabi [**Dab90**] adopted a statistical approach for recognizing Arabic typewritten characters. In this approach the characters are segmented and recognized by using accumulative invariant moments as feature descriptors.

In 1992 V. Margner [**Mar92**] used outer contours to segment an Arabic word into characters. The word is divided into a series of the curves by determining the start and end points of the word. Whenever the outer contour changes sign a character is segmented.

In 1998 E. J. Mohammed [**Moh95**] design and implement an arabic character recognizer. The complex moment concept is adopted as a method of matching. Different measurement of character feature have been used for identifying the characters, such as Root Mean Square (RMS) distance or gradient parameters.

In 2001 T. O. Robert [**Rob01**] designed a structural recognition approach for extracting morphological features and performing classification without

relying on domain knowledge. This system employs a statistical classification technique to perform discrimination based on structural features is a natural solution. A set of morphological features is suggested as the foundation for the development of a suite of structure detectors to perform generalized feature extraction for structural pattern recognition in time-series data.

In 2002 C. Kam-Fai [**Kam02**] proposed a syntactic (structural) approach for the analysis of on-line handwritten mathematical expressions. The authors used Definite Clause Grammar (DCG) to define a set of replacement rules for parsing mathematical expressions.

1.3 Aim of the Project

The present work aims at utilize moments invariant descriptors to recognize the isolated Arabic characters. Almost, this is carried out by testing the adopted system on the printed characters as a primary stage, determines the efficiency of the recognition system, and then applies the adopted system on the handwritten Arabic characters.

1.4 Thesis Outlines

In addition to current chapter, the remaining chapters in present thesis drop through three chapters. In the following, a detailed explanation on each one of them is found.

◆ Chapter Two "*Character Recognition Approaches*"

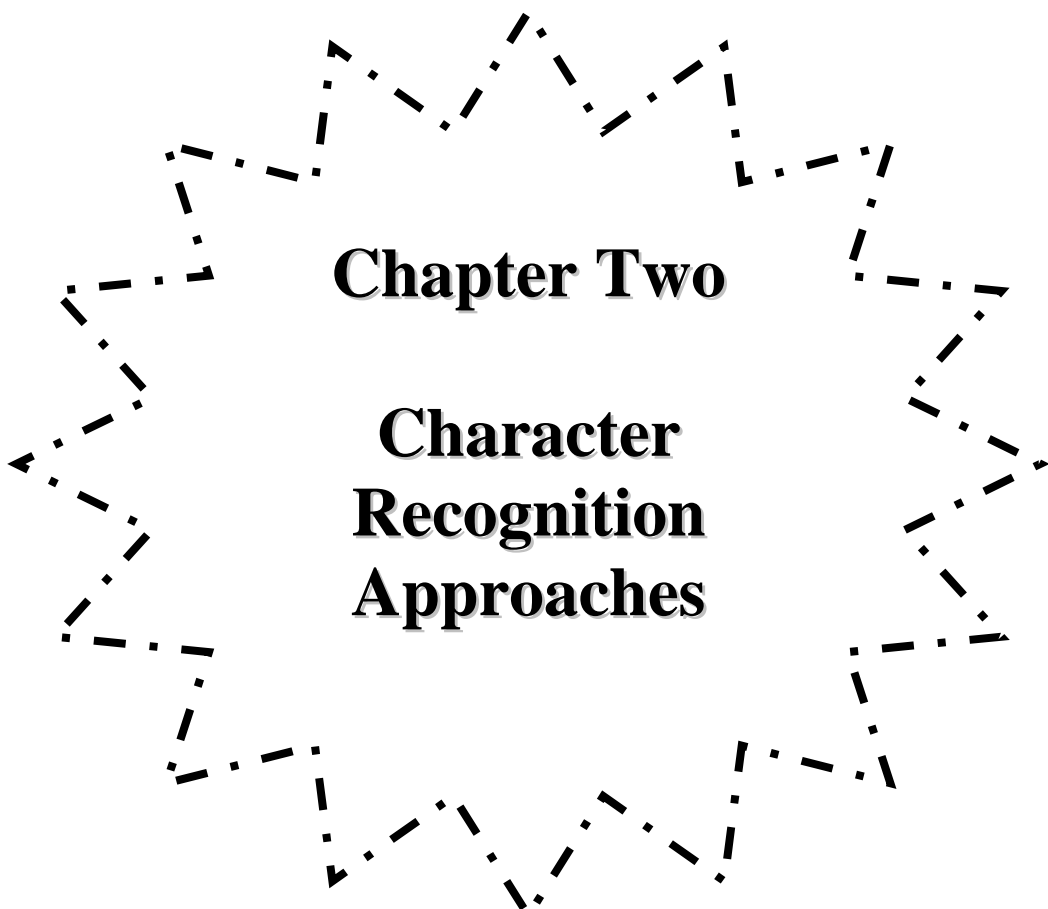
This chapter presents the basic concepts of the recognition and discuss the types of approaches.

◆ Chapter Three "*Character Recognition System*"

This chapter deals with the mathematical and programming details of the adopted approach. The used method are explained the results.

◆ Chapter Four "*Conclusion and Suggestion for future work*"

This chapter contains some of conclusions appeared during the time of the current work, which actually result from the analysis of the input/output information. Moreover, it contains some suggestions that should be noted in the future work.



Chapter Two

Character Recognition Approaches

Chapter Two

Character Recognition Approaches

2.1 Introduction

Pattern recognition techniques are among the most important tools used in the field of machine intelligence. The pattern recognition can be defined as the categorization of input data into identifiable classes by extracting significant features or attributes of the data from a background of irrelevant detail [Gon78]. Thus, the study of pattern recognition problems may logically divide in to two major categories;

- 1- The study of the pattern recognition capability of human beings and other living organisms.
- 2- The development of theory and practical techniques for machine implementation of a given recognition task [Mer05].

There are two fundamental approaches to implement a pattern recognition system; *statistical* and *structural*. Each approach employs different techniques within the description and classification tasks which constitute a pattern recognition system.

Statistical pattern recognition draws from established concepts in statistical decision theory to discriminate among data from different groups based upon quantitative features of the data. The quantitative nature of statistical pattern recognition makes it difficult to discriminate among groups based on the morphological (i.e., shape based or structural) sub patterns and their interrelationships embedded within the data. This limitation provided the impetus for the development of a structural approach to pattern recognition.

Structural pattern recognition sometimes referred to as syntactic pattern recognition due to its origins in formal language theory, relies on syntactic grammars to discriminate among data from different groups based upon the morphological interrelationships (or interconnections) present within the data.

Structural pattern recognition systems have proven to be effective for data which contain an inherent, identifiable organization such as character or digit recognition [Taa05]. Handwritten character recognition proves to be challenging problem due to the large variance the data may exhibit, not only there are changes and distortions from one writer to another, but even for samples produced by the same writer . Figure (2.1) shows the different schemes exist under the term character recognition.

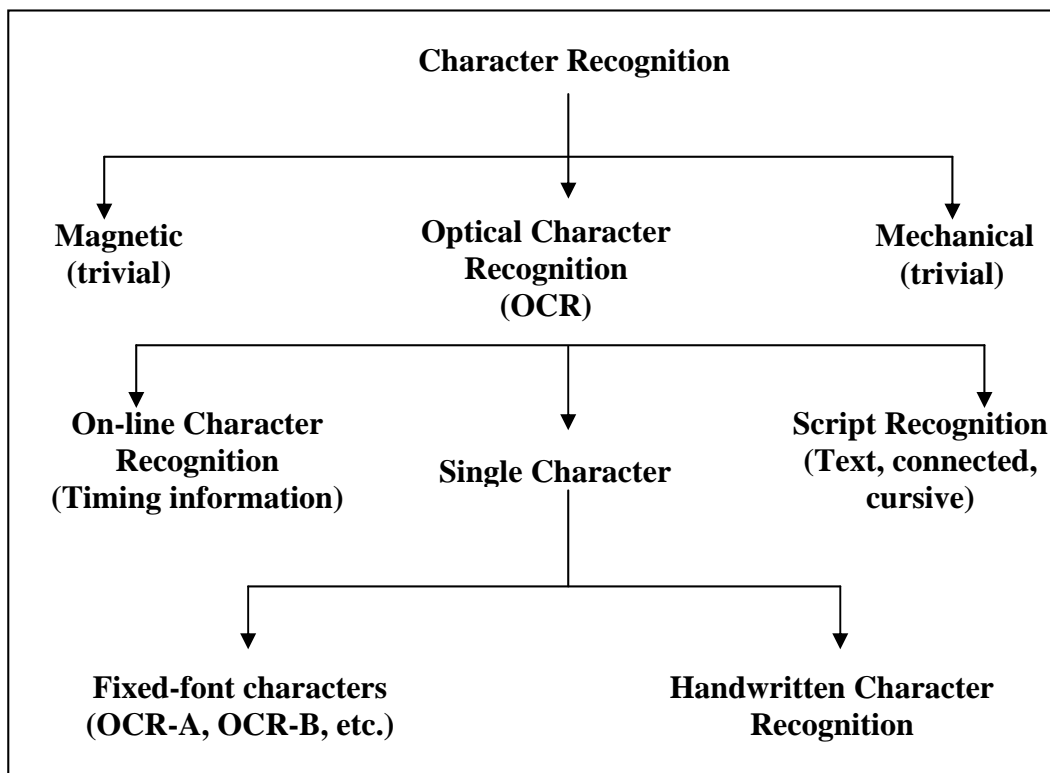


Figure (2.1) General areas covered under term "Character Recognition" [Moh95].

The order of difficulty of character recognition problems is (starting from the most difficult); script recognition, handwritten character recognition, on-line character recognition, fixed-font character recognition and the trivial task of magnetic or mechanical characters.

2.2 Machine Learning [Tho02]

Machine Learning is the study of methods for programming computers to learn. Computers are applied to a wide range of tasks, and for most of these it is relatively easy for programmers to design and implement the necessary software. However, there are many tasks for which this is difficult or impossible. These can be divided into four general categories. First, there are problems for which there exist no human experts. For example, in modern automated manufacturing facilities, there is a need to predict machine failures before they occur by analyzing sensor readings.

A machine learning system can study recorded data and subsequent machine failures and learn prediction rules. Second, there are problems where human experts exist, but where they are unable to explain their expertise. This is the case in many perceptual tasks, such as speech recognition, hand-writing recognition, and natural language understanding. Virtually all humans' exhibit expert-level abilities on these tasks, but none of them can describe the detailed steps that they follow as they perform them. Fortunately, humans can provide machines with examples of the inputs and correct outputs for these tasks, so machine learning algorithms can learn to map the inputs to the outputs. Third, there are problems where phenomena are changing rapidly. In finance, for example, people would like to predict the future behavior of the stock market, of consumer purchases, or of exchange rates. These behaviors change frequently, so that even if a programmer could construct a good predictive computer program, it would need to be rewritten frequently. A learning program can relieve the programmer of this burden by constantly modifying and tuning a set of learned prediction rules. Fourth, there are applications that need to be customized for each computer user separately. Consider, for example, a program to filter unwanted electronic mail messages. Different users will need different filters. It is unreasonable to expect each user to program his or her own rules, and it is infeasible to provide every user with a software engineer to keep the

rules up-to-date. A machine learning system can learn which mail messages the user rejects and maintain the filtering rules automatically.

Machine learning addresses many of the same research questions as the fields of statistics, data mining, and psychology, but with differences of emphasis. Statistics focuses on understanding the phenomena that have generated the data, often with the goal of testing different hypotheses about those phenomena. Data mining seeks to find patterns in the data that are understandable by people. Psychological studies of human learning aspire to understand the mechanisms underlying the various learning behaviors exhibited by people (concept learning, skill acquisition, strategy change, etc.).

2.3. Characteristic of Arabic Alphabets [Tim01]

Due to the cursive nature of the script, there are several characteristics that make recognition of Arabic distinct from the recognition of Latin scripts or Chinese see figure (2.2).

أ ب ت ث ج ح خ
د ذ ر ز س ش ص
ض ط ظ ع غ ف ق
ك ل م ن
ه و ي

Figure (2.2) Letters of the isolated Arabic alphabet.

Arabic has 28 letters in the alphabet. It is based on 18 distinct shapes that vary according to their connection to preceding or following letters. Using a combination of dots and symbols above and below these shapes, the full complement of 28 consonants can be constructed.

Arabic is a cursive language. There are no capital letters and some letters are not connected to the letters that follow them. Thus, words cannot be segmented based on pen-up/pen-down information or space between letters. Block or hand printed letters do not exist in Arabic. In summary, many researchers have been working on cursive script recognition for more than three decades. Nevertheless, the field remains one of the most challenging problems in pattern recognition and all the existing systems are still limited to restricted applications. Arabic has four forms for each letter depending on the position of the letter in each word. These are initial, medial, final and isolated. A key difference between Latin scripts and Arabic is the fact that many letters only differ by a dot(s) but the primary stroke is exactly the same. This highlights the need for a good feature extractor/classifier for the secondary stroke(s).

2.4 Automatic Character Recognition Systems

In this section, an overview of Automatic Character Recognition (ACR) techniques is presented; Data is captured from its source to the computers by various data acquisition techniques. The ACR methodologies are very much dependent on the type of the equipment used for data acquisition. The text type is another determining factor for the ACR techniques. In the following, the classification of the ACR techniques will be given.

2.4.1 Systems Classified According to Data Acquisition

The progress in Automatic Character Recognition systems is evolved in two categories according to the mode of data acquisition:

- On-line character recognition systems.
- Off-line character recognition systems.

Off-line character recognition captures the data from paper through optical scanners or cameras whereas the on-line recognition systems utilize the digitizers which directly capture writing with the order of the strokes, speed, pen-up and pen-down information. [Naf98].

2.4.1.1 On-line Character Recognition Systems [Tia91]

The problem of recognizing handwriting recorded with a digitizer as a time sequence of pen coordinates is known as on-line character recognition. Whenever the digitizer captures the data during writing, the ACR system with or without a lag makes the recognition. The digitizers are mostly electromagnetic-electrostatic tablets which send the coordinates of the pen tip to the host computer at regular intervals. Some digitizers use pressure-sensitive tablets which have layers of conductive and resistive material with a mechanical spacing between the layers. There are also, other technologies including laser beams and optical sensing of a light pen.

While nothing opposes the idea of a computer that would use multiple input modalities including speech, keyword and pen, some applications call for a pen-only computer interface; in social environment, speech does not provide enough privacy, for small hand-held devices and for large alphabet, the keyboard is cumbersome. Applications are numerous; personal organizer, personal communicator, notebook, data acquisition device for order entries, inspections, inventories, surveys, etc.

The on-line handwriting recognition problem has a number of distinguishing features, which must be exploited to get more accurate results than the off-line recognition problem;

- It is adaptive. The immediate feed-back is given by the writer whose corrections can be used to further train the recognizer.
- It is a real time process. It captures the temporal or dynamic information of the writing.

On the other hand, the disadvantages of the on-line character recognition are as follows

- The writer requires special equipment, not as pen and paper which is comfortable and natural to use.
- It can not be applied to documents printed or written on papers.
- Punching is much faster and easier than handwriting for small size alphabet such as English or Arabic.

2.4.1.2 Off-line Character Recognition Systems [Naf98]

Off-line character recognition is also, known as "Optical Character Recognition" (OCR); because the image is converted into a bit pattern by an optically digitizing device such as optical scanner or camera. The recognition is done on this bit pattern data for both printed and hand-written text. The research and development is well progressed for the OCR of the printed documents.

The bit pattern data is shown by a matrix of pixels. This matrix can be very large. In order to meet the complexity and sophistication and to insert much data in recognition, most scanners are designed to have an x-y resolution of typically 100-1600 dots per inch.

The major advantage of the off-line recognizers is to allow the previously written and printed texts to be processed and recognized. Some applications of the off-line recognition are large scale data processing such as postal address

reading, cheque sorting, short hand transcription, automatic inspection and identification, reading aid for visually handicapped.

The drawbacks of the off-line recognizers, compared to on-line recognizers are summarized as follows:

- Off-line conversion usually requires costly and imperfect pre-processing techniques prior to feature extraction and recognition stages.
- They do not carry temporal or dynamic information such as the number and order of pen-on and pen-off movements, the direction and speed of writing and in some cases, the pressure applied while writing a character.
- They are not real-time recognizers.

2.4.2 Systems Classified According to Text Type [Tia91]

There are two main areas of interest in character recognition, namely:

- Printed Character Recognition.
- Hand-written Character Recognition.

The problem of printed character recognition is relatively well understood and solved with little constraints. When the documents are typed on a high quality paper with modern printing technologies. On the other hand, hand-written character recognition systems have still limited capabilities even for recognition of the Latin characters.

2.4.2.1 Printed Character Recognition

The printed texts include all the printed materials such as books, newspapers, magazines, and documents which are the outputs of typewriters, printers or plotters. On the basis of the capabilities and complexities printed characters can be further classified as:

- Fixed-font Character Recognition (recognition of a specific font).
- Multi-font Character Recognition (recognition of more than one font).
- Omni-font Character Recognition (recognition of any font).

The above classes of printed character recognition problems are well studied. However, the recognition rates of the commercially available products are very much dependent on the age of the documents, quality of paper and ink which may result in significant data acquisition noise.

2.4.2.2 Hand-Written Character Recognition

Handwritten character recognition, based on the form of written communication, can be divided into two categories- cursive script and hand-printed characters. In practice, however, it is difficult to draw a clear distinction between them. A combination of these two forms can be seen frequently. Based on the nature of writing and the difficulty of segmentation process.

2-5 Character Recognition Paradigm

Since there are common aspects between group of some techniques, and other common aspects between other group of techniques. Therefore these technique can be classified into three major approaches based upon the common aspects of groups, these are:

2.5.1 Statistical Approach

In the statistical approach, each pattern is represented in terms of (n) features or measurements and is viewed as a point in a d -dimensional space. The goal is to choose those features that allow pattern vectors belonging to different categories to occupy compact and disjoint regions in a d -dimensional feature space. The effectiveness of the representation space (feature set) is determined by how well patterns from different classes can be separated. Given a set of training patterns from each class, the objective is to establish decision boundaries in the feature space which separate patterns belonging to different classes. In the statistical decision theoretic approach, the decision boundaries are

determined by the probability distributions of the patterns belonging to each class, which must either be specified or learned [Dev96].

2.5.2 Geometrical Approach (Test Method)

The most common aspects of all techniques used in this approach are geometrical features such as, line, angles of intersected lines, curves, etc. Therefore series of tests are applied in order to determine distinctive features in the unknown character which are compared to that learned characters. This approach is specific for a given application whereby the tests are designed for each particular problem. In the case where the number of classes to be identified is great, this approach becomes difficult to apply [Pav75].

2.5.3 Template Matching Approach

One of the simplest and earliest approaches to pattern recognition is based on template matching. Matching is a generic operation in pattern recognition which is used to determine the similarity between two entities (points, curves, or shapes) of the same type. In template matching, a template (typically, a 2D shape) or a prototype of the pattern to be recognized is available. The pattern to be recognized is matched against the stored template while taking into account all allowable pose (translation and rotation) and scale changes. The similarity measure, often a correlation, may be optimized based on the available training set. Often, the template itself is learned from the training set. Template matching is computationally demanding, but the availability of faster processors has now made this approach more feasible [Rob00].

2.5.4 Syntactical (Structural) Approach

The recognition in this approach is done through a description of the pattern in terms of primitive elements and relations between them. *The syntactical technique* makes use of the results obtained from the theory of

formal languages which have been developed in other areas of computer science. The important aspect of this method is the possibility of using a grammar and its recursive nature to describe a pattern by a string of characters. The first applications of this method are the coding of contours in the images (chromosomes...) this approach has been generalized to three-grammar [Fu82]. Meanwhile *the structural technique* is similar to the syntactical technique in that it makes use of a graph representation of a pattern; the main difference is, however, the absence of a grammar. The necessity of such representation and has been recognized since the early structural techniques [Rot76].

2.5.5 Moments Based Approach

The seven Moments constitute an important set of parameters for image analysis. The low order moment contain significant information about simple object. They have been used in finding the location and orientation of an object. Moment invariants have been used as features for pattern recognition. The 0th order moment represent the total mass (area for binary image) of the object. The first order moments locate the centroid of an object in the image. The angle of the principle axis, which characterizes the orientation of the object in the image, can be found from the lower order moments up to the second-order moments. The location, size and orientation are the fundamental description of an object. They have the desirable property of being invariant under the object translation, scaling and rotation [Kep90]. However, since moments have such power of describing an object, which requires certain mathematical notations, it was selected to contribute in building the proposed character recognition system as presented in chapter three.

2.6 Proposed Character Recognition Systems

The designed character recognition system based on the series of operations needed to construct the optical character recognition, the functional structure of pattern recognition system show in figure (2.3) the following sections will show more details about these operations.

Input

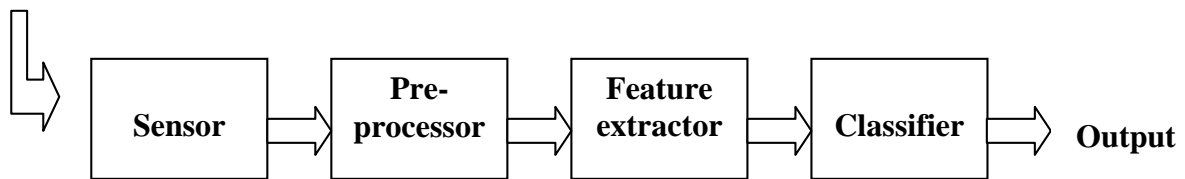


Figure (2.3) Functional structure of pattern recognition system [Lei07].

2.6.1 Sensor [Lei07]

The conversion from printed page to digital image often involves specialized hardware like an optical scanner that attempts to determine the color value at evenly spaced points on the page. The scanning resolution will determine how many of these points will be inspected per unit of page length.

Typically this is specified in dots or pixels per inch, thus a document scanned at a resolution of 300 Dot Per Inch (DPI) will have been sampled at 300 evenly spaced points for each inch of each page. At each of these sample points or pixels the color depth will determine to what extent the recognized color matches the true color on the page. One of the more common color depths involves using a single byte to store each of the red, green and blue channels (plus an optional additional byte used to store opacity information). Since each byte of storage is made up of 8 bits, $2^8 = 256$ unique shades of a color can be represented. Since any color can be created by mixing red, green, and blue, the desired color is approximated using the closest shade of red, green, and blue. Note that color depth is often measured in Bits Per Pixel (BPP).

Image that contains the text to be recognized is acquired by using scanner and a bitmap image with true colors will be saved for further processing.

2.6.2 Pre-processing

The pre-processing stage includes the following pre-processes:

- 1- Noise Removal.
- 2- Binarization.
- 3- Segmentation.

2.6.2.1 Noise Removal

During the scanning process, differences between the digital image and the original input (beyond those due to quantization when stored on computer) can occur. Hardware or software defects, dust particles on the scanning surface, improper scanner use, etc. can change pixel values from those that were expected. Such unwanted marks and differing pixel values constitute noise that can potentially skew character recognition accuracy.

Furthermore, certain marks or anomalies present in the original document before being scanned (from staples, or telephone line noise during fax transmission etc.) constitute unwanted blemishes or missing information that one may also like to rectify and correct before attempting character recognition. In this project the *median filtering* is used [Lei07].

In *median filtering* the input pixel is replaced by the median of the pixels contained in the neighborhood, the algorithm for median filtering requires arranging the pixel gray values in the neighborhood in ascending or descending order and picking up the value at the center of the array. Generally the size of the neighborhood is chosen as odd number so that a well-defined center value exists. If, however, the size of the neighborhood is even the median is taken as the arithmetic mean of the two values at the center. Some of the properties of median filter are:

- It is a nonlinear filter.
- It is useful in removing isolated lines or pixels while preserving spatial resolution. It is found that median filter works well on binary noise but not so well when the noise is Gaussian.
- Its performance is poor when the number of noise pixels is greater than or equal to half the number of pixels in the neighborhood [Hua79].

2.6.2.2 Image Binarization

Images in this stage are considered to be binary. The pixels in binary image can assume only two values, 0 or 1; the binary images are thus least expensive, since the storage and also processing requirement is least. Examples of binary images are line drawings, printed text on a white page, or silhouette. These images contain enough information about the objects in the image that can be recognized easily. There are a number of applications in computer vision where binary images are used for object recognition, tracking, and so on. The applicability of binary images is limited because the overall information content in such images is limited [Jai95].

A gray level image may be converted to a binary image by thresholding process. The process of converting the image into binary mode is called binarization.

Several approaches to binarization have been discussed in the literature but they typically fall into one of two categories. Global methods treat each pixel independently, converting each to black or white based on a single threshold value. If a pixel's color intensity is higher than the global threshold it is assigned one value, otherwise it is assigned the opposite value. In contrast local methods, make use of the color information in nearby pixels to determine an appropriate threshold for a particular pixel. The goal of the binarization is to separate the character from the background in the gray image and reduce the image color into Black & White. [Sna04].

2.6.2.3 Image segmentation

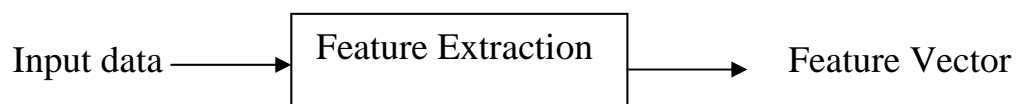
It is generally the first step in any attempt to analyze or interpret an image automatically. It is defined to be the process of partitioning the image into distinct region that are meant to correlate strongly with objects or features of interests in the image. It also regarded as a process of grouping together pixels that have similar attributes.

2.6.3 Feature Extraction [Mar05]

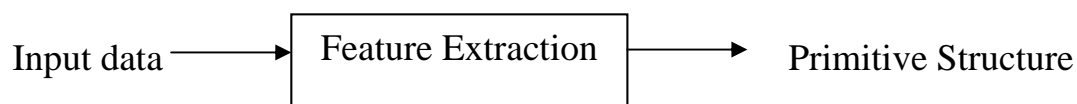
Feature is a set of information represent the observed data efficiently such that minimizing the within class pattern variability while enhancing the between class pattern variability.

There are two main types of features:

1- Statistical (Numerical, Quantitative) features



2- Structural (Syntactical, Quantitative) features



Feature extraction process will generate feature sets that represent characters occurrences in the image. In current work, features are extracted by using *character moments*. In order to recognize an object in an image, we need to make two choices. The first one concerns the selection of a characteristic feature of each object. This feature must have in general some properties as invariance by rotation, scale or translation of the object, which is appropriate to the objective of the current thesis.

It can be directly computed on the original image or after wards segmentation result as for example a contour detection. The second choice

concerns the decision criteria for the object recognition among one of its known objects in the knowledge database using the previous features.

2.6.3.1 Shape Features [Tin05]

Shape is another image feature. Shape can roughly be defined as the description of an object minus its position, orientation and size. Therefore, shape features should be invariant to translation, rotation, and scale, when the arrangements of the objects in the image are not known in advance. To use shape as an image feature, it is essential to segment the image to detect object or region boundaries; and this is a challenge. Techniques for shape characterization can be divided into two categories. The first category is *boundary-based*, using the outer contour of the shape of an object. The second category is *region-based*, using the whole shape region of the object. The most prominent representatives of these two categories are Fourier descriptors and moment invariants. The main idea behind the Fourier descriptors is to use the Fourier-transformed boundaries of the objects as the shape features, whereas the idea behind moment invariants is to use region-based geometric moments that are invariant to translation and rotation.

2.6.3.2 Hu's Moment Computation [Qin03]

In region-based invariants, all of the pixels of the image are taken into account to represent the shape. Because region-based invariants combine information of an entire image region rather than exploiting information just at the boundary points, they can capture more information regarding the image.

Moment-based invariants are the most common region-based image invariants which have been used as pattern features in many applications. Hu in 1961 introduced a set of moment-based invariants using nonlinear combinations

of regular moments. Hu's seven moments invariants have the desirable properties of being invariant under image translation, scaling, and rotation.

Hu identified seven normalized central moments as shape features, which are also scale invariant. These seven invariants are expressed by the following equations:

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x,y) dx dy \dots\dots\dots (2.1)$$

For $p,q=0,1,2\dots\dots\dots$

Where m_{pq} is the $(p+q)^{th}$ order moment of the continuous image function $f(x,y)$.

The central moments of $f(x,y)$ are defined as:

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q f(x,y) dx dy \dots\dots\dots (2.2)$$

Where $\bar{x} = m_{10} / m_{00}$ and $\bar{y} = m_{01} / m_{00}$, which are the centroid of the image.

For digital images the integrals are replaced by summations and m_{pq} becomes:

$$\mu_{pq} = \sum_x \sum_y x^p y^q f(x,y) \dots\dots\dots(2.3)$$

Then the central moments are changed to:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x,y) \dots\dots\dots (2.4)$$

The central moments of order 3 are as follows:

$$\mu_{10} = \sum_x \sum_y (x - \bar{x})^1 (y - \bar{y})^0 f(x,y) = \frac{m_{10}}{m_{00}} - \frac{m_{10}}{m_{00}} = 0 \dots\dots\dots(2.5)$$

$$\mu_{11} = \sum_x \sum_y (x - \bar{x})^1 (y - \bar{y})^1 f(x,y) = \frac{m_{11}}{m_{00}} - \frac{m_{10} m_{01}}{m_{00}^2} \dots\dots\dots(2.6)$$

$$\mu_{20} = \sum_x \sum_y (x - \bar{x})^2 (y - \bar{y})^0 f(x, y) = m_{20} - \frac{2m_{10}^2}{m_{00}} + \frac{m_{10}^2}{m_{00}} = m_{20} - \frac{m_{10}^2}{m_{00}} \dots\dots(2.7)$$

$$\mu_{02} = \sum_x \sum_y (x - \bar{x})^0 (y - \bar{y})^2 f(x, y) = m_{02} - \frac{m_{01}^2}{m_{00}} \dots\dots\dots(2.8)$$

$$\mu_{30} = \sum_x \sum_y (x - \bar{x})^3 (y - \bar{y})^0 f(x, y) = m_{30} - 3\bar{x}m_{20} + 2m_{10}\bar{x}^2 \dots\dots\dots(2.9)$$

$$\mu_{12} = \sum_x \sum_y (x - \bar{x})^1 (y - \bar{y})^2 f(x, y) = m_{12} - 2\bar{y}m_{11} - \bar{x}m_{02} + 2\bar{y}^2m_{10} \dots\dots(2.10)$$

$$\mu_{21} = \sum_x \sum_y (x - \bar{x})^2 (y - \bar{y})^1 f(x, y) = m_{21} - 2\bar{x}m_{11} - \bar{y}m_{20} + 2\bar{x}^2m_{01} \dots\dots(2.11)$$

$$\mu_{03} = \sum_x \sum_y (x - \bar{x})^0 (y - \bar{y})^3 f(x, y) = m_{03} - 3\bar{y}m_{02} + 2\bar{y}^2m_{01} \dots\dots\dots(2.12)$$

The normalized central moments, denoted by η_{pq} , are defined as:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^\gamma} \dots\dots\dots(2.13)$$

Where $\gamma = (p + q) / 2 + 1 \dots\dots\dots(2.14)$

For $p + q = 2, 3, \dots$ see figure (2.4).

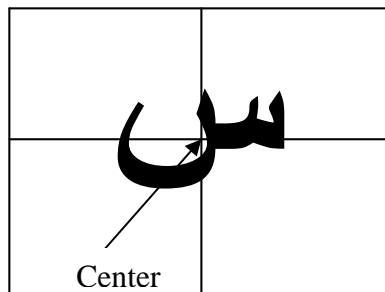


Figure (2.4) Normalized image of character (س)

From the second and third moments, a set of seven invariant moments can be derived. They are given by:

$$\phi_1 = \eta_{20} + \eta_{02} \dots\dots\dots (2.15)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \dots\dots\dots (2.16)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \dots\dots\dots (2.17)$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \dots\dots\dots (2.18)$$

$$\left. \begin{aligned} \phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ &+ (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \right\} \dots\dots\dots (3.19)$$

$$\left. \begin{aligned} \phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ &+ 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \end{aligned} \right\} \dots\dots\dots (2.20)$$

$$\left. \begin{aligned} \phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ &+ (3\eta_{21} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \right\} \dots\dots\dots (2.21)$$

Figure (2.5) shows the behavior for Hu's seven Moments values for Arabic character (س).

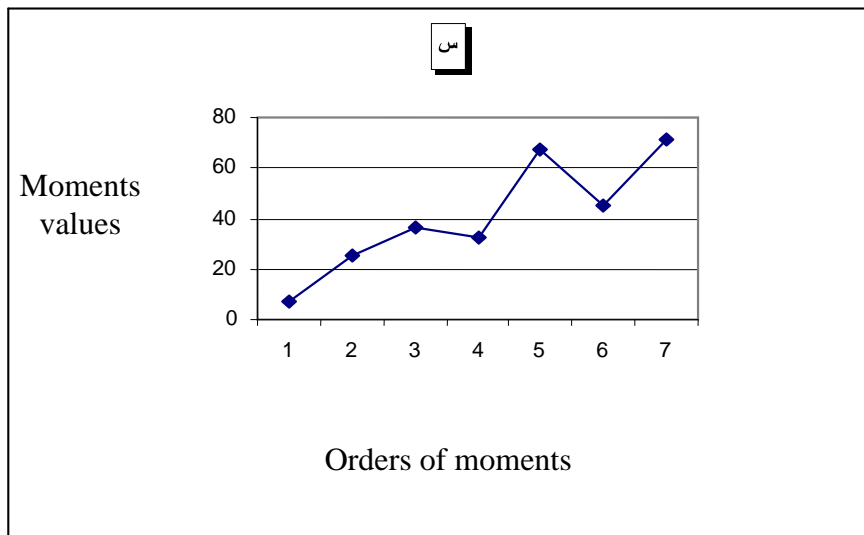


Figure (2.5) Hu's seven Moments Behavior of Arabic Character (س)

2.7 Comparable Model

When working with image representations of symbols from an alphabet, the similarity should attempt to classify each symbol to a specific class.

Since each symbol image is represented by a matrix of pixel intensity values located by the co-ordinates of its rectangular bounding box, similarity should be calculated using this information in some manner. Often, this is carried out by converting the m row by n column matrix representation into a single vector of pixels of length $m \times n$. These vectors can then be thought of as defining points in an $m \times n$ dimensional Euclidean space, where each pixel's value contributes to the final point location along a single dimension. By representing each symbol image as a point in Euclidean space, this allows us to determine similarity of two images based on the distance between their defined points.

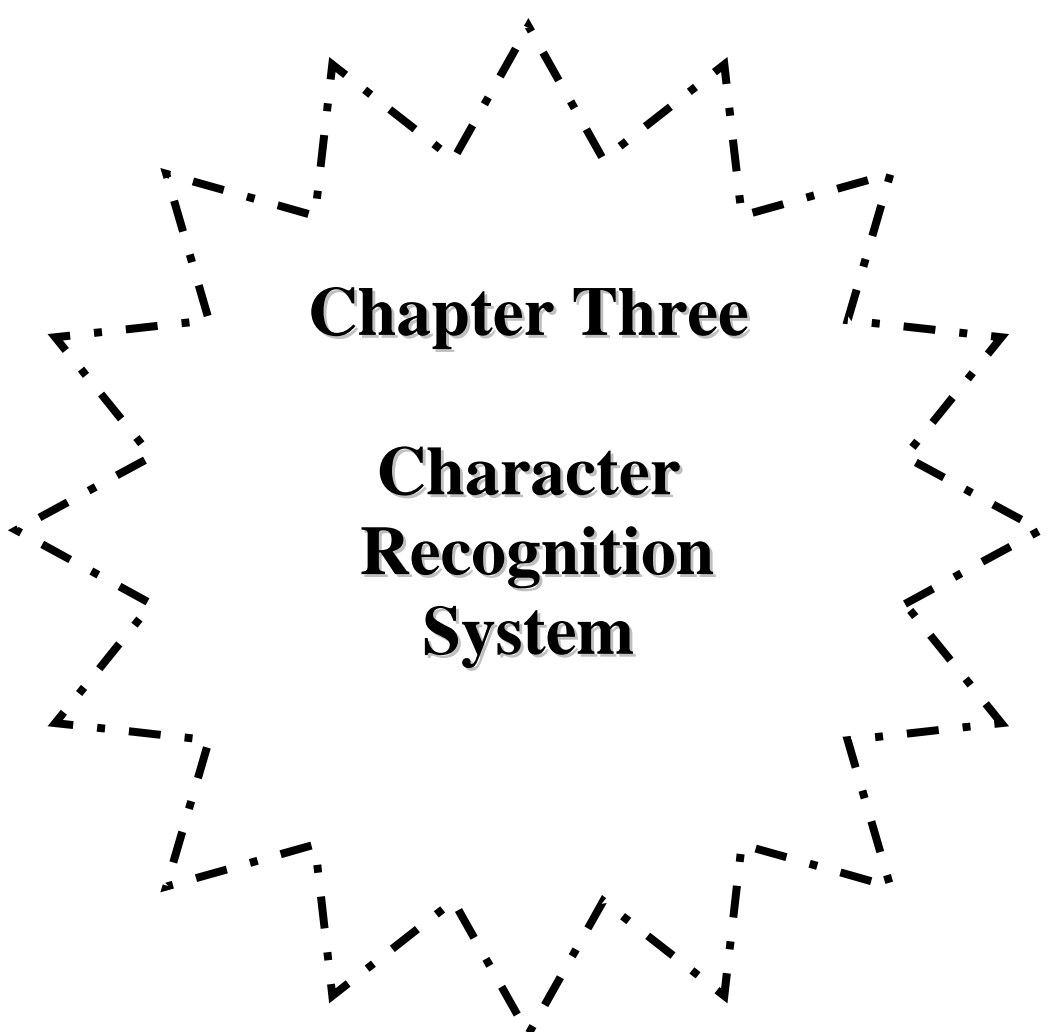
In order to recognize an object in an image, it was need to make two choices. The *first* one concerns the selection of a characteristic feature of each object. This feature must have in general some properties as invariance by rotation, scale or translation of the object.

It can be directly computed on the original image or afterwards segmentation result as for example a contour detection. The *second* choice concerns the decision criteria for the object recognition among one of its known objects in the knowledge database using the previous features.

The Euclidean distance metric is typically what one person appeals to when the term distance is used in its natural or everyday sense. The Euclidean distance between two points is measured as the length of a straight line used to connect them. For two symbol image vectors A and B both composed of n pixels, this distance DE is formally defined in Equation (2.22) [Lei07].

$$DE = \sqrt{\sum_{i=1}^n (A(i)-B(i))^2} \dots\dots\dots (2.22)$$

The quantities *A(i)* and *B(i)* in Equation (2.22) denote the intensity value of the *ith* pixel in image A and B respectively.



Chapter Three

**Character
Recognition
System**

Chapter Three

Character Recognition System

3.1 Introduction

The principal function of a pattern recognition system is decision-making concerning the class membership of the pattern, and with which class to be compared. Pattern recognition system involves several major functions starting from the input pattern until the deciding which class the pattern belongs to.

The sensor function is simply the measurement device that transforms the input pattern into a form suitable for machine manipulation. Although some simple pattern recognition methods operate on the input data directly from the sensor, it is common practice to follow the sensor with a preprocessor and feature extractor. Moreover, the preprocessing function removes unnecessary or corrupting elements from the measured data, while the feature extractor computes from preprocessed data, for the features required in classification. Finally, these features are input into the classifier, whose function is to yield a decision concerning the class membership of the pattern being processed. This chapter describes the method that adopted in the character recognition process, which depends on the theoretical principles and mathematical expressions mentioned in previous chapter. The most popular Arabic font are Thuluth, Koufi, Naskh, Dewani and Rokaa. Each of them has its typeface that can be recognized from others. Rokaa font is near to the traditional font of arabic characters, which is used in this thesis. Figure (3.1) shows the stages needed to constraint the character recognition .

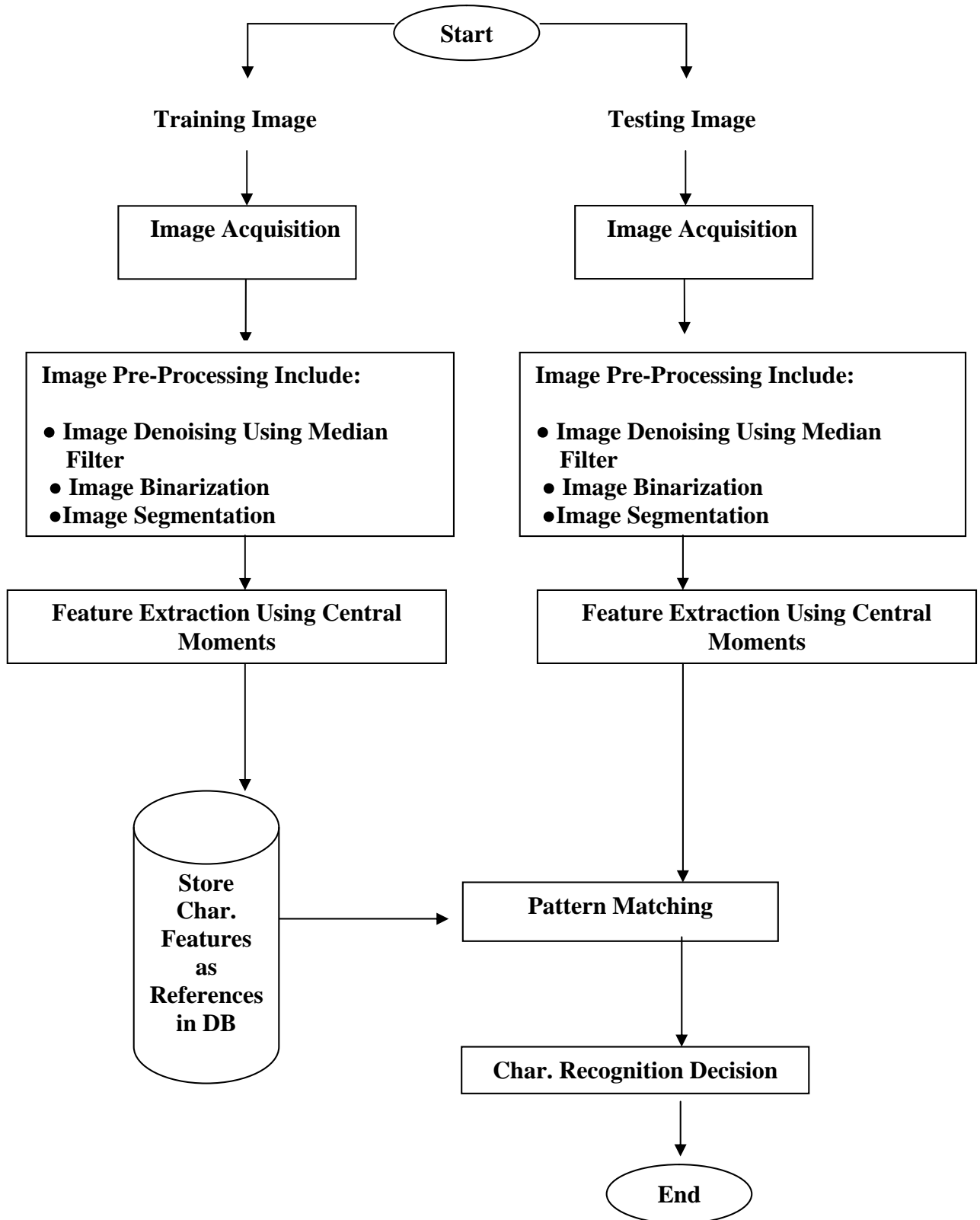


Figure (3.1) Series of operations needed to construct the optical character recognition.

The adopted method passes through some of image preparing processes. The following steps point out the main sequenced operations of the present work.

- 1- Get an image have multi-characters within.
- 2- Separate each character by determining a minimum box that encloses the character.
- 3- Normalized each sub-image by determining its size.
- 4- Extract the features from each sub-image.
- 5- Match the extracted features with those existing in the library to determine the type of character.
- 6- Repeat steps 4 and 5 for each sub-image until end of them.

3.2 Image Acquisition

In image acquisition process the images of characters are scanned using scanner device of type (*canon*) and using white papers of type (*A4*), the image are scanned in *300* dpi resolutions and saved as 8 bit per pixel bitmap.

3.3 Image Denoising (Algorithm and Results)

The denoising process will remove the noise coming during scanning process. Three filter types are adopted in this work Median filter, Minimum filter and Maximum filter with mask filter size (3×3) to choose the value of each pixel from the values around it.

It was found that using median filter for the images that contains characters gives good results than using the maximum filter or minimum filter, because when the minimum filter was used noise will be increased and characters in the image will be like a bold characters and this case will cause problems in the segmentation process, also when the maximum filter was used the characters in the image will loss some parts of them, and this will be also cause another problems in the segmentation process, so that the median filter was used to remove the noise from image of characters.

Algorithm (3.1) show how to perform the median filtering process on the image, this algorithm performs the following:

- 1- Perform a mask of size (3×3) on the image data, transfer the values to a one dimensional array.
- 2- Sort the values of array ascendingly or descendingly.
- 3- Choose the median value from the array as new value of output image.

Figures (3.2) and (3.3) show the images before and after denoising process for both printed and hand written Arabic characters respectively.

Algorithm (3.1) Denoising Filter

Input:

P_DATA (): image data
 H : height of the image
 W : width of the image

Output: image with out noise (Change the contents of P_DATA())

```

1- For all i, j Do {where  $1 \leq i \leq H-2$  and  $1 \leq j \leq W-2$ }
2-   Set z ← 0
3-   For all x, y Do {where  $0 \leq x \leq 2$  and  $0 \leq y \leq 2$ }
4-     Set Median(z) ← P_DATA(x + i - 1, y + j - 1)
5-     Set z ← z + 1
6-   End for
7-   For all x, y Do {where  $0 \leq x \leq z-2$  and  $x+1 \leq y \leq z-1$ } //Sort Mask
8-     Check If Median(x) > Median(y) Then
9-       Median(x) ↔ Median(y) // swapping process
10-    End If
11-  End for
12-  Set Buffer(i, j) ← Median (z / 2)
13-End for
14-For all i, j Do {where  $0 \leq i \leq H-1$  and  $0 \leq j \leq W-1$ }
15-  Set P_DATA(i, j) ← Buffer(i, j)
16-End for
17-End.
```

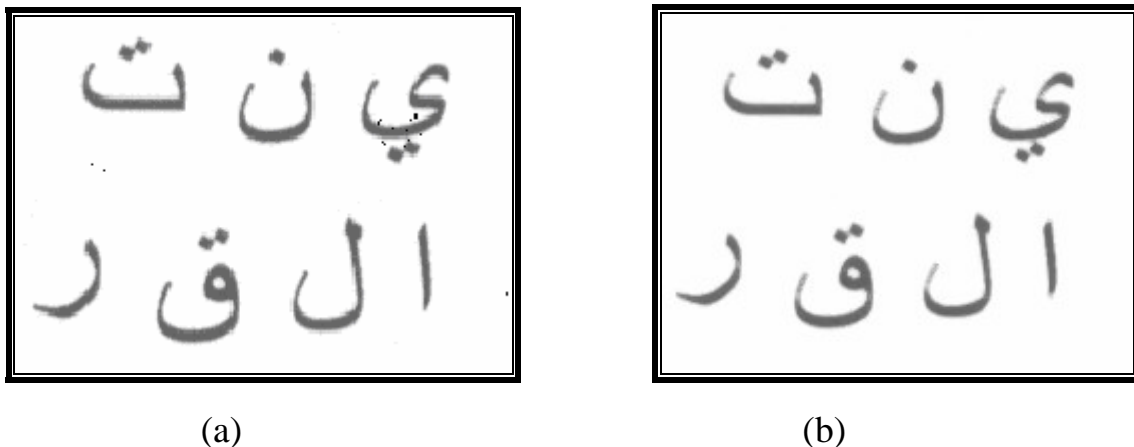


Figure (3.2) Image of printed Arabic characters.

(a) Before denoising process.

(b) After denoising process.

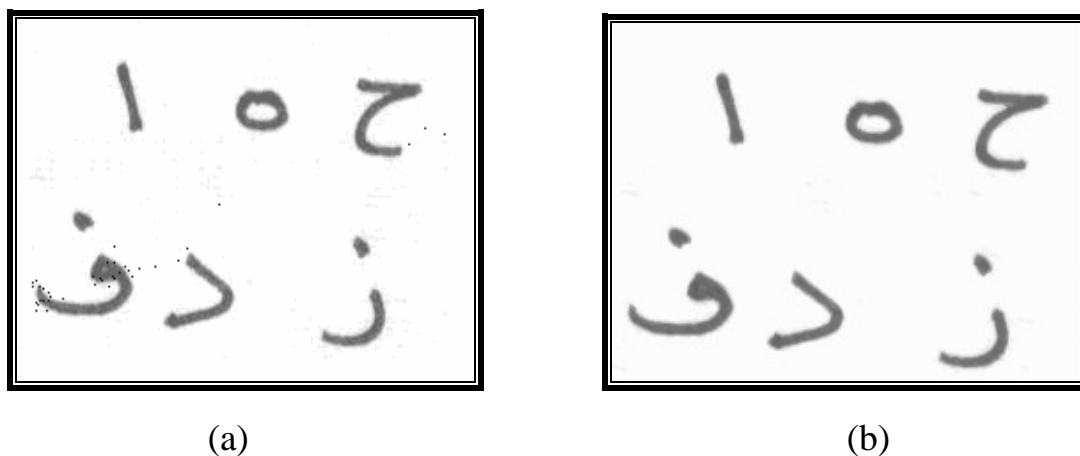


Figure (3.3) Image of hand written Arabic characters.

(a) Before denoising process.

(b) After denoising process.

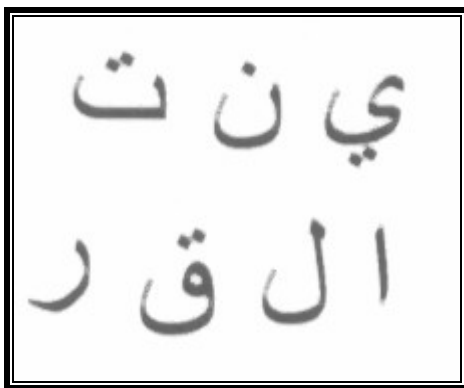
3.4 Image Binarization (Algorithm and Results)

In the binarization process the image will be converted to binary image (i.e. black and white) using the adaptive threshold, it was impotent perform the binarization process after denoising process.

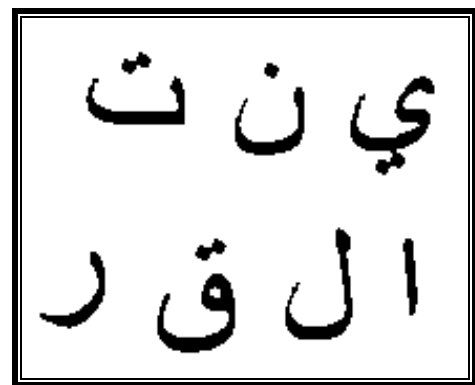
If the binarization process doing directly from the scanner device the noise will still on the paper, so that the binarization process performed after denoising process.

Algorithm (3.2) shows how to perform the binarization process, this algorithm can be performs as follows:

- 1- Find the average (T), of the image.
- 2- Estimate the summation (M_1) of values that greater than (T) and count their number (NuM_1).
- 3- Estimate the summation (M_2) of values that less than or equal to (T) and count their number (NuM_2).
- 4- Compute $Z_1 = M_1 / NuM_1$, and $Z_2 = M_2 / NuM_2$.
- 5- The threshold is $T = (Z_1 + Z_2) / 2$.
- 6- According to the threshold, each pixel in the image will be transfer to either 0 (black) or 1 (white). Figures (3.4) and (3.5) show the images before and after binarization process for both printed and hand written Arabic characters respectively.



(a)



(b)

Figure (3.4) Image of printed Arabic characters.

(a) Before binarization process.

(b) After binarization process.

Algorithm (3.2) Image Binarization**Input:**

P_DATA () : image data (results from denoising process)

H : height of the image

W : width of the image

Output: Binary image Change the contents of P_DATA() to either zero or one)

```
1- Set Average ← 128
2- set T ← Average
3- Do Until Abs(T - T0) < 1
4- initialize ( M2, NuM1, NuM2, M1 ) all to zero
5- For all i, j Do { where 0 ≤ i ≤ H-1 and 0 ≤ j ≤ W-1 }
6-   Check If P_DATA(i, j) > T Then
7-     Set M1 ← M1 + P_DATA(i, j)
8-     Increment NuM1 by 1
9-   Else
10-    Set M2 ← M2 + P_DATA(i, j)
11-    Increment NuM2 by 1
12-   End If
13- End for
14- Set M1 ← M1 / NuM1: Set M2 ← M2 / NuM2
15- Set T0 ← T: Set T ← 0.5 * (M1 + M2)
16- loop
17- For all i, j Do { where 0 ≤ i ≤ H-1 and 0 ≤ j ≤ W-1 }
18-   Check If P_DATA(i, j) < T Then
19-     Set P_DATA(i, j) ← 0
20-   Else
21-     Set P_DATA(i, j) ← 1
22-   End If
23- End for
24- End.
```

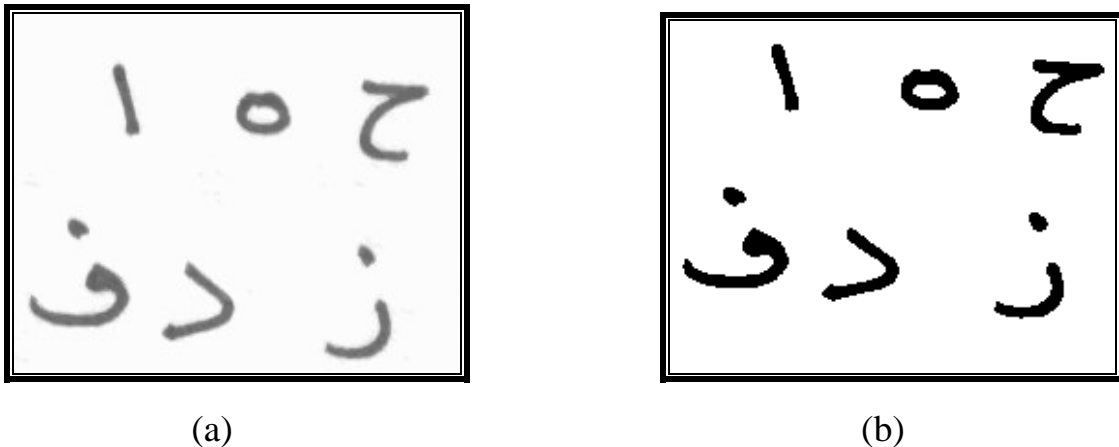


Figure (3.5) Image of handwritten Arabic characters.

(a) Before binarization process.

(b) After binarization process.

3.5 Image Segmentation (Algorithms and Results)

In the segmentation process each character in the image will be determined by minimum box around it to process each character separately; to perform the process of segmentation must perform the following:

- 1- Extract image data from the pre-processed image.
- 2- Determine the upper and lower boundaries for each line of characters in the image by algorithm (3.4).
- 3- Determine the left and right boundaries for each character in every line obtained from above step by algorithm (3.5).
- 4- Determine the upper and lower boundaries for each character obtained in each line so that the minimum box can be determined by algorithm (3.6).
- 5- Create an image for each character by algorithm (3.7).

After enclosed each character by its minimum box normalized the size of each image of characters. While the size of characters increased during the image acquisition, It was found that the size (32×32) is not enough for the segmented characters because the image of characters was scanned with 300 dpi

resolution so that the size of characters will be as large as it before the scanning process. And also found that the size (64×64) not enough for all characters. In this work the size of window (image) of each character will be normalized to (128×128).

It was note that there are characters have dot(s) with it like: (ي، ن، ق، ف، غ، ظ، ض، ش، ز، ذ، خ، ج، ث) and there are another characters have second part with it like (أ، آ، و، ك) in the segmentation process the dot (or dots) and the second part of the character will not be separate from the body of the character. The number of pixels between dot or second part and the body of the character considered to be up to 7 pixels and this also depends on the font size and font type. In the case of hand written characters the number of pixels between the characters and their dots difficult to be expected where each character can be written in different way and different size. Algorithm (3.3) shows how the segmentation process was performed.

Algorithm (3.3) Character Segmentation

Input: P_DATA(): image data (results from binarization process)

H : height of the image

W : width of the image

Output: Create an image for each character

1-Get IMAGE DATA from the Preprocessed Image

2- Perform row scan for pixels data equal to zero (i.e., black pixel) to count how many lines of characters in the pre-processed image by algorithm (3.4).

3- Perform column scan for the output from the above step to determine the left and right boundaries for each character in every line of image by algorithm (3.5).

4- Perform row scan again for each character segmented vertically in the above step by algorithm (3.6).

5- Generate an image for each segmented character by algorithm (3.7).

6- End.

Algorithm (3.4) Row scan

Input: P_DATA (): image data (binary image results from binarization process)

H : height of the image

W : width of the image

Output: NoofLines // Number of lines in image

```

1-For all i Do {where  $0 \leq i \leq H-1$ } //Initialize record of Lines (U: Up , D: Down) to -1
2-   Set Lines(i).u  $\leftarrow$  -1: Set Lines(i).D  $\leftarrow$  -1
3-End for
4-Set NoofLines  $\leftarrow$  0
5-For all i, j Do {where  $0 \leq i \leq H-1$  and  $0 \leq j \leq W-1$ }
6-   Check If P_DATA(i, j) = 0 Then
7-     Check If Lines(NoofLines).u = -1 Then
8-       Set Lines(NoofLines).u  $\leftarrow$  i
9-     End If
10-  Else
11-    Check If Lines(NoofLines).u  $\neq$  -1 Then
12-      Set Lines(NoofLines).D  $\leftarrow$  i: increment NoofLines by 1
13-    End If
14-  End If
15-End for
16-Set R  $\leftarrow$  0
17-For all i, j Do {where  $0 \leq i \leq \text{NoofLines} - 2$  and  $i + 1 \leq j \leq \text{NoofLines} - 1$ }
18-  Check If Lines(i).D = Lines(j).u - 1 Then
19-    Set Lines(i).D  $\leftarrow$  Lines(j).D
20-  Check If j = NoofLines - 1 Then
21-    Set Lines(R).u  $\leftarrow$  Lines(i).u: Set Lines(R).D  $\leftarrow$  Lines(i).D
22-    Increment R by 1: Set i  $\leftarrow$  j - 1
23-  End If
24-  Else
25-    Set Lines(R).u = Lines(i).u: Set Lines(R).D  $\leftarrow$  Lines(i).D
26-    Increment R by 1: Set i  $\leftarrow$  j - 1
27-  End If
28-End for
29-Set NoofLines  $\leftarrow$  R

```

After the number of lines in image was determined in the row scan process, then perform column scan on this image. In this step the left and right boundaries for each character in every line in image will be determined. Figures (3.6) and (3.7) show the images before and after segmentation process for both printed and hand written Arabic characters respectively.

Algorithm (3.5) column scan

Input: NoofLines :Number of lines in image results from algorithm (3.4)

H: height of the image

W: width of the image

Output: NoofChar : Number of characters

```

1-initilize L, NoofChar, TotalChar , Counter to zero
2- Set CharHW  $\leftarrow$  128: Set CharHeader  $\leftarrow$  Header
3-For all L Do{where  $0 \leq L \leq$  NoofLines - 1 }
4-   Set Si  $\leftarrow$  Lines(L).u: Set Ei  $\leftarrow$  Lines(L).D: Set NoofChar  $\leftarrow$  0
5-   For all i Do{where  $0 \leq i \leq$  1023}
6-     Set CharBorders(i).u  $\leftarrow$  -1:   Set CharBorders(i).L  $\leftarrow$  -1
7-     Set CharBorders(i).D = -1:   Set CharBorders(i).R  $\leftarrow$  -1
8-   End for
9-   For all j,i Do {where  $0 \leq j \leq$  W - 1 and  $S_i \leq i \leq$ To  $E_i$  } //Char Borders
10-    Check if P_DATA(i, j) = 0 Then
11-      Check If CharBorders(NoofChar).L = -1 Then
12-        Set CharBorders(NoofChar).L  $\leftarrow$  j
13-      End If
14-    Else
15-      Check If CharBorders(NoofChar).L  $\neq$  -1 Then
16-        Set CharBorders(NoofChar).R  $\leftarrow$  j: Set CharBorders(NoofChar).u  $\leftarrow$  Si
17-        Set CharBorders(NoofChar).D  $\leftarrow$  Ei : increment NoofChar by 1
18-      End If
19-    End If
20-  End for
21-  Set R  $\leftarrow$  0
22-  For all i,j Do {where  $0 \leq i \leq$  NoofChar - 1 and  $i + 1 \leq j \leq$  NoofChar}
23-    Check If CharBorders(i).R = (CharBorders(j).L - 1) Then
24-      Set CharBorders(i).R  $\leftarrow$  CharBorders(j).R
25-      Check If j = NoofChar Then
26-        Set CharBorders(R).L  $\leftarrow$  CharBorders(i).L
27-        Set CharBorders(R).R  $\leftarrow$  CharBorders(i).R
28-        Increment R by 1: Set i  $\leftarrow$  j - 1
29-      End If
30-    Else
31-      Set CharBorders(R).L  $\leftarrow$  CharBorders(i).L
32-      Set CharBorders(R).R  $\leftarrow$  CharBorders(i).R
33-      Increment R by 1: Set i  $\leftarrow$  j - 1
34-    End If
35-  End for
36-Set NoofChar  $\leftarrow$  R
37- End For

```

Algorithm (3.6) Next row scan

Input: NoofChar: Number of characters results from the algorithm (3.5)

Out put: updata the up and down for each character

```

1- For all k Do { where  $0 \leq k \leq \text{NoofChar} - 1$  }
2-   Set  $S_j \leftarrow \text{CharBorders}(k).L$ 
3-   Set  $E_j \leftarrow \text{CharBorders}(k).R$ 
4-   Set  $nU \leftarrow -1$ 
5-   Set  $nD \leftarrow -1$ 
6-   For all i Do { where  $\text{CharBorders}(k).u \leq i \leq \text{CharBorders}(k).D - 1$  }
7-     For all j Do { where  $S_j \leq j \leq E_j$  }
8-       Check If  $P\_DATA(i, j) = 0$  Then
9-         Check If  $nU = -1$  Then
10-          Set  $nU \leftarrow i$ 
11-          Else
12-            Set  $nD \leftarrow i$ 
13-          End If
14-        End If
15-      End for
16-End for

```

Algorithm (3.7) create character image

Input: Image_Name: name of the image

P_DATA(): image data

H: image height

W: image width

Output: create an image

```

1- Set Header.fsize  $\leftarrow H * W + 1078$ 
2- Set Header.width  $\leftarrow W$ 
3- Set Header.height  $\leftarrow H$ 
4- Set Header.imagesize  $\leftarrow H * W$ 
5- Open file(give it Image_Name) for binary and print in it the Header values
6- Set  $k \leftarrow 0$ 
7- For all i,j Do { where  $H - 1 \geq i \geq 0$  Step -1 and  $0 \leq j \leq W - 1$  }
8-   Set  $PIXELS(k) \leftarrow P\_DATA(i, j)$ 
9-   Increment k by 1
10-End for
11- save PIXELS on the file and close it
12-End.

```

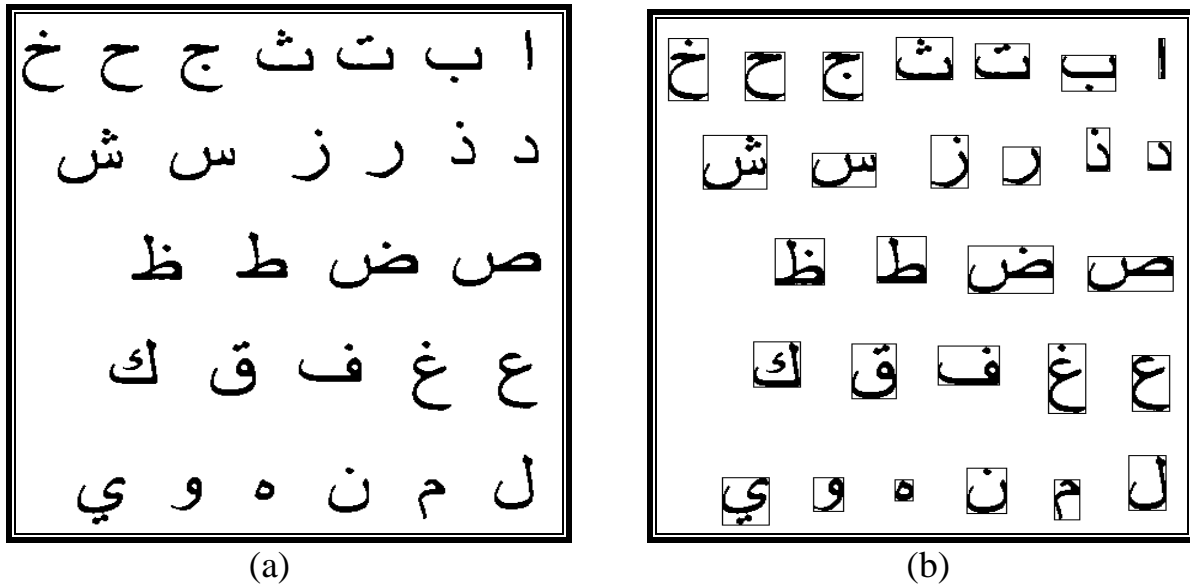


Figure (3.6) Image of printed Arabic characters.

(a) Before segmentation process.

(b) After segmentation process.

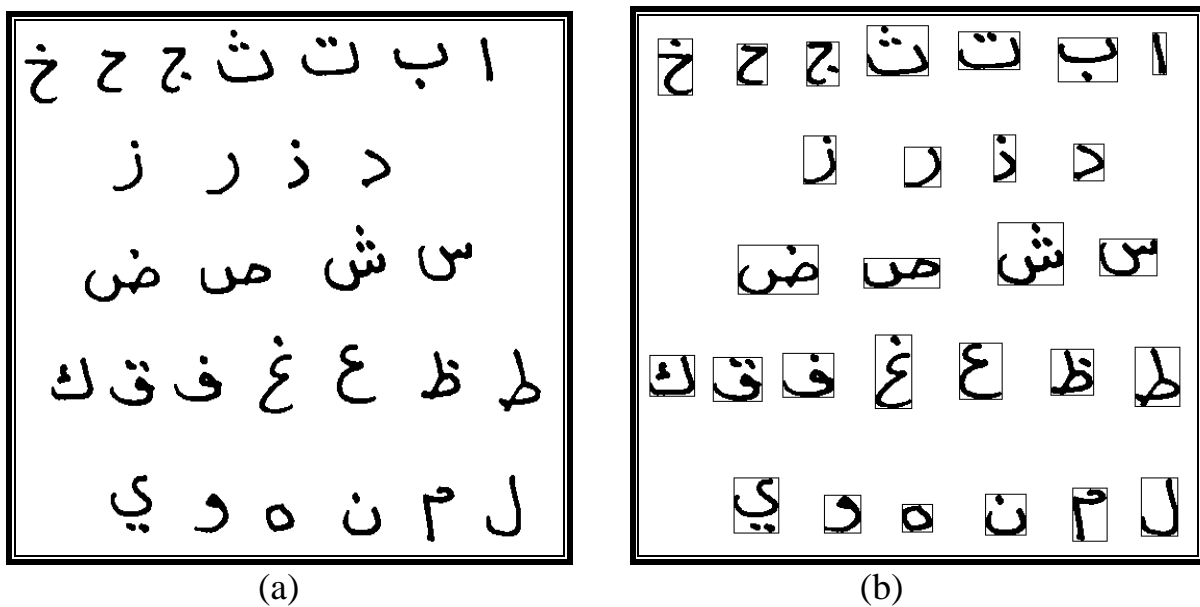


Figure (3.7) Image of hand written Arabic characters.

(a) Before segmentation process.

(b) After segmentation process.

The normalization process was important for hand written characters where the characters have different size, so that in this work the window of each character will be (128×128) , during the practical this size process the problem of writing the characters in different size.

3.6 Feature Extraction (Algorithm and Results)

The set of moments has been shown to be invariant to rotation and scale change. as shown in tables (3.1 to 3.3) the results for images in figure (3.8).

The feature extraction process extracts the features from the training and testing images for all characters (printed). In this work, the character moments (as explained in chapter two) was used as features represents each character, table (3.4) shows features for all training characters, and table (3.5) shows features of testing characters in figure (3.9). To perform the process of features extraction one should perform the following steps:

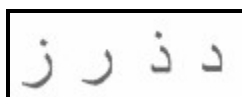
- 1- Compute (*mpq*) value by equation (2.3) in chapter two.
- 2- Compute *Central Moment* value by equation (2.4).
- 3- Compute (*npq*) value by equation (2.13).
- 4- Compute moment's values by equations (2.15 - 2.21).



(a)



(b)



(c)

Figure (3.8) (a) Original characters

(b) Rotate the Original characters by 45°

(c) Half Size of original characters

Table (3.1) moment invariants for the image in figure (3.8) (a)

Mom. Order	د	ذ	ر	ز
1	7.310902	7.308427	7.3066	7.303604
2	31.80135	28.75181	30.63034	28.1405
3	43.56854	39.9241	40.41712	38.26755
4	33.93864	33.1655	32.97742	32.04677
5	72.50706	69.48486	69.42756	66.77023
6	50.32519	47.58441	48.39635	46.96899
7	71.32059	67.45759	70.27789	66.63087

Table (3.2) moment invariants for the image in figure (3.8) (b)

Mom. Order	د	ذ	ر	ز
1	7.311354	7.308304	7.307242	7.304463
2	29.61597	28.11388	27.2803	26.53532
3	40.14907	38.63153	37.65379	36.3426
4	34.15628	33.59711	33.60384	32.66678
5	72.18881	71.11051	69.71465	67.58281
6	49.25549	49.32193	47.35371	46.29332
7	69.64899	67.78216	68.74391	66.72507

Table (3.3) moment invariants for the image in figure (3.8) (c)

Mom. Order	د	ذ	ر	ز
1	7.32763	7.327291	7.32729	7.326116
2	35.71868	34.21991	35.09195	34.15151
3	47.23835	45.61013	45.18116	45.21255
4	37.64503	37.27551	37.31693	36.31708
5	79.73325	78.47817	78.52587	76.68049
6	55.64886	54.39322	55.53623	53.73009
7	77.03333	75.47568	76.23093	75.44853

Algorithm (3.8) shows how to extract the features for characters. To notice the features of testing handwritten characters see the appendix.

Algorithm (3.8) Compute 7 Central Moments

Input: Data for each character

Output: Hu's Moment for each character

- 1- Set $m_{00} \leftarrow mpq(0, 0)$
- 2- Set $m_{10} \leftarrow mpq(1, 0)$
- 3- Set $m_{01} \leftarrow mpq(0, 1)$
- 4- Set $m_{20} \leftarrow mpq(2, 0)$
- 5- Set $m_{02} \leftarrow mpq(0, 2)$
- 6- Set $ib \leftarrow m_{10} / m_{00}$
- 7- Set $jb \leftarrow m_{01} / m_{00}$
- 8- Set $N_{20} \leftarrow Npq(ib, jb, 2, 0)$
- 9- Set $N_{02} \leftarrow Npq(ib, jb, 0, 2)$
- 10- Set $N_{11} \leftarrow Npq(ib, jb, 1, 1)$
- 11- Set $N_{12} \leftarrow Npq(ib, jb, 1, 2)$
- 12- Set $N_{21} \leftarrow Npq(ib, jb, 2, 1)$
- 13- Set $N_{30} \leftarrow Npq(ib, jb, 3, 0)$
- 14- Set $N_{03} \leftarrow Npq(ib, jb, 0, 3)$
- 15- compute moment's values using equations (2.15 to 2.21) in chapter two for each character
- 16-End.

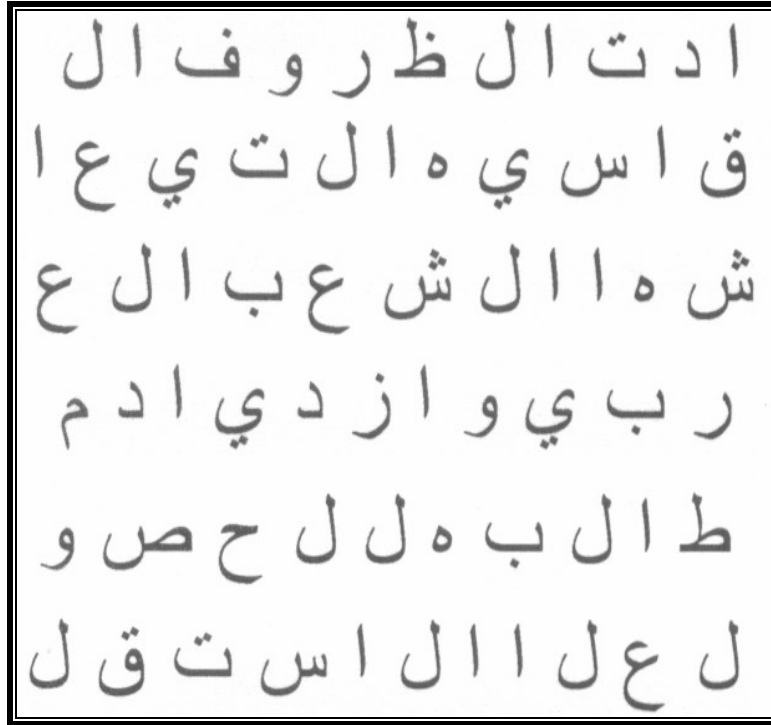


Figure (3.9) Testing printed Arabic characters.

Table (3.4) Features of training characters.

Character	Mom.1	Mom.2	Mom.3	Mom.4	Mom.5	Mom.6	Mom.7
ا	7.315547	30.57006	42.49714	37.19798	76.72368	56.67027	78.72356
ب	7.287325	27.581	38.02573	33.80986	69.62821	48.18415	68.5119
ت	7.284317	29.09393	36.50372	31.71916	65.68723	47.27404	64.38364
ث	7.281477	29.46027	36.20384	31.3296	65.05502	46.58116	63.32306
ج	7.276409	27.04892	39.389	34.86793	72.42255	48.51801	70.6516
ح	7.2803	27.00901	39.27912	34.58548	72.21841	48.2348	70.07925
خ	7.277173	26.34933	36.7227	32.9495	67.82705	46.46526	66.83982
د	7.310902	31.80135	43.56854	33.93864	72.50706	50.32519	71.32059
ذ	7.308427	28.75181	39.9241	33.1655	69.48486	47.58441	67.45759
ر	7.3066	30.63034	40.41712	32.97742	69.42756	48.39635	70.27789
ز	7.303604	28.1405	38.26755	32.04677	66.77023	46.96899	66.63087
س	7.280565	26.61958	37.86796	33.59595	69.27319	47.02021	71.32785
ش	7.271932	26.61887	35.66991	30.95939	63.90469	44.49693	64.35136
ص	7.25324	24.20267	34.63298	31.61171	64.73541	43.91716	64.90322
ض	7.250596	24.49913	33.22619	30.65544	62.29718	43.87067	62.77864
ط	7.268446	27.11559	37.30414	30.56212	64.43479	44.1512	61.92638

ظ	7.265818	27.38254	37.55418	30.73588	64.71629	44.43199	62.38324
ع	7.275075	26.61097	38.1994	32.88679	68.64079	46.40483	65.86539
غ	7.27391	25.76097	35.56521	31.72832	65.08688	45.28416	64.90989
ف	7.275876	27.51961	35.51212	30.52454	63.21819	47.41483	64.05402
ق	7.269657	27.46378	39.34139	31.01042	65.92944	46.70201	65.10788
ك	7.271386	29.11914	38.46244	31.00058	65.88887	48.17005	65.89212
ل	7.289391	27.31222	37.06761	31.65022	65.5159	47.37194	66.29751
م	7.303197	29.82782	44.72677	34.20906	73.67507	49.46453	68.69041
ن	7.29605	28.97339	41.43269	31.99921	70.87226	46.66278	64.7299
ه	7.310819	35.03924	46.59023	36.03575	77.28263	54.97655	74.95672
و	7.301809	30.69802	41.17402	33.37029	71.59973	49.2901	68.88318
ي	7.273513	28.24759	37.6734	33.49772	68.72269	47.62258	70.33869

Table (3.5) Features of testing characters.

Character	Mom.1	Mom.2	Mom.3	Mom.4	Mom.5	Mom.6	Mom.7
ا	7.315052	30.53451	43.9119	38.76373	80.69562	54.85365	78.79976
د	7.309571	31.42059	43.29649	33.97339	72.12917	50.32146	72.88552
ت	7.28509	29.94974	36.67977	31.54067	65.56526	48.54458	63.87173
ا	7.316143	30.71912	43.19307	37.68117	78.12246	53.04269	77.77497
ل	7.289474	27.35086	36.91985	31.6053	65.36298	49.6499	65.64728
ظ	7.266125	27.27065	37.68729	30.70704	64.75866	44.34803	62.29482
ر	7.308362	30.55589	40.18925	32.87397	69.0732	49.35492	68.54008
و	7.302472	31.00427	41.12444	33.20076	72.34634	49.33508	67.96004
ف	7.274006	27.12955	35.32277	30.40901	62.90659	45.71236	64.37602
ا	7.315761	30.76279	42.85559	37.41795	78.83512	53.09181	75.82462
ل	7.290824	27.28065	36.90474	31.49815	65.23347	46.44605	66.9651
ق	7.27255	27.72891	38.73013	31.12678	65.76868	48.62975	64.98486
ا	7.315885	30.71159	42.87339	38.4632	78.63669	54.48927	78.88544
س	7.281032	26.60277	37.79335	33.5484	69.07627	46.91425	71.68919
ي	7.27179	28.25557	37.45668	33.20449	68.40941	47.43887	68.15803
ه	7.311544	34.50494	46.80396	36.21409	78.02625	53.72979	73.17904
ا	7.31587	30.86615	42.9612	37.47332	77.80198	52.92998	77.2404
ل	7.290444	27.34537	37.1808	31.62324	65.55937	46.98106	67.51373
ت	7.285006	29.38002	36.55925	31.65758	65.64095	47.49052	64.22896
ي	7.272496	28.34184	37.49969	32.79147	67.5498	46.96859	70.76007
ع	7.275973	26.70132	38.16545	32.88307	68.51619	46.49604	65.82895
ا	7.316012	30.6659	44.56455	39.49002	81.51479	54.83336	80.15676

ش	7.273046	26.78478	36.26976	31.06542	64.38557	44.50916	67.0413
ه	7.310935	34.05183	47.33868	36.5404	78.25701	53.87184	74.27302
ا	7.314806	30.59298	42.81021	38.22984	78.33806	56.35951	80.16183
ا	7.31518	30.5757	42.54584	37.43477	77.77792	53.48029	76.06542
ل	7.291338	27.53609	37.22754	31.75475	65.75175	48.25137	66.37212
ش	7.271688	26.56732	35.99447	31.0943	64.22614	44.44336	65.6887
ع	7.276769	26.7761	38.03354	32.92843	68.82313	46.46898	66.02644
ب	7.291436	27.68238	38.35828	34.14996	70.36741	49.33504	70.05171
ا	7.315044	30.59969	42.96345	38.06643	78.09097	53.83235	78.66727
ل	7.29012	27.4426	37.04663	31.51287	65.31212	46.69518	66.63873
ع	7.277397	26.78259	38.09958	32.91035	68.80809	46.45387	65.97582
ر	7.307889	31.03763	40.52057	33.01797	69.49141	48.68303	69.78265
ب	7.2915	27.7155	38.54965	34.13734	70.50967	50.17615	70.97394
ي	7.274566	28.3357	37.5204	33.34752	68.68259	47.64973	68.4059
و	7.302609	30.97764	41.19164	33.21387	73.56021	49.16813	67.70035
ا	7.316364	30.80505	43.5839	39.18226	80.05843	55.41617	80.27072
ز	7.305167	28.3279	38.54347	32.22211	67.10851	47.38827	66.88255
د	7.30996	31.52589	43.12843	33.7917	71.9737	50.12367	71.32493
ي	7.273773	28.36497	37.74887	33.03681	67.96107	47.22887	68.35756
ا	7.315798	30.49371	42.74019	37.73256	77.67677	56.30762	79.03942
د	7.309712	31.65745	42.73422	33.85299	71.79581	50.39554	70.75356
م	7.304129	29.96684	47.11253	34.44175	75.28621	49.69753	69.1264
ط	7.274066	27.28137	37.89334	30.78301	65.05178	44.46235	62.24684
ا	7.31543	30.53993	42.69145	37.48087	77.44336	54.3394	76.95423
ل	7.293434	27.31775	37.12341	31.76424	65.73362	47.05724	67.19461
ب	7.291357	27.67867	38.16669	34.16274	70.22455	48.98868	69.63411
ه	7.310843	33.9859	45.63031	35.6599	75.89587	53.12046	74.28146
ل	7.292052	27.37726	37.14486	31.68848	65.619	47.18809	66.76593
ل	7.290809	27.31423	36.95712	31.55468	65.33666	46.5776	67.68321
ح	7.280483	27.09519	39.44921	34.47123	72.68986	48.58968	69.90612
ص	7.25589	24.34023	34.92989	31.80804	65.17709	44.2037	65.15181
و	7.30271	31.03027	41.20455	33.17008	71.93522	49.40748	67.97345
ل	7.291834	27.36832	37.11161	31.7105	65.65437	46.99118	68.4278
ع	7.277407	26.64127	37.98772	32.86257	68.03482	46.71885	65.74265
ل	7.291398	27.48231	37.0247	31.60793	65.42451	47.31362	65.92627
ا	7.315906	30.64406	43.68723	38.62089	80.90884	54.46503	78.25464
ا	7.316496	30.7776	43.16426	37.73681	78.97952	53.32146	76.52579
ل	7.291983	27.42805	37.20428	31.70469	65.67756	47.13992	67.27256
ا	7.31612	30.79373	42.63544	37.50579	77.18394	53.10694	77.4116

س	7.282094	26.66718	37.66631	33.49126	68.8778	46.83265	69.17411
ت	7.289097	29.34102	36.63251	31.86473	65.98357	47.24487	64.54713
ق	7.273012	27.69134	39.10685	31.00586	65.58984	47.15555	64.76826
ل	7.292685	27.4032	37.2118	31.75657	65.75807	47.48087	66.74925

3.7- Pattern Matching

In the pattern matching process, the Euclidean distance used to show the percentage accuracy of matching between training and testing characters, as shown in equation (2.22). The matching process was performed between the features extracted from training characters and the testing characters. Algorithm (3.9) shows how to perform the pattern matching process.

Algorithm (3.9) Pattern Matching

Input: Features of (testing and training) characters

Output: Percentage accuracy.

Display the best matched characters onto a ListBox

- 1- Read CharImage from files,
- 2- Extract its H & W with Char_DATA
- 3- Compute the 7 central moments as a Feature Extraction Method on Char_DATA
- 4- **If** Training **then** write features on Training_File
- 5- **Else**
- 6- **If** Testing **then**
- 7- Extract Features onto a 1-D array and Compare it with the Training File
- 8- Find the best matched character and compare it with the Test_Texti.txt file
- 9- Compute the percentage accuracy
- 10- Display the Recognized charcters onto a ListBox
- 11- **Else**
- 12- **If** OCR **then**
- 13- Extract Features onto a 1-D array and Compare it with the Training File
- 14- Display the best matched characters onto a ListBox
- 15- **End if**
- 16- **End.**

3.8 Recognition Decision

The recognition decision ratio for some characters contained in one image depends on the following:

- ▶ Number of characters in the testing image.
- ▶ Type of characters in the testing image.
- ▶ How many times the same character was repeated.
- ▶ The order of moments that are used for matching.
- ▶ The text type (i.e. printed characters or hand-written characters).

Two samples of images are tested in this work, the first one is printed Arabic characters and the second is hand written characters.

1- printed characters:

In this stage the image of printed characters shown in Figure (3.9) contains 65 characters, some of these characters are repeated like (, ع , ل). When the characters in this image are tested, It was found that when all the orders of moments are used the percentage accuracy equal (87.692307%), while when the (second order, third order and fourth order) of moments are used, the percentage accuracy became (96.923076%). Table (3.6) proves that the (second, third and fourth) orders of moment giving good results than the other orders. Table (3.7) shows the recognition of characters using all orders of moments and recognition of characters when the specific orders of moments are used. In this table the characters in shading cells are not recognized correctly.

Table (3.6) Recognition results using specific orders of moments.

Moments order	Percentage accuracy
1 st	50.76923%
2 nd	44.61538%
3 rd	50.76923%
4 th	46.15384%
5 th	21.53846%
6 th	23.07692%
7 th	33.84615%
1 st , 2 nd , 3 rd , 4 th , 5 th , 6 th , 7 th	87.6923%
1 st , 2 nd , 3 rd , 4 th , 5 th , 6 th	92.3076%
1 st , 2 nd , 3 rd , 4 th , 5 th , 7 th	87.6923%
1 st , 2 nd , 3 rd , 4 th , 6 th , 7 th	83.0769%
1 st , 2 nd , 3 rd , 5 th , 6 th , 7 th	86.1538%
1 st , 2 nd , 4 th , 5 th , 6 th , 7 th	84.6153%
1 st , 3 rd , 4 th , 5 th , 6 th , 7 th	83.0769%
2 nd , 3 rd , 4 th , 5 th , 6 th , 7 th	87.6923%
2 nd , 3 rd , 4 th	96.92307%
5 th , 6 th , 7 th	61.53846%
1 st , 2 nd , 3 rd , 4 th	96.92307%
1 st , 2 nd	46.15384%
1 st , 3 rd	50.76923%
1 st , 4 th	46.15384%
2 nd , 3 rd	83.07692%
2 nd , 4 th	92.30769%
3 rd , 4 th	89.23076%
5 th , 6 th	38.46153%
5 th , 7 th	69.23076%
6 th , 7 th	40%

1 st , 2 nd , 3 rd , 4 th , 5 th	93.8461%
1 st , 2 nd , 3 rd , 4 th , 6 th	93.8461%
1 st , 2 nd , 3 rd , 4 th , 7 th	83.0769%
1 st , 2 nd , 3 rd	83.07692%
1 st , 2 nd , 4 th	92.30769%
1 st , 3 rd , 4 th	89.23076%
1 st , 5 th , 6 th , 7 th	61.5384%
1 st , 4 th , 5 th , 6 th	46.1538%
4 th , 5 th , 6 th , 7 th	64.6153%
1 st , 2 nd , 5 th	75.3846%
1 st , 3 rd , 6 th , 7 th	66.1538%
1 st , 2 nd , 5 th , 7 th	80%
1 st , 2 nd , 5 th , 6 th	80%

Table (3.7) Recognition decision of printed characters.

Input character	Recognized by 7-Mom.	Recognized by 2 nd , 3 rd , and 4 th Mom.
ا	ا	ا
د	د	د
ت	ت	ث
ا	ا	ا
ل	ل	ل
ظ	ظ	ظ
ر	ر	ر
و	و	و
فا	ش	فا
ا	ا	ا
ل	ل	ل

ق	ك	ق
ا	ا	ا
س	س	س
ي	ب	ي
ه	ه	ه
ا	ا	ا
ل	ل	ل
ت	ت	ت
ي	ي	ي
ع	ع	ع
ا	ا	ا
ث	غ	ث
ه	ه	ه
ا	ا	ا
ا	ا	ا
ل	ل	ل
ث	ث	ث
ع	ع	ع
ب	ب	ب
ا	ا	ا
ل	ل	ل
ع	ع	ع
ر	ر	ر
ب	ج	ب
ي	ب	ي
و	و	و
ا	ا	ا

ز	ز	ز
د	د	د
ي	ي	ي
ا	ا	ا
د	د	د
م	م	م
ظ	ظ	ظ
ا	ا	ا
ل	ل	ل
ب	ب	ب
ه	ه	ه
ل	ل	ل
ل	ل	ل
ح	ح	ح
ص	ص	ص
و	و	و
ل	ل	ل
ع	ع	ع
ل	ل	ل
ا	ا	ا
ا	ا	ا
ل	ل	ل
ا	ا	ا
س	ب	س
ث	ث	ث
ق	ق	ق
ل	ل	ل

2- hand-written characters:

In this phase:

- The characters written by type of font that are most of peoples used it in most times which is .
- Characters that are tested written in different way by different persons using pen of type (Soft) for writing on white paper.
- The (second, third and fourth) orders of moments are used for matching, because it was given height percentage accuracy than the other orders.

In this work some characters are tested and gives different percentage accuracy, as shown in tables (3.8-3.13). In this table the characters in the shading cells are not recognized correctly, this belongs to the different in the size and shape of the same character and the training characters that the test characters matched with it considered to be standard shape (printed characters).

Table (3.8) Recognition results of character (ف) written by different writers.

Writers	Input character	Rec. Results
1		ف
2		ف
3		ف
4		ف
5		ف

Table (3.9) Recognition results of character (ج) written by different writers.

Writers	Input character	Rec. Results
1		ج
2		ع
3		ج
4		ن
5		ب

Table (3.10) Recognition results of character (غ) written by different writers.

Writers	Input character	Rec. Results
1		ك
2		ك
3		ك
4		ك
5		ك

Table (3.11) Recognition results of character (ض) written by different writers.






Writers	Input character	Rec. Results
1		ض
2		ض
3		ض
4		ض
5		ض

Table (3.12) Recognition results of character (ظ) written by different writers.











Writers	Input character	Rec. Results
1		ش
2		س
3		ش
4		ش
5		ض

Table (3.13) Recognition results of character (ز) written by different writers.

Writers	Input character	Rec. Results
1		ز
2		ز
3		ز
4		ع
5		ل

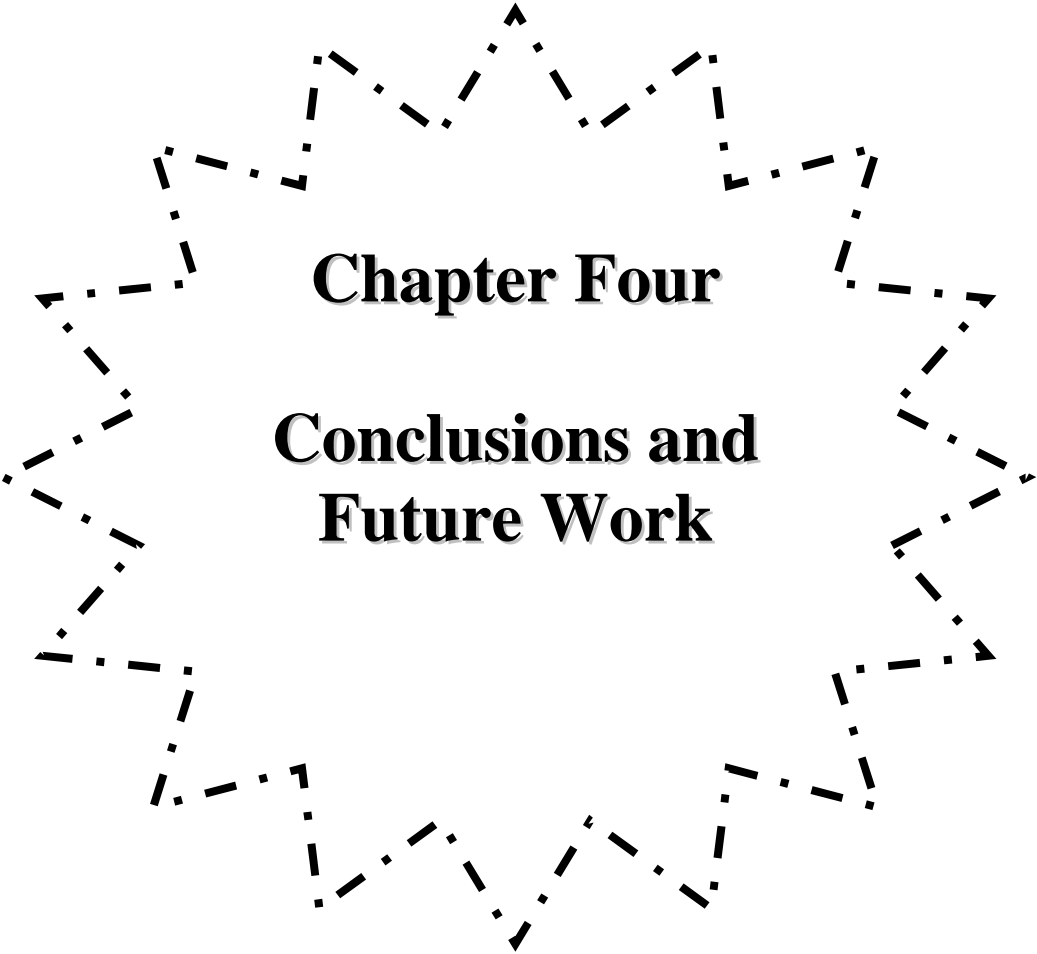
Note that, in appendix more tested of hand written characters.

3.9 Discussion

It was very interested to find the most useable parameter among adopted order of moments, since the use of all them sometimes indicates some weakness in the recognition decision. This prepares to search on the mono-directional moments that share with each other to strength the recognition ratio.

Table (3.6) shows the use of the all moment orders for the input characters shown in Figure (3.9). It is noticeable that when each order was used as alone, the percentage accuracy of first fourth orders higher than the percentage accuracy of last three orders of moments. Also when used all orders with each other the percentage accuracy was (87.6923%), it was note that affect each order on the other as following: remove the 7th Order the result was increased, remove the 6th Order not affect on the results, remove (5th, 4th, 3rd, 2nd) orders the results was decreased and remove the 1st not affect on the results.

While the first order moment show very small variation and it was not affect when it was shared with other moments in the recognition task, this indicates it is useless individually, so that it can not be employed in the recognition. During the practical the percentage accuracy of coalition work of the (2nd, 3rd and 4th) higher than the resulted moments of orders (5th, 6th and 7th) which appears less recognition percentage in comparison with other orders. Also when different orders of moments used with each other as mentioned in the results shown in table (3.6) all of these lead us to one result which is the (2nd, 3rd and 4th) giving higher percentage accuracy which improve that the second moment is a measure of gray-level contrast that can be used to establish descriptors of relative smoothness, the third moment is a measure of the skewness of the histogram while the fourth moment is a measure of its relative flatness, the fifth and higher moments are not so easily related to character shape. From all of this handwritten characters recognized using (2nd, 3rd and 4th) which are giving good results.



Chapter Four

**Conclusions and
Future Work**

Chapter Four

Conclusions and Future Work

4.1 conclusions

From the current work, it can be concluded that:

► Hu's seven moments matching is an efficient technique for printed Arabic character recognition. Recognition system has been performed on the printed Arabic characters and the percentage accuracy for recognize 65 printed characters was 96.92307%, while in hand written characters, the recognition percentage is decreased due to irregularities appears in the handwritten characters.

► It was found that the variation in the first order moments was very small, so that it can not be employed in the recognition. While the second order moments, third order moment and fourth order moments giving higher recognition rate than other order moments.

► The fifth and higher moments are not so easily related to character recognition.

4.2 Future Work

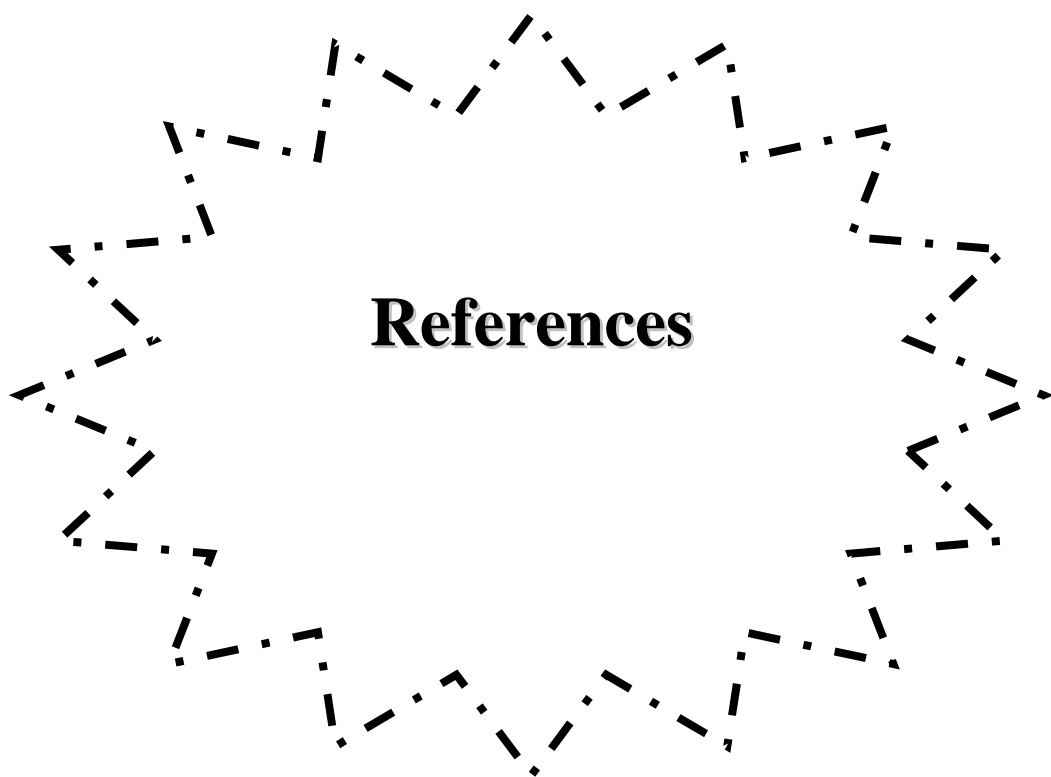
Some important proposed aspects for future investigations are given:

◆ The order of moments is sensitive to style where it was depends on the spatial information, therefore future work is required to make investigation in the relationships between the order of moment and the style of the character.

◆ The gradient of moments affects by the noise and deformation, therefore, it can be studied the relationship between the gradient of moments with the noise and deformation.

◆ Perform edge thinning which it is an attempt to represent the structural shape of a plane region and reduce it to a graph; this reduction may be accomplished by obtaining the skeleton of the region via a thinning algorithm. This step will reduce some of the variance that is usually found in characters like the width of their edges, therefore, it considered as a uniforming process to make all the characters with 1 pixel width.

◆ Although this research thesis develops a recognizer of Arabic text with a certain type of font style, can be add other types of fonts and styles and support the user with access to interactively deciding which font in the existing library is nearest before starting the recognition task.



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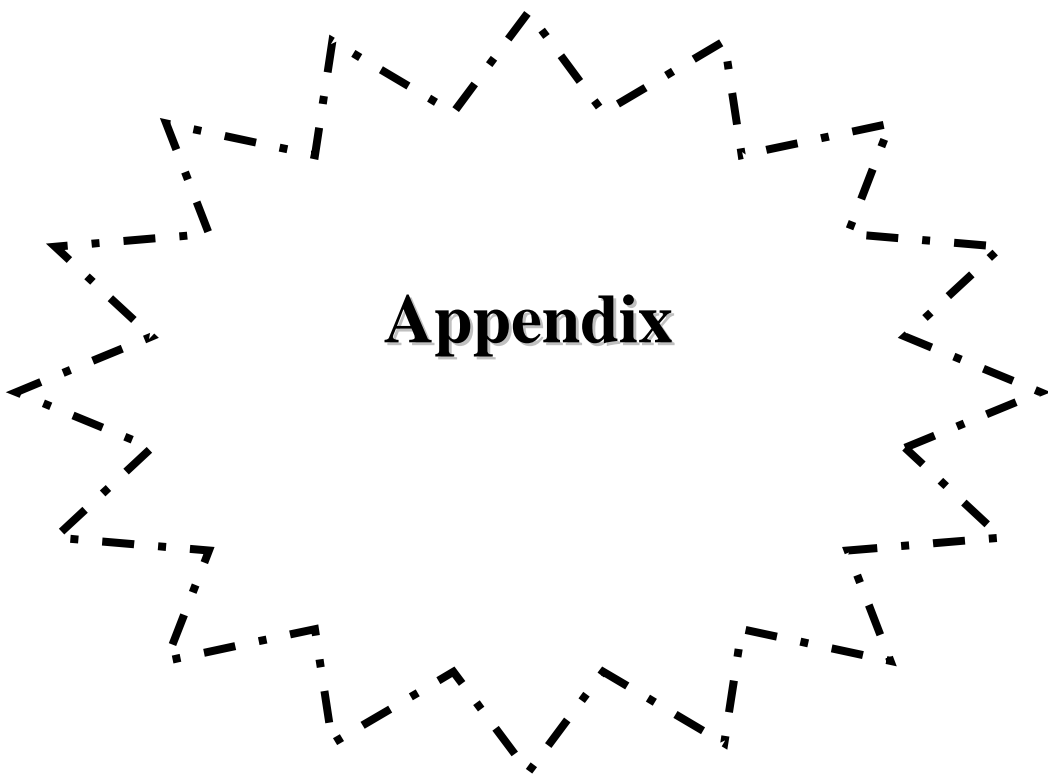
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Appendix

Table (1) Features of testing character ف

Character	Mom1	Mom2	Mom3	Mom4	Mom5	Mom6	Mom7
ف	7.267456	27.4133	34.97936	30.05857	62.30326	43.80428	63.40422
ف	7.263379	26.17107	33.41296	29.71725	60.94698	43.44284	62.08093
ف	7.265194	30.54745	35.70778	30.23279	62.82766	45.53017	64.90718
ف	7.259233	27.40888	34.6127	29.93696	62.01619	44.14101	63.88693
ف	7.249269	25.17774	32.97499	29.34661	60.18499	42.60125	61.19062
ف	7.260846	27.54739	34.66724	30.25289	62.34188	44.97364	63.50227
ف	7.250003	25.84065	34.10297	29.9977	61.70858	44.51361	63.00478
ف	7.265599	28.15552	35.7021	30.42297	63.14661	45.2205	63.40263
ف	7.254569	26.79295	34.19987	29.72202	61.27252	43.72283	61.89961
ف	7.272798	26.93312	34.99648	30.25161	62.56841	44.36965	62.11423
ف	7.269261	27.17932	35.527	30.75059	63.53622	45.03674	63.47112
ف	7.267631	27.59413	35.16519	30.32687	62.80112	44.50374	62.17427
ف	7.25615	27.39744	34.61882	30.13373	62.14133	43.89693	62.64175
ف	7.256061	25.95361	33.96564	29.61565	61.0704	43.11981	60.93383
ف	7.248302	25.95785	33.85144	29.30854	60.61335	42.51978	60.11628
ف	7.262079	26.9438	34.76558	30.09042	62.39341	44.47845	61.48408
ف	7.268048	29.09233	36.21772	31.05225	64.28249	45.66378	65.25107
ف	7.260115	27.49269	35.35398	29.98803	62.36049	44.02205	61.57447
ف	7.276576	28.14089	35.6581	30.49489	63.31253	44.78516	64.07693
ف	7.267062	28.10091	35.40265	30.3011	62.74372	44.81005	63.55304

Table (2) Features of testing character ॐ

Character	Mom1	Mom2	Mom3	Mom4	Mom5	Mom6	Mom7
ॐ	7.270134	27.08948	38.38297	35.28392	72.11476	48.8361	72.56828
ॐ	7.253691	27.18406	37.86198	32.39317	67.38271	46.63436	69.78333
ॐ	7.275457	27.6122	40.83363	36.14824	75.73351	49.95447	73.25936
ॐ	7.215377	25.02766	36.6615	31.4788	67.59609	44.04078	63.20394
ॐ	7.278899	27.90201	38.10574	34.10518	70.77201	48.26597	69.61765
ॐ	7.279694	27.93991	39.84371	34.80342	72.43327	49.60419	72.37795
ॐ	7.279984	28.47687	39.36253	34.75826	72.0565	49.07512	70.22581
ॐ	7.272771	28.3493	38.71453	33.58543	69.60824	49.77849	67.23228
ॐ	7.281943	27.96092	41.0927	37.48083	77.50507	54.26484	75.15917
ॐ	7.271109	26.45272	42.61427	38.10927	79.29336	51.44321	78.37408
ॐ	7.275282	27.73526	40.0531	35.16326	72.94357	49.74523	70.56512
ॐ	7.254004	27.17612	39.4015	35.19215	72.72613	49.44176	71.91148
ॐ	7.260358	26.61211	40.00121	34.74553	74.2571	51.84527	69.5179
ॐ	7.262239	26.73897	37.55745	35.78946	73.08768	49.28189	72.84868
ॐ	7.266705	27.35126	42.54261	34.71534	75.44127	50.83182	73.26151
ॐ	7.263629	26.72926	37.7015	38.47754	76.31509	52.47021	76.89263
ॐ	7.267468	27.05986	38.35966	39.93016	79.42526	53.77988	80.51699
ॐ	7.262506	26.29485	38.96204	37.66334	76.22057	50.84541	76.72264
ॐ	7.259173	26.49525	38.98932	36.0447	73.32342	49.7367	73.50986
ॐ	7.26231	27.29288	37.97223	33.52653	69.92023	47.17297	67.93943

Table (3) Features of testing character غ

Character	Mom1	Mom2	Mom3	Mom4	Mom5	Mom6	Mom7
غ	7.255045	23.59429	34.9576	30.23007	62.56033	42.88426	60.52436
غ	7.252999	23.6642	34.74081	32.52503	66.08889	44.35739	65.26826
غ	7.265438	24.73791	35.00724	31.35401	64.2076	44.1181	64.85191
غ	7.236696	24.01401	34.28245	30.10908	62.05503	42.13548	60.60546
غ	7.260639	24.50221	35.15899	31.70546	64.68169	44.19545	64.5191
غ	7.264663	24.43693	34.77587	31.83372	65.09769	44.20488	64.26334
غ	7.262594	24.83584	35.42825	31.48049	65.07832	44.02345	63.6087
غ	7.262774	24.50266	35.83567	31.09702	64.12254	46.36236	62.53931
غ	7.263336	24.61634	34.16856	30.90525	63.87553	45.93592	62.04815
غ	7.261582	24.29068	33.92847	31.46744	63.84463	43.69683	63.41045
غ	7.265109	24.95131	34.20251	31.0099	63.76348	44.37444	62.17999
غ	7.229713	23.51615	33.07572	29.89048	61.07254	44.69715	60.12835
غ	7.269408	25.14984	36.0046	32.40638	66.12852	45.3979	66.41096
غ	7.265197	25.52377	36.40493	32.26455	66.41949	45.76414	66.81631
غ	7.258098	24.33825	34.45073	31.53218	64.42033	46.23174	65.20253
غ	7.264865	24.94021	34.95721	30.91506	63.50081	45.66644	62.306
غ	7.26719	25.25565	36.54685	32.26423	66.31799	45.35825	65.92751
غ	7.264361	24.71477	35.6635	31.69763	65.48191	44.06776	63.59671
غ	7.259548	24.23328	35.70295	30.75895	63.52402	43.51096	63.28497
غ	7.258033	24.28134	35.85031	32.07919	65.56995	44.59188	65.61314

Table (4) Features of testing character ض

Character	Mom1	Mom2	Mom3	Mom4	Mom5	Mom6	Mom7
ض	7.240337	24.45023	33.40693	30.08277	61.43432	42.70626	61.61219
ض	7.252912	25.41212	34.10235	30.31265	62.01899	43.12695	63.20728
ض	7.247306	24.22751	33.23646	30.28592	61.61114	42.47878	61.85094
ض	7.236795	24.00864	32.98504	30.42384	61.62008	42.77453	62.53468
ض	7.217194	23.52951	32.27944	29.10559	59.3708	43.37978	59.99991
ض	7.212417	24.0707	34.26954	30.77245	62.83815	43.23184	64.14156
ض	7.236681	24.62763	34.96376	30.68873	63.00854	43.28237	64.27159
ض	7.241087	23.8127	33.36235	30.37667	61.75571	42.67226	62.42562
ض	7.246949	24.57477	33.07265	30.01887	61.07294	42.50974	61.75477
ض	7.230438	24.13666	33.14514	29.79827	60.99313	41.9594	60.53856
ض	7.222189	23.38451	32.7723	29.83379	60.81097	41.6988	60.85381
ض	7.238925	25.12441	33.97635	30.52398	62.57419	43.08815	61.6599
ض	7.240071	24.87186	33.83382	30.12428	61.66298	42.78664	62.09481
ض	7.24509	25.06778	33.99133	30.30669	62.01156	42.87181	62.28984
ض	7.247884	25.24223	33.41246	29.92957	61.255	42.60424	60.87848
ض	7.249551	25.49987	33.91709	30.15302	61.84666	42.97793	61.44394
ض	7.246674	24.76364	33.29547	30.28261	61.65627	42.73608	61.7688
ض	7.246124	24.49284	33.54463	30.56232	62.31134	42.90605	61.99461
ض	7.244448	24.44227	33.84941	30.42333	62.11193	43.16319	62.65806
ض	7.247792	24.6903	33.50443	30.01571	61.38631	42.44442	61.24995

Table (5) Features of testing character ظ

Character	Mom1	Mom2	Mom3	Mom4	Mom5	Mom6	Mom7
ظ	7.240451	26.93324	36.15723	30.14299	62.94811	45.37836	64.36704
ظ	7.228362	25.58582	35.08138	29.08587	60.76543	42.2431	59.78022
ظ	7.218229	25.57267	34.82479	29.54923	61.37063	42.79049	62.33468
ظ	7.257565	26.71207	36.42996	30.7477	64.10979	44.87122	64.16389
ظ	7.255772	25.91539	35.31841	31.14152	64.20634	46.94631	64.48306
ظ	7.255526	25.87463	34.10555	30.71091	63.66215	43.82262	61.86797
ظ	7.25682	27.50016	35.19918	31.7952	65.17214	45.71861	64.74509
ظ	7.2629	27.5619	35.66102	31.49789	64.5861	45.59582	65.9734
ظ	7.252297	26.46113	35.62061	31.13576	64.21236	45.02932	63.73586
ظ	7.258091	28.5942	36.66988	32.28203	66.50969	47.44933	67.9143
ظ	7.247634	26.06223	35.51523	31.17846	64.53652	47.78491	66.53111
ظ	7.25371	27.81337	36.485	31.43496	64.97742	47.98685	67.97294
ظ	7.257079	27.00771	36.08881	30.89746	63.93454	45.61988	64.61919
ظ	7.254752	28.22059	36.55219	31.03288	64.33383	47.22195	67.30556
ظ	7.257463	28.51423	37.33693	31.15544	65.00854	46.4818	65.40567
ظ	7.258035	27.13425	37.20255	30.90323	64.46539	56.76631	65.93105
ظ	7.257004	28.04768	36.20539	31.73106	65.74561	45.86942	64.34023
ظ	7.262014	27.61141	37.33374	31.15336	64.98062	47.24891	66.16106
ظ	7.261252	27.74731	36.58651	31.67018	66.49078	46.09177	63.6763
ظ	7.262156	26.84078	37.60883	31.16949	65.46373	44.61186	63.23587













Table (6) Features of testing character ج

Character	Mom1	Mom2	Mom3	Mom4	Mom5	Mom6	Mom7
ج	7.297592	28.42428	38.90013	31.93332	66.90378	48.026	67.53091
ج	7.299254	27.94322	38.36726	31.98547	66.67634	48.38843	66.6846
ج	7.29923	27.44556	38.95245	32.31585	67.59946	46.54681	68.72701
ج	7.292525	27.01533	38.216	32.07939	66.72538	46.18154	66.74366
ج	7.293197	27.14121	37.7126	31.89219	66.21634	46.55931	66.14409
ج	7.295342	27.20375	38.20052	31.95046	66.54045	46.23301	66.87901
ج	7.297246	27.43663	38.14999	32.14006	66.81053	46.26984	67.49023
ج	7.295318	28.16774	38.88774	31.91039	66.83506	47.4632	66.84924
ج	7.293839	27.04702	37.85551	31.85924	66.24368	47.78734	66.24185
ج	7.295018	26.83773	37.67548	31.81542	66.07449	45.7641	66.28751
ج	7.294901	27.29787	39.24198	31.72357	66.72309	47.70553	66.38821
ج	7.298668	28.28154	39.2392	32.98768	68.61213	51.30988	68.60284
ج	7.295225	29.11475	39.44118	31.64035	66.73547	47.99948	66.27489
ج	7.297196	28.95444	42.01264	32.25231	69.17109	48.20018	67.64083
ج	7.293068	27.44854	39.00585	31.57003	66.41357	46.40492	65.74163
ج	7.286625	26.91091	36.52428	30.871	64.10007	46.86377	64.57683
ج	7.291129	26.77784	37.52318	31.69337	65.80164	46.73041	65.73744
ج	7.294202	27.51459	38.34658	31.97455	66.78398	47.64189	67.68858
ج	7.294542	27.81059	40.33891	32.50827	68.61346	46.88655	66.80622
ج	7.292812	27.08202	38.3423	31.73479	66.32737	47.20064	66.12659

Table (7) Recognition results of character (ف) written by different writers.

Writers	Input character	Rec. Results
1		ف
2		ك
3		ف
4		ف
5		ف
6		ف
7		ف
8		ف
9		ك
10		ك
11		ف
12		ت
13		ف
14		ف
15		ف

Table (8) Recognition results of character (ج) written by different writers.

Writers	Input character	Rec. Results
1		ج
2		ج
3		ي
4		ي
5		ي
6		ج
7		ج
8		ج
9		ج
10		ج
11		ج
12		ج

13		ع
14		ع
15		ع

Table (9) Recognition results of character (ع) written by different writers.

Writers	Input character	Rec. Results
1		ع
2		ع
3		ع
4		ع
5		ع
6		ع
7		ع
8		ع

9		ض
10		ض
11		ض
12		ض
13		ض
14		ض
15		ض

Table (10) Recognition results of character (ض) written by different writers.

Writers	Input character	Rec. Results
1		ض
2		ض
3		ض
4		ض
5		ض

6		ظ
7		ظ
8		ظ
9		ظ
10		ظ
11		ظ
12		ظ
13		ظ
14		ظ
15		ظ

Table (11) Recognition results of character (ظ) written by different writers.

Writers	Input character	Rec. Results
1		ظ
2		ظ

3	٤٠	٤٠
4	٤٠	٤٠
5	٤٠	٤٠
6	٤٠	٤٠
7	٤٠	٤٠
8	٤٠	٤٠
9	٤٠	٤٠
10	٤٠	٤٠
11	٤٠	٤٠
12	٤٠	٤٠
13	٤٠	٤٠
14	٤٠	٤٠
15	٤٠	٤٠

Table (12) Recognition results of character (ز) written by different writers.

Writers	Input character	Rec. Results
1		ز
2		ز
3		ز
4		ل
5		ل
6		ق
7		ذ
8		ك
9		ن
10		ق
11		ط
12		ل
13		ز

14	ز	ذ
15	ز	ز

الخلاصة

تميز النمط جزء ضروري في الانظمة المتقدمة لمعالجة الصور. اللغة العربية تمتلك اربع اشكال لكل حرف بالاعتماد على موقع الحرف من الكلمة. وهذه المواقع هي في بداية الكلمة، الوسط، النهاية او منفصل. هذا البحث يهتم بتمييز الحروف العربية المفصولة باستخدام مفهوم العزوم السبعة. العزوم ودوال العزوم تستخدم على نطاق واسع كخصائص عامة ثابتة للصور في تمييز الحروف.

تمييز الحرف يتم بمرحلتين الاولى مرحلة التدريب والثانية مرحلة الاختبار وهذا يتضمن العديد من الوظائف الرئيسية تبدأ من ادخال الحرف و تنتهي بتمييزه. هذه الوظائف هي: المعالجة المسبقة، استخلاص الخصائص و مطابقة الحروف. تتضمن المعالجة المسبقة: ادخال الصورة، ازالة الشوائب باستخدام المرشح المتوسط، تحويل الصورة الى صورة ثنائية و اخيرا فصل الحروف. مطابقة الحروف تتضمن حساب (مسافة اقليدس) بين الحروف المراد اختبارها والحروف المخزونة.

تم تطبيق نظام التمييز على الحروف المطبوعة وكانت نسبة الدقة لتمييز 65 حرف مطبوع 96.92307 بينما في الحروف المكتوبة يدويا نسبة التمييز، قلت نسبة الى عدم الانتظامية التي تظهر في الحروف المكتوبة يدويا.



جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة النهرين
كلية العلوم

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رسالة

مقدمة الى قسم علوم الحاسبات في جامعة النهرين كجزء من متطلبات
نيل درجة الماجستير في علوم الحاسبات

من قبل

رغد خريبط راشد الخالدي

(بكالوريوس جامعة النهرين 2005)

إشراف

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2008

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