



**A Model for Handwriting Recognition Using
Wavelet Function and Genetic Algorithm**
**نموذج لتمييز الكتابه اليدويه باستخدام الداله الموجية وخوارزميه
التوريث**

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Examination Committee Decision**

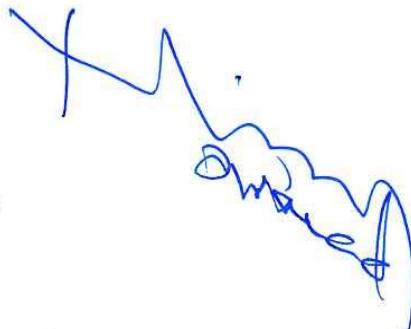
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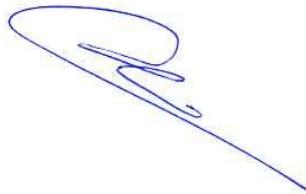
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Ali Ibrahim AL Alusi

Department of Computer Information system

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DEDICATION

I dedicate this thesis to my parents, who first planted the seeds of knowledge and wisdom in me. From my birth and throughout the stages of my life, they encouraged me with love and care and directed me to seek out knowledge and excellence. They instigated me to pursue my dreams until they come true which led me to the completion of this endeavor.

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”In the name of Allah the Most Gracious the Most merciful”. My guidance cannot come true except from Allah, in Him I trust, to Him I repent, and to Him praise and thanks always go. I would like also to thank Dr. Hussein H. Owaied for his valuable contributions, corrections, and discussions. Gratitude is also due to the Middle East University and to the Faculty members of Information Technology for their valuable information that was rendered to us during the courses of our studies .

I would like to thank my parents, my brothers, and my family for their support during my study, encouragement and the extreme freedom they have given me.

I would like to thank all my friends who helped me and everyone supported me.

الإهادء

إلى من كله الله بالهيبة والوقار .. إلى من علمني العطاء بدون انتظار .. إلى من أحمل أسمه بكل افتخار .. أرجو من الله أن يمد في عمرك لترى ثماراً قد حان قطافها بعد طول انتظار

والدي الغالي

إلى من كان دعاؤها سر نجاحي وشمعة طريفي، عنوان ونبع العطاء...

والدتي الحبيبة

إلى من هم أقرب إلى من روحي

إلى من شاركني حضن الام وبهم استمد عزتي وإصراري

.... إخواني الأحباء

إلى بهجة النفس والروح، إلى رفاق الدرب الطويل.... أصدقائي الأولفياء

A Model for Handwriting Recognition Using Wavelet Function and Genetic Algorithm

Abstract

One of the main problems of pattern recognition is focused on character recognition. There are many researches involved to find better way, to increase the accuracy of matched characters and digits in different languages, besides the techniques and methods used in pattern recognition are variety in different stages of character recognition processes.

This thesis presents the design and implementation of handwritten text recognition model using a hybrid technique, which consists of the Mayer wavelet function and genetic algorithms, to recognize the handwriting characters.

The model design consists of many parts, these are; image loading, selection part of an interesting phrases, cropping and separating each character alone, applying median and thinning filter to enhance an image, resizing an image, feature vector by extraction features of each character based on Meyer wavelet, and finally in the recognition stage applying a Genetic algorithm.

This thesis is concerned with the Pattern recognition of (isolated English characters) using wavelet and genetic algorithm to satisfy a successful recognition operation. The unknown character is read out from an image and from many operations to manipulate it and extract its features, to compare these features with saved chromosome database features.

This thesis we have selected the Meyer wavelet transformation to extract features handwriting characters. In extraction procedure, image, which maybe attacked, is pre-filtered by combination of median and thinning filters to increase distinction information. The extracted result for each character using the Mayer wavelet is represented as a chromosome of (3422) bits. The model is implemented and tested by using Matlab2012.

نموذج لتمييز الكتابه اليدويه باستخدام الداله الموجية وخوارزميه التوريث

الملخص

أحدى المشاكل الرئيسية في التعرف على الانماط هو التعرف على الحروف . وهناك عدد من البحوث في هذا المجال للحصول على أفضل الطرق التي تزيد من دقة التعرف على الحروف والأرقام في لغات مختلفه، با لاضافة الى التقنيات و الأساليب المستخدمة في التعرف على الانماط وتتنوع في مراحل مختلفة من عمليات التعرف على الحروف .

في هذه الاطروحة نقدم تصميم وتنفيذ نموذج لتحسين التعرف على النص المكتوب بخط اليد باستخدام تقنية مكونة من الوظائف الموجية وخوارزمية الجينات التي تميز الاحرف المكتوبه بخط اليد لآيجاد دقة افضل في التعرف.

النموذج المصمم يحتوي على عدة اجزاء وهي(تحميل الصورة ، اختيار الجزء المراد التعرف عليه من الصورة ، قص وفصل كل حرف، تطبيق تقنيه فلتر الوسط والفلتر الرقيق لتحسين الصورة ، اعادة صورة الحرف بحجم مختلف، استخلاص الخصائص للحرف باستخدام موبيجات (ماير) وفي المرحلة الاخيرة من التعرف على الحرف نطبق الخوارزمية الجينية).

وهذه الاطروحة تتعلق بالتعرف على الاحرف الانكليزية باستخدام الموبيجات والخوارزميات الجينية، للحصول على عملية تعرف ناجحة . الحرف الغير معروف يتم قراءته من الصورة ومن ثم يتم تطبيق عدد من العمليات لاستخراج خصائص، ونثم مقارنة هذه الخصائص مع خصائص احرف مخزونه في قاعدة البيانات من خلال الجينات .

في هذه الاطروحة استخدمنا موبيجات (ماير) التي اقتربناها لاستخراج الخصائص من الاحرف المكتوبة باليد. في عملية استخراج الخصائص ، قد تكون الصورة مشوهه، فيتم ادخالها على فلتر الوسط والفلتر الرقيق لزيادة عملية التمييز. النتائج المستخلصة من موبيجات ماير تُنقل في (3422) قطعه. يتم التطبيق والاختبار للنموذج باستخدام برنامج (مات لاب 2012) .

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List of Abbreviations

Abbreviation	Meaning
AMF	Adaptive Median Filter
ANN	Artificial Neural Network
CV	Computer Vision
DCT	Discrete Cosine Transforms
DWT	Discrete Wavelet Transforms
FT	Fourier Transform
GA	Genetic Algorithm
GUI	Guide User Interface
NLP	Natural Language Processing
OCR	Optical Character Recognition
PR	Pattern Recognition

CHAPTER ONE

INTRODUCTION

1.1 Introduction

1.2 Handwritten text Recognition

1.3 Feature Extraction for Handwriting Recognition

1.4 Character Recognition

1.5 Problem definition

1.6 Objective of the study

1.7 Thesis Chapters Layout

Chapter One

Introduction

1.1 Introduction

Francisco Casacuberta in 2006 claims that, “Natural language processing (NLP) is a subfield of artificial intelligence and linguistics. It studies the problems of automated generation and understanding of natural human languages. Natural language generation systems convert information from computer databases into normal-sounding human language, and natural language understanding systems converting samples of human language into more formal representations that are easier for computer programs to manipulate”.

Many of the simulation software packages have been used for mimic human functions in auto machine operation and self-automation tasks. One of these machines used to recognize a generic object which is considered one of the key challenges faced by Computer Vision (CV) and Pattern Recognition (PR) technologies.

Although there have been several techniques used and implemented to recognize objects, which are working in different and many fields such as Signal Processing and stochastically system, there are many problems related to Computer Vision (CV) and Pattern Recognition (PR).

In addition to that, these fields use various applications of Handwritten Character Recognition and its variety in techniques and methods. The off-line and on-line character recognition has many techniques and uses different approaches which some of them have complex and require more research compared to others.

The tools of handwritten character recognition are very important because there are different people have different handwriting formats and styles. Handwriting recognition

provides efficiency when converting the document of image from any image file format into more word processor formats.

There are many applications of the off-line recognition usually regarded as large-scale data processing. (Chetan S, 2009), identifying many applications of the off-line handwriting recognition, these are:

1. Postal address reading
2. Check sorting
3. Office automation for text entry
4. Automatic inspection
5. Person identification
6. Signature Verification
7. Bank-Check Processing
8. Writer Recognition

In this thesis we consider another application area, which is automation of handwritten documents images. Since, in reality there are many important old documents required to process by computer systems. Therefore it is necessary to convert them into typed digital documents and the first phase of this area is the handwritten documents images.

1.2 Handwritten text Recognition

Nafiz Arica in (1999) introduced article title “An Overview of Character Recognition Focused on Off-line” claims that Handwriting recognition can be divided into two categories; cursive and hand-printed script.

The nature of writing and the difficulty of segmentation process have been considered by many researchers defining four styles of handwritten recognition these are.

1. Boxed Discrete Characters: Boxed discrete characters require the writer to write each character within its own box on a specific form. These boxes can be easily traced in image.
2. Spaced Discrete Characters: The Spaced Discrete Characters can be segmented reliably by means of horizontal projections, creating a histogram of gray values in the image over all the columns and picking the valleys of this histogram as points of segmentation.
3. Run Cursive Script Writing: In pure cursive handwriting, a word is formed mostly from a single stroke. This makes segmentation by the traditional projection or connected component methods ineffective.
Secondly, shape discrimination between a character that look alike, such as U and V, I and 1, O and 0, is also difficult and requires the context information
4. Mixed Cursive and Discrete: In some languages, such as Arabic, there are characters, which may be different from the others according to the number or position of dots. Therefore it is necessary to adapt the mixed cursive and discrete, which are called cursive or mixed written texts and require more sophisticated approaches compared to the previous cases.

1.3 Feature Extraction for Handwriting Recognition

Text extraction from document images is a major problem in document image analysis in which one document, input image contains both text and graphics are processed to produce two output images, one containing text and the other containing graphics.

. A reliable extraction method is required to make it usable in automatic document processing systems.

Currently, the applications of such text extraction algorithms automatically process texture documents and architectural/engineering drawings, automatic reading of postal addresses and flexible forms. (Thai V. Hoang & Salvatore T., 2010) which propose feature properties for the text extraction algorithms, such as:

1. Aspect Ratio:

Aspect ratio is obtained by dividing the height of the character through width of the having character. Then having divided the entire set of characters, the result obtained is used in recognition of the distorted characters especially for touching broken and heavily printed characters. Distorted character aspect ratio is always less than its original value and in case of a touching character it is always higher than in the original.

2. Percent of pixels above horizontal half point:

The percentage of the number of black pixels in a normalized character frame described the horizontal position of points in character frame. The percentage of black pixels is used as a feature value because characters are often written in black.

3. Percent of pixels to right of vertical half point:

The percentage of the number of black pixels in a normalized character frame described the vertical position of points in character frame. The percentage of black pixels is used as a feature value because characters are often written in black

4. Number of strokes:

The input character is converted as a sequence of virtual or horizontal stroke segments, which is considered as a good feature exactly describing the complete structure of a character average distance from image center.

5. Reflect of x, y coordinates:

There are methods used to compute the coordinate mapping functions of x-axis and y-axis based on the projections of image intensity. For online patterns, the projections can be calculated directly from the trajectory without converting to a 2D image.

1.4 Character Recognition

Recognition is regarded as a basis attribute of human beings, as well as for other living creatures. The character recognition process is among the many intelligent activities of the human brain system. The character recognition process can be regarded as pattern recognition and defined as a process, which leads to a proper decision. The quality of this decision can only be measured by statistic relating to the number of "good" and "bad" classifications. Also pattern recognition can be defined as an area of science concerned with discriminating objects on the basis of information available about them. Each distinct of information about objects is called a feature.

The problem of pattern recognition may be regard as one discriminating the input data. There are many methods have been used for pattern recognition and these methods can be classified into four major groups: statistical, structural, syntactical, and neural network methods (Majida, at el, 2010).

1.5 Problem definition

The character recognition problem has been approached in many ways and various recognition methods have been suggested. Some of the method has been especially developed for the character recognition and most of them are borrowed from other fields of pattern recognition. In this Thesis the following problems have been identified, these are:

1. Extraction the physiological and behavioral characteristics from handwriting text.
2. Classification of the extracted characteristics.
3. Identification of handwriting text based on their characteristics
4. Sometimes different methods are combined for example, simple methods are used for pre-classification and final decision is required with more sophisticated methods.
5. The recognition procedure is basically very simple: after preprocessing some features extracted from the unknown character, which is then classified as the classes whose members have the most similar features, therefore required method for classification of features.
6. The requirement arises for combination of both methods of character recognition and features extraction and classification.

1.6 Objective of the Study

The main objectives of this research are:

1. Study most of the existing tools for extracting the characteristics
2. The choice of an image similarity measure which quantitatively tells how to select a reference images is close to the unknown image.
3. Design algorithms for extracting the characteristics.
4. Design algorithms for Classification of the extracted characteristics.
5. Design a model for automatic hand writing recognition.
6. Design the model for character recognition using wavelet function and genetic algorithm
7. Create database consists of handwriting characters for both Types of characters (small and capital letters).

1.7 Thesis Chapters Layout

The thesis is divided into six chapters. This chapter provides an introduction to the concept of natural language, pattern recognition, handwriting recognition and character recognition. It also introduces the problems statement and the objectives of this research.

The rest of this thesis is organized as follows:

Chapter Two: This chapter will focus on the literature survey of the pattern recognition and image processing which are related to the handwritten recognition, and related work with Wavelet Function and Genetic Algorithm.

Chapter Three: The techniques and methods used in pattern of character recognition have been discussed, instead the wavelet and genetic algorithm have taken a place in this chapter which is considered main techniques used in the model.

Chapter Four: proposed model and the main phases of the character recognition have been discussed. In addition to that, the methods of each phase and the methods and techniques used in the design have been discussed in details.

Chapter Five: Implementation of The proposed model and the experimental results has been discussed in this chapter.

Chapter six: The conclusion and future work has been discussed in this chapter.

CHAPTER TWO

Literature Survey

2.1 Over view

2.2 Related Works

Chapter Two

Literature Survey

2.1 Overview

There are many researchers have been done in the fields of pattern recognition and image processing which are related to the handwritten recognition, so in the following sections we concentrate on the most related research for the handwritten recognition.

2.2 Using Artificial Immune and Wavelet Packet Transform

(Yu Yang, 2011) introduce an approach based on handwritten Nepali character recognition strategy using artificial immune system and wavelet packet transform proposed and carefully experimented. With 116 feature coefficients extracted from 32*32 Nepali character images as they feature vector, where 84 were from wavelet packet transform and 32 achieved by horizontal and vertical histogram, while consonant antibody libraries for its character categories were trained and built to recognize handwritten Nepali consonant characters with artificial immune algorithm.

2.3 Using Genetic Algorithm for Handwritten Recognition.

(Chomtip, 2011) claims that the main objective of this research is focused on recognized Thai handwritten characters using genetic algorithm technique. The feature extracted from character information has bits string chromosome in a genetic algorithm, also, in this research, experiment was conducted on more than 10,000 Thai characters divided for training (8,160) and for testing (2040), and the recognition rate was 88.24%.

2.4 Using Discrete Hopfield Neural Network and Wavelet Transform

In (Xinyu et al., 2011), Character recognition is a branch of pattern recognition, the problem of noisy character image recognition is solved by discrete Hopfield neural network which is used as associative memory and wavelet transform theory in the paper. The important original data is extracted from each character image, which is a learning data of neural network. The character image is recognized by discrete Hopfield neural network and de-noising by the wavelet transforms theory. Noisy samples of character recognition show that the method is accurate and efficient.

2.5 Using Wavelet Compression for Recognize

(Ali et al., 2010) implemented a character recognition system to recognize printed and handwritten character from A to Z. This project presents new construction of character recognition tool using the technique similar to that used in image compression such as wavelet compression or JPEG compression. Wavelet compression is chosen as the technique implemented for this project. Compression technique extracted the important coefficient from the images. The Euclidean distance between the coefficient of the test images and training images is computed. Character is considered recognized if the Euclidean distance calculated is smaller than the Global threshold value of 258. This character recognition system also has 18.81% of false rejection rate and 21.88% for false acceptance rate.

2.6 Using Artificial Neural Networks

In (Chetan S, 2009) this problem demonstrates how a simple pattern recognition system can be designed. Note that the training process did not consist of a single call as a training function. Instead, the network was trained several times on various input vectors. In

this case, training a network on different sets of noisy vectors forced the network to learn how to deal with noise, a common problem in the real world.

2.7 Using Genetic Algorithm for Character Recognition.

In (Kimura, Suzuki, & Odaka, 2009) the proposed a novel method of feature selection for character recognition using genetic algorithms (GA). The feature is assigned to the chromosome, and values of "1" and "0" are given to the chromosome; corresponding to features that are respectively used and unused for recognition. GA decreases the number of chromosomes which take the value of "1" while changing generations. The proposed method selects only genes for which the recognition rate of training samples exceeds the predetermined threshold as a candidate of the parent gene and adopts a reduction ratio in the number of features used for recognition as a fitness value. Consequently, it becomes possible to reduce the number of features while maintaining the recognition rate. On the experiment for similar-shaped character recognition, the proposed method achieved a higher recognition rate and larger decrease of the number of features compared with Fisher's criterion

2.8 Using Wavelet for pattern recognition

(Guan-Chen Pan, 2008) introduces basic concept of using wavelet for pattern recognition, and he focused on this research on symbols and alphabets through steps of processes, and used ring-projection-wavelet-fractal method to recognize, and in classification used minimum average-loss, minimum error-probability, and orthogonal wavelet series in classifier design.

The robust algorithm for handwriting segmentation has been applied to segment from a word selected from a paragraph of handwritten text image. Each segmented characters have been converted into column vectors 625 values which then fed into neural network.

The output of neural network fed into the genetic algorithm which has been developed used the concept of correlation which helps to optimized, the efficiency up to 71% (Shashank 2008).

2.9 Using Genetic Algorithm for Pattern Recognition.

(Pornpanomchai, C., Daveloh, 2007) applied a genetic algorithm in the pattern of cellular automata and through Conway's rules of the game of life, to generate a system of printed Thai character recognition. The system consisted of two main parts, namely, recognition training and recognition testing. The printed character images fed to the first part were derived from standard character patterns widely used in computer currently totaling 72, 864 characters, and the image has amounted up to 1,015 characters.

The findings in this research revealed that the database used was of large size and data was transformed from a table frame of 64 x 64 pixels to be stored in the form of bit strings. A table size of 64 x 64 pixels was used to enable a wide variety of distribution patterns of the stable state of each character, making its identity more obvious.

This, of course, caused a modification process in each generation till the final generation which took a long time while the database was used to represent the population of the final generation of each character that must be large enough for the bit string used to represent these characters.

This would enable the system to recognize a character based on its frequency with the largest number of those bit string patterns. Out of 1,015 printed Thai characters tested, it was found that the system could recognize (accept) 986 characters or 97.14 %, while rejecting 6 characters or 0.59 % and misrecognizing 23 characters or 2.27 %. The recognition speed is 85 seconds per character on the average.

2.10 Using Genetic Algorithm for Chinese Character Recognition

(Ke-Jian, Xue-Dong, & Bao-Lan, 2002) focused on improvement of the accuracy of a character recognition system, besides this system has the recognition rate that it takes in consideration, and finally significant rate to introduce an excellent post-processing method. A Chinese Character Recognition Post-processing (CCRP) based on genetic algorithm is introduced in this paper.

This genetic algorithm relies on the Chinese character itself and context information. Experiment shows that this method obtains quite good result. The character recognition rate of the tested text is from 94.99% up to 95.92% after post-processing and thus improves 0.93%.

2.11 Using Wavelet Transform based on Human perception

In (Correia, et al, 2002) claim that the human vision system effortlessly recognizes familiar shapes despite changes and distortions found in retinal images. This work proposes a novel approach for recognition of handwritten characters based on human perception. The wavelet transform is used to simulate the multi-resolution capability of vision and to extract features such as fixation points and image details in horizontal, vertical and diagonal directions. A previous system which uses wavelet directional features yielded a recognition rate of 98.25% using the NIST numerals database.

2.12 Genetic Algorithm Approach for Handwritten Recognition

(Daming Shi, et al, 1998) are claimed: First, the general transformed divergence among classes, which is derived from Mahalanobis distances, is proposed to be the fitness function in the feature selection based on GA. Second, a special crossover operator other than traditional one is given. Third, a special criterion of terminating selections is inferred from the criterion of minimum error probability in a Bayes. Finally the fourth point is a comparison of method with the feature selection based on branch-and-bound algorithm (BAB), which is often used to reduce the calculation of feature selection via exhaustive search. This research, has been used a genetic algorithms (GA) to design a feature selection approach for handwritten Chinese character recognition.

CHAPTER THREE

Methodology for Character Recognition

3.1Character Recognition Overview

3.2Preprocessing Techniques

3.3Feature Extraction

3.4Genetic Algorithms

Chapter Three

Methodology for Character Recognition

3.1 Character Recognition Overview

The character recognition recently has many applications in computationally, such as Optical Character Recognition (OCR), Document Classification application, Computer Vision systems, Samples and Shape Recognition and Biometric Authentication (signature and handwritten).

There are many applications of OCR such as postal processing, script recognition, banking issues, passport authentication and language identification.

The field of character recognition has important issues in: Image Processing, Machine Vision, and Artificial Intelligence. Therefore, OCR cannot be applied without the help of Image Processing and/or Artificial Intelligence. Any OCR system goes through numerous phases including: data acquisition, preprocessing, feature extraction, classification and post-processing.

Data preprocessing describes any type of processing performed on raw data to prepare it for another processing procedure. Hence, preprocessing is the preliminary step which transforms the data into a format that will be more easily and effectively processed. Therefore, the main task of preprocessing is to decrease the variation that causes a reduction in the recognition rate and increases the complexities, The preprocessing is an essential stage prior to feature extraction since it controls the suitability of the results for the successive stages (Swamy , & Swapneel, 2007).

3.2 Preprocessing Techniques

(Ahmed, Mohamad, & Choong-Yeun, 2011), Claims that “Most of the preprocessing of character recognition applications use grey or binary images”. Such images may also contain non-uniform background and/or watermarks making it difficult to extract the document text from the image without performing some kind of preprocessing”. So the Preprocessing techniques are applied on color and noisy images, grey-level or binary document images containing text and/or graphics. Therefore; the desired result from preprocessing is a binary image containing text only.

3.2.1.1 Image Enhancement Techniques

Image enhancement means improving the quality of images for human perception with the use methods for removing noise, reducing blurring, increasing contrast and providing more detail. The techniques may be used to enhance the image varieties among contrast stretching, threshold, histogram equalization, and log and power law transformations (Alan et al., 2005). In the following subsections we will provide some of the techniques used in image enhancement.

3.2.1.2 Noise Removal

A noise in Image can be removed by using median filter Technique is a nonlinear digital filtering. The noise removal is typically used in pre-processing step to improve the image. Median filtering is widely implemented in digital image (Ery, & David, 2009).

3.2.1.3 Skew Detection

In image processing, especially when input image and the sensitivity of many document image analysis methods require a rotation of the image, document skew should be corrected.

Skew detection techniques can be divided into many activities these are; analysis of projection profile, Hough transform, connected components, clustering, and finding the correlation between lines techniques (Atallah, & Khairuddin, 2009; Mohammed et al., 2007).

3.2.1.4 Page segmentation

To separate text from image, a page segmentation techniques used, focused on finding textured regions which is a character in gray scale image, which separate lines and graphs also. The result is an image with only text. Document segmentation is classified in three categories: top-down, bottom-up and hybrid techniques. The top-down methods recursively segment large regions in a document into smaller sub regions stage constitute of the final segmentation results. On the other hand, the bottom-up methods start by grouping pixels of interest and merging them into larger blocks or connected components, such as characters which are then clustered into words, lines or blocks of text. The hybrid methods are the combination of both top-down and bottom-up strategies (Mohammed et al., 2007; Yuan, 1996)

3.2.2 Thinning Filter

Thinning is a morphological operation that is used to remove selected foreground pixels from binary images, somewhat like erosion or opening. Thinning is a data reduction process that erodes an object until it is one-pixel wide, producing a skeleton of the object making it easier to recognize objects such as characters.

Thinning is normally only applied to binary images, and produces another binary image as output.

Thinning erodes an object over and over again (without breaking it) until it is one-pixel wide. On the other hand, the medial axis transform finds the points in an object that form lines down its center. (MR DANIEL, 2009).

3.3 Feature Extraction

In image contains the text handwritten text, the features in this case has information which can be extracted from the characters. This information is passed onto the matcher to assist in the classification process.

In feature extraction stage each character is represented as a feature vector, which becomes its identity. The major goal of feature extraction is to extract a set of features, to increase the recognition rate and decrease the amount of elements. Feature extraction methods are based on 3 types of features, these are:

1. Statistical
2. Structural
3. Global transformations and moments

3.3.1 Statistical Features

Representation of a character image by statistical distribution of points takes care of style variations to some extent. The major statistical features used for character representation are:

- Zoning
- Projections and profiles
- Crossings and distances

3.3.1.1 Zoning

Zoning is a technique for handwritten character recognition. When a zoning method is considered, the pattern image is subdivided into zones each one providing regional information related to a specific part of the pattern. The character image is divided into NxM zones. From each zone features are extracted to form the feature vector.

The goal of zoning is to obtain the local characteristics instead of global characteristics as shown in figure (3.1) (Hamdi, & Maher, 2011).

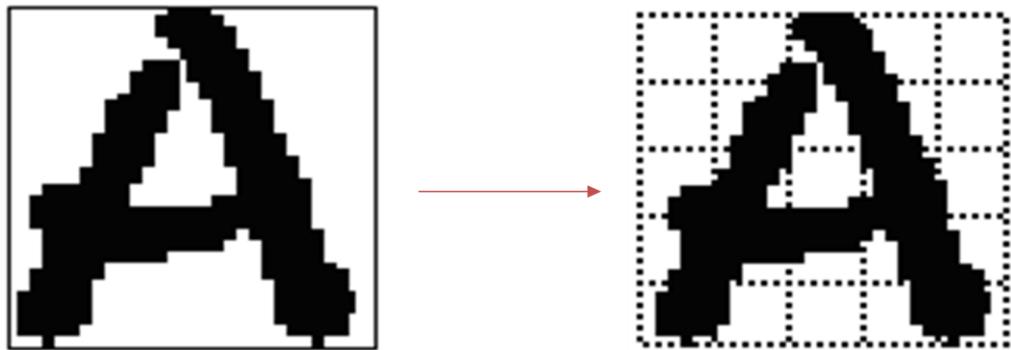


Figure (3.1) Zoning Features (Pulak purkait, 2009).

A. Zoning – Density Features.

The number of foreground pixels, or the normalized number of foreground pixels, in each cell is considered a feature, darker squares indicate higher density of zone pixels, as shown in figure (3.2), and the features could be characters, symbols, or cuneiforms (Mohammed et al., 2007).

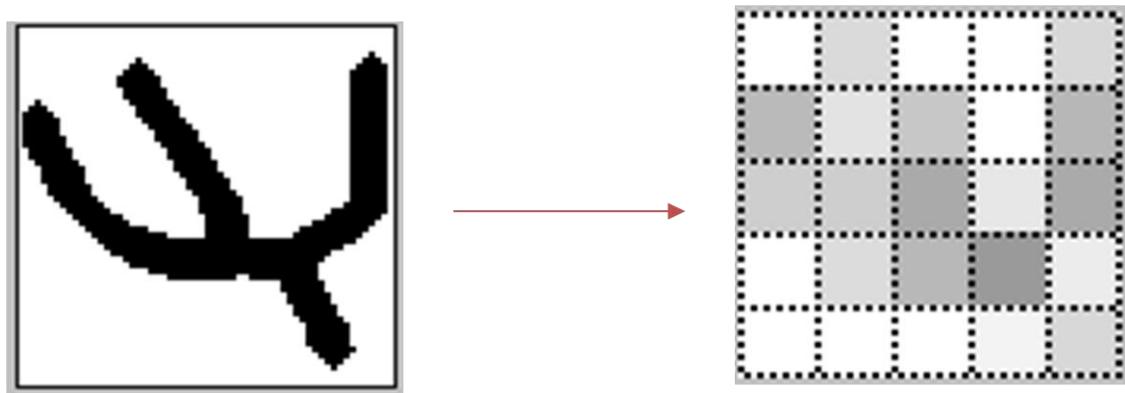


Figure (3.2), Zoning – Density Features (Pulak purkait, 2009).

B. Zoning – Direction Features.

The zoning according to direction features is based on the contour of the character image, as shown in figure (3.3).

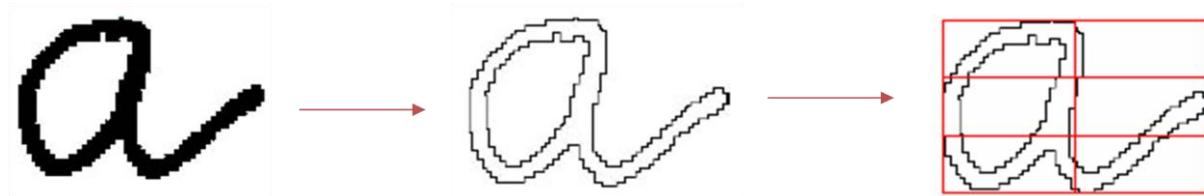


Figure (3.3) Zoning-Direction Features (Pulak purkait, 2009).

For each zone the contour is followed and a directional histogram and it represents the average number of distances computed and does not depend on the number of prototypes and they show linear space complexity. Besides that, the directional histogram is obtained by analyzing the adjacent pixels in a 3x3 neighborhood, as shown in figure (3.4) (Mohammed et al., 2007).

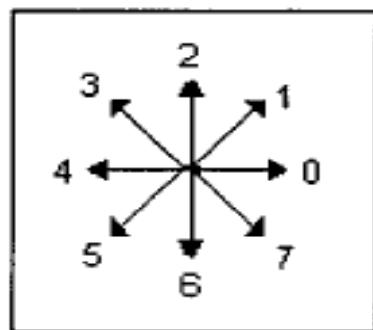


Figure (3.4) Directions of Feature

The zoning according to direction features can also be based on the skeleton of the character image. The skeleton is important for object representation and recognition. Also, Skeleton-based representations are the abstraction of objects, which contain both shape features and topological structures of original objects, as shown in figure (3.5).

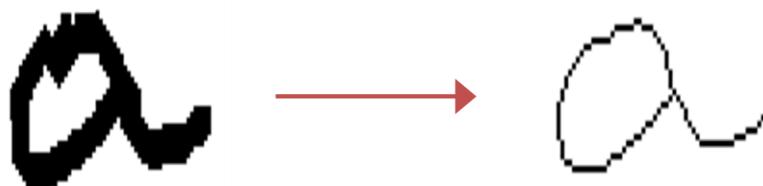


Figure (3.5) convert an image to skeleton (Xiang B., Longin J., Latecki, & Wen-Yu L., 2007).

Distinguish individual line segments for characters are composed of line segments and curves. Every line segment or curve can be extended along a certain direction. A curve that joins itself at some points forms a loop as shown in figure (3.6).

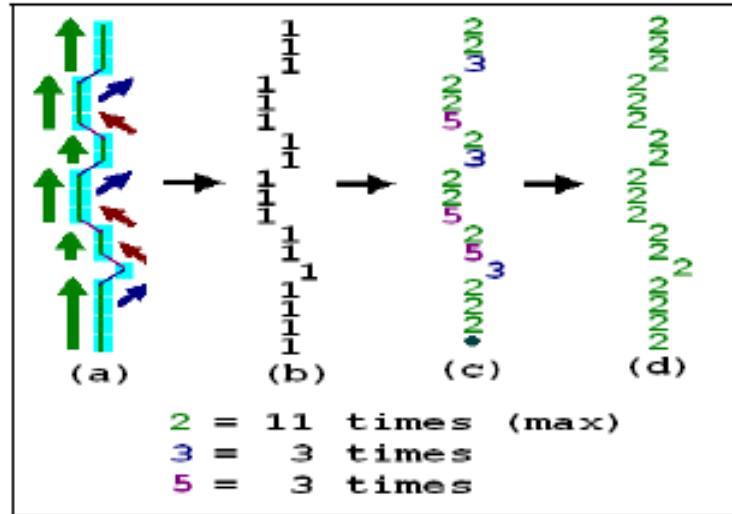


Figure (3.6) Line segments of characters (Pulak purkait, 2009).

The labeling line segment information, line type normalization, and line segments are coded with a direction number, sought to simplify each character's boundary or thinned representation through identification of individual stroke or line segments in the image as shown in figure (3.7).

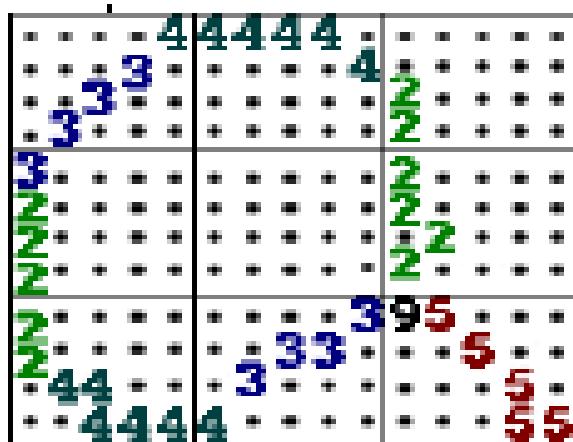


Figure (3.7) line segment of character (a) with direction numbered (M. Blumenstein, B. Verma, & H. Basli, 2003).

The line segments that would be determined in each character image were categorized into four types: 2) Vertical lines, 4) Horizontal lines, 3) Right diagonal and 5) Left diagonal.

3.3.1.2 Projections and profiles

The basic idea behind using projections is that character images, which are 2-D signals, can be represented as 1-D signal. These features, although independent to noise and deformation, depend on rotation.

A. Projection histograms: means count the number of pixels in each column and row of a character image. Projection histograms can separate characters such as “m” and “n”, as shown in figure (3.8) (Mohammed et al., 2007).

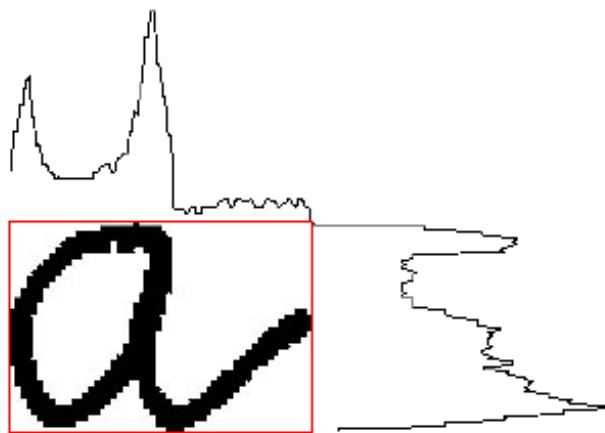


Figure (3.8) Projection Histogram of Character (a) (Pulak purkait, 2009).

B. Profiles: The profile counts the number of pixels (distance) between the bounding box of the character image and the edge of the character. The profiles describe well the external shapes of characters and allow to distinguish between a great number of letters, such as “p” and “q”, as shown in figure (3.9)(Mohammed et al., 2007).

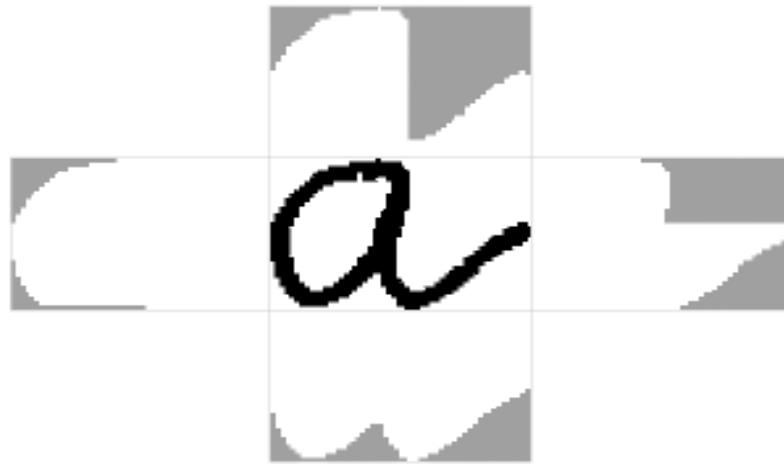


Figure (3.9) Profile bounding box of character (a) (Pulak purkait, 2009).

Profiles can also be used to the contour of the character image,

Extract the contour of the character,

Locate the uppermost and the lowermost points of the contour,

Calculate the in and out profiles of the contour, as shown in figure (3.10).

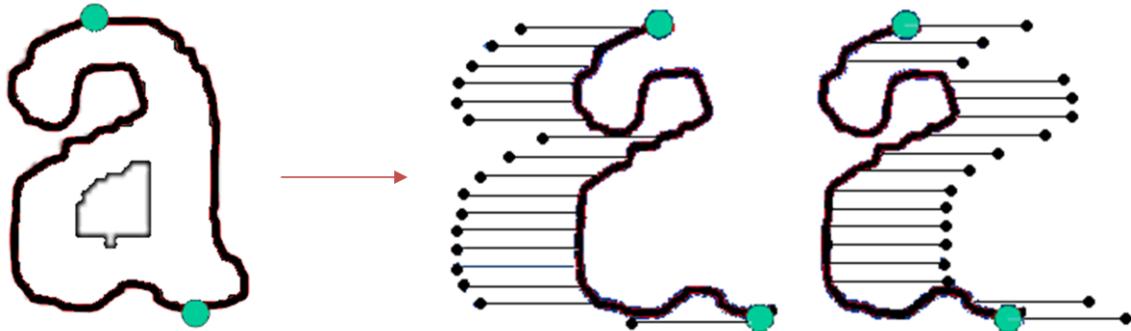


Figure (3.10) profile contour of character (a) (Dusan C., & Dejan G., 2011).

3.3.1.3 Crossings and Distances

Crossings is used to count the number of transitions from background to foreground pixels for all vertical and horizontal lines through the character image, instead of the distances, calculate the distances of the first image pixel detected from the upper and lower

boundaries, of the image, along vertical lines and from the left and right boundaries along horizontal lines, as shown in figure (3.11) (Mohammed, 2007).

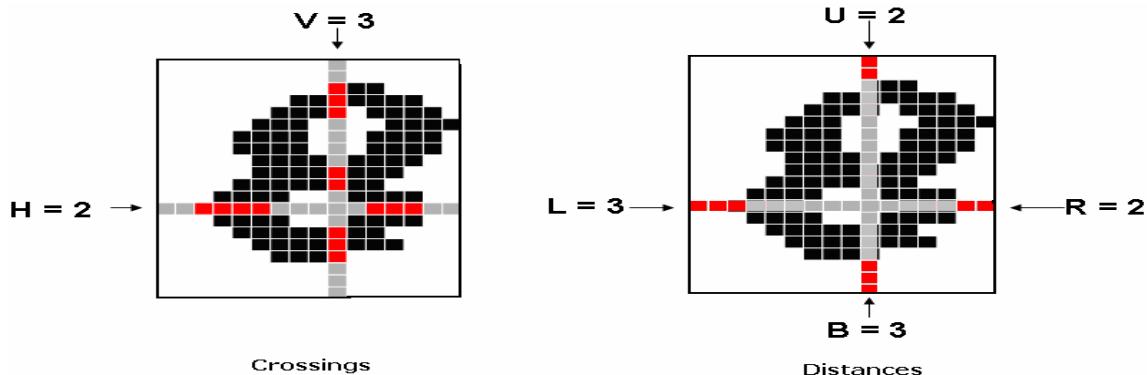


Figure (3.11) Crossing and Distance

3.3.2 Structural Features

Pulak purkait in 2009 defines the structural features are based on topological and geometrical properties of the character. These character features can be aspect ratio, cross points, loops, branch points, strokes and their directions, inflection between two points, horizontal curves at top or bottom. So the characters will be represented by structural features with high tolerance to distortions and style variations.

This type of representation for character as structural features may also encode some knowledge about the structure of the character or may provide some knowledge as to what sort of components make up that character as shown in figure (3.12) (Pulak purkait, 2009).



Figure (3.12) crossing points and loop structural features (Pulak purkait, 2009).

The structural feature extraction has been used for method for recognizing Greek handwritten characters (MR DANIEL, 2009). There are three types of features, these are:

- Horizontal and Vertical projection histograms, as shown in figure (3.13)
- Radial histogram, as shown in figure (3.13)
- Radial out-in and radial in-out profiles, as shown in figure (3.14)

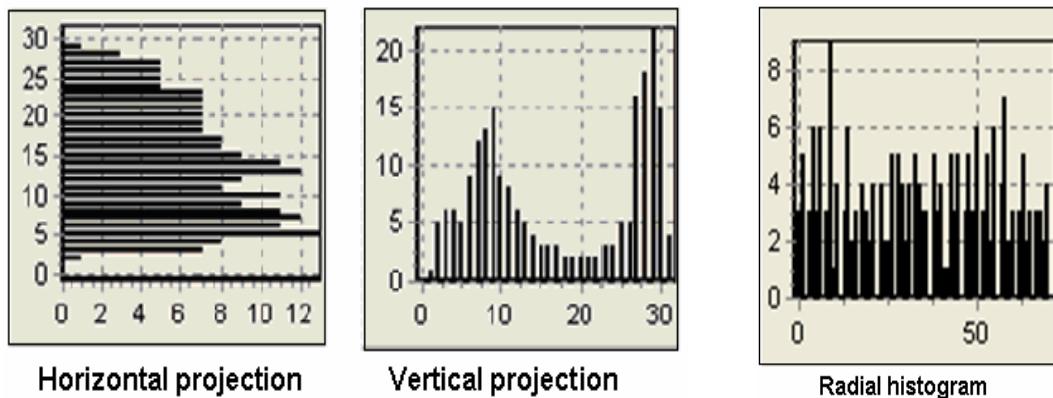


Figure (3.13): Horizontal and Vertical projection histograms, (Lin-Lin Li, 2009).

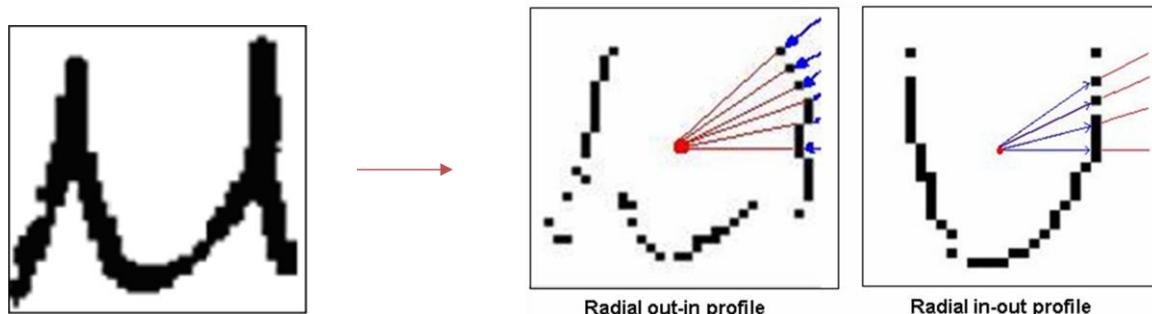


Figure (3.14) Radial out-in and radial in-out profiles

3.3.3 Global Transformations - Moments

The Fourier Transform (FT) of the contour of the image is calculated. Since the first n coefficients of the FT can be used in order to reconstruct the contour, then these n coefficients are considered to be a n-dimensional feature vector that represents the character, as shown in figure (3.15) (Hmadi, & Maher, 2011).

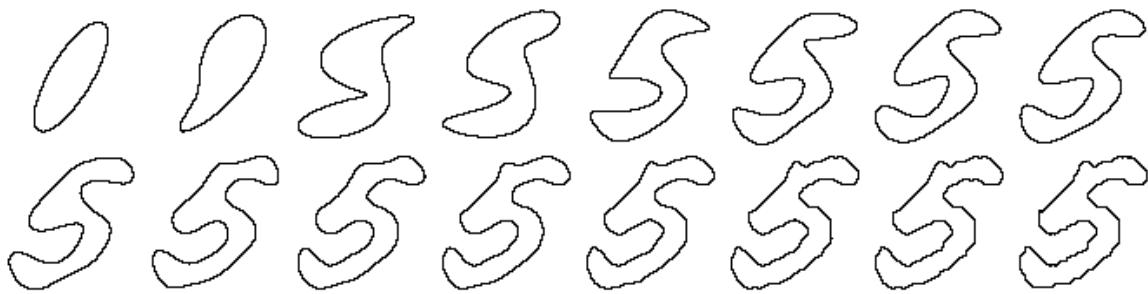


Figure (3.15) Contour of Image based on FT (Pulak purkait, 2009).

There are many techniques adopted to extract the features of the characters, such as, Discrete Cosine Transforms (DCT) and Discrete Wavelet Transform (DWT). Which are widely used in the field of digital signal processing applications (Chomtip et al., 2011).

3.3.3.1 The DCT Transform

The DCT is a technique for converting an image into elementary frequency components (Alan Dix et al., 2005). It represents an image as a sum of sinusoids of varying magnitudes and frequencies.

With an input image, x , the DCT coefficients for the transformed output image, y , are computed according to equation shown below. In the equation, x , is the input image having $N \times M$ pixels, $x(m, n)$ is the intensity of the pixel in row m and column n of the image, and $y(u, v)$ is the DCT coefficient in row u and column v of the DCT matrix.

$$y(u, v) = \sqrt{\frac{2}{M}} \sqrt{\frac{2}{N}} a_m a_n \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left\{ x(m, n) \times \frac{(2m+1)u\Pi}{2M} \cos \frac{(2n+1)v\Pi}{2N} \right\}$$

Where

N, M is the dimension of the input image

n, m are the intensity of pixel in row (m) and in column (n).

u, v are the DCT coefficient indexes of input image (u is row, and v is column)

Where

$$a_u = \begin{cases} \frac{1}{\sqrt{2}} & u = 0 \\ 1 & u = 1, 2, \dots, M - 1 \end{cases}$$

$$a_v = \begin{cases} \frac{1}{\sqrt{2}} & v = 0 \\ 1 & v = 1, 2, \dots, N - 1 \end{cases}$$

The image is constructed by applying inverse DCT operation according to equation below:

$$x(m, n) = \sqrt{\frac{2}{M}} \sqrt{\frac{2}{N}} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \left\{ a_m a_n (u, v) \times \cos \frac{(2m+1)u\Pi}{2M} \cos \frac{(2n+1)v\Pi}{2N} \right\}$$

The popular block-based DCT transforms segments image to non-overlapping blocks and applies DCT to each block. This results in giving three frequency coefficient sets: low frequency sub-band, mid-frequency-sub-band and high frequency sub-band. DCT-based watermarking is based on two facts. The first fact is that much of the signal energy lies at low-frequencies sub-band which contains the most important visual parts of the image. The second fact is that high frequency components of the image are usually removed through compression and noise attacks. The watermark is therefore embedded by modifying the coefficients of the middle frequency sub-band so that the visibility of the image will not be affected and the watermark will not be removed by compression (Ahmed, Mohamad, & Choong-Yeon, 2011).

3.3.3.2 The DWT Transform

The wavelet transform decomposes an image into a set of band limited components which can be reassembled to reconstruct the original image without error. Since the bandwidth of the resulting coefficient sets is smaller than that of the original image, the

coefficient sets can be down sampled without loss of information. Reconstruction of the original signal is accomplished by up sampling, filtering and summing the individual sub bands. For 2-D images, applying DWT corresponds to processing the image by 2-D filters in each dimension. The filters divide the input image into four non-overlapping multi-resolution coefficient sets, a lower resolution approximation image (LL1) as well as horizontal (HL1), vertical (LH1) and diagonal (HH1) detail components. The sub-band LL1 represents the coarse-scale DWT coefficients while the coefficient sets LH1, HL1 and HH1 represent the fine-scale of DWT coefficients. To obtain the next coarser scale of wavelet coefficients, the sub-band LL1 is further processed until some final scale N is reached.

When N is reached we will have $3N+1$ coefficient sets consisting of the multi-resolution coefficient sets LLN and LHX, HLX and HHX where x ranges from 1 to N.

Due to its excellent ratio-frequency localization properties, the DWT is very suitable to identify the areas in the host image where a watermark can be embedded effectively. In particular, this property allows the exploitation of the masking effect of the human visual system such that if a DWT coefficient is modified, only the region corresponding to that coefficient will be modified. In general most of the image energy is concentrated at the lower frequency coefficient sets LLx and therefore embedding watermarks in these coefficient sets may degrade the image significantly. Embedding in the low frequency coefficient sets, however, could increase robustness significantly. On the other hand, the high frequency coefficient sets HHx include the edges and textures of the image and the human eye is not generally sensitive to changes in such coefficient sets.

This allows the watermark to be embedded without being perceived by the human eye. The agreement adopted by many DWT-based watermarking methods, is to embed the watermark in the middle frequency coefficient sets HLX and LHX is better in perspective of imperceptibility and robustness (HUANG Wei, LU Xiaobo, & LING Xiaojing, 2005).

3.4 Genetic Algorithms

The genetic algorithm (GA) I techniques used for recognition with features taken from preprocessing such as image reading and feature extraction using wavelet transform.

Usually the GA begins like any other optimization algorithm by defining the optimization variables together with the cost function. The path through the components of the GA is shown as a flowchart in Figure (3.16). Each part of the flowchart is discussed in detail in this chapter. (Randy L., Haupt, & sue Ellen Haupt. 2004).

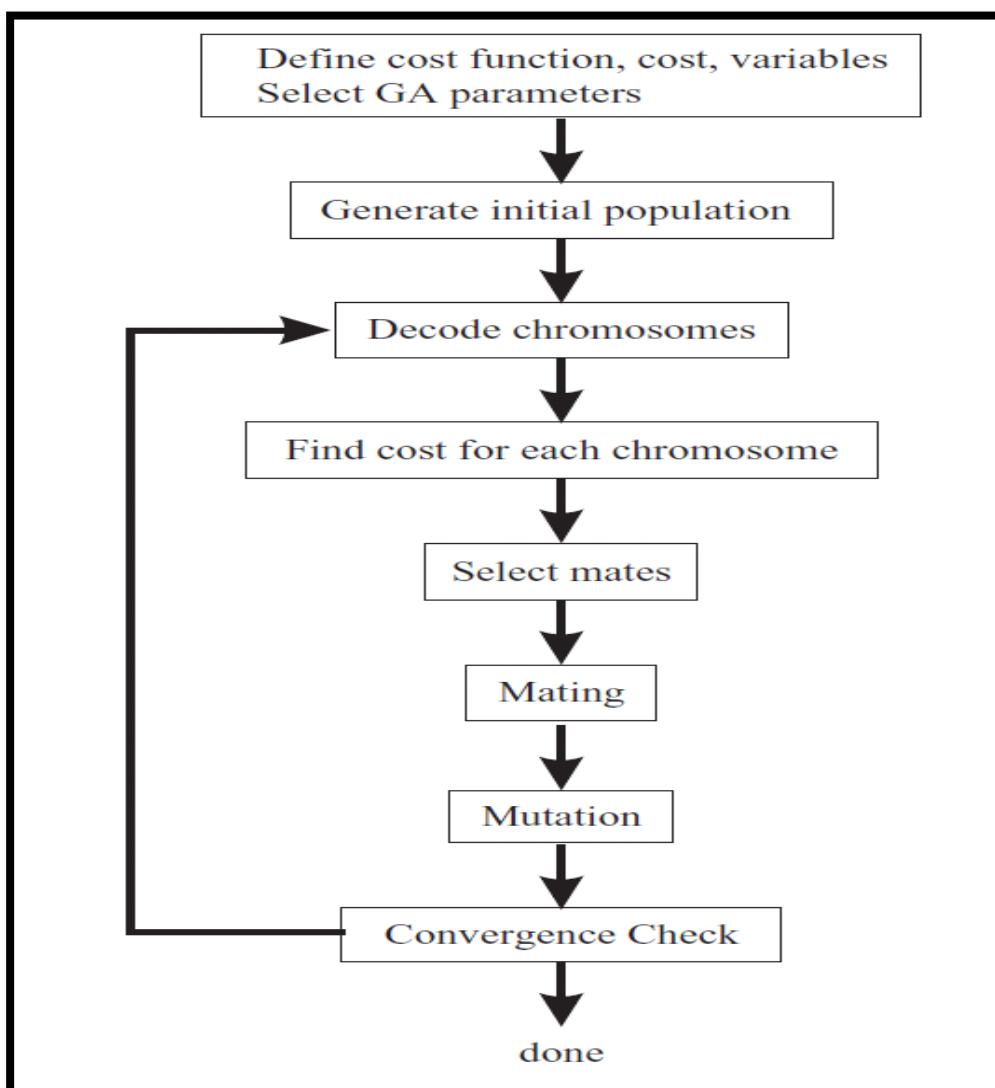


Figure (3.16): flowchart of a GA (Randy L., Haupt, & sue Ellen Haupt. 2004).

3.4.1 Selecting the Variables and the Cost Function

There are many variables considered in GA so the user must decide which variables of the problem are most important. Usually the cost function generates an output from a set of input variables (a chromosome). The cost function may be a mathematical function, an experiment, or a game. The object is to modify the output in some desirable fashion by finding the appropriate values for the input variables. One way of computing the cost is the difference between the desired and actual temperatures of the water. So that determining an appropriate cost function and deciding which variables to use are intimately related. The term fitness is extensively used to designate output of the objective function in the GA literature.

The GA begins by defining a chromosome or an array of variable values to be optimized. If the chromosome has Nvar variables (an Nvar-dimensional optimization problem) given by p1, p2, Then the chromosome is written as an Nvar elements row vector.

$$\text{Chromosome} = [p_1, p_2, p_3, \dots, p_{N\text{var}}]. \dots \quad (3.1)$$

For instance, searching for the maximum elevation on a topographical map

Requires a cost function with input variables of longitude (x) and latitude (y)

$$\text{Chromosome} = [x, y]. \dots \quad (3.2)$$

Where $N\text{var} = 2$. Each chromosome has a cost found by evaluating the cost function,

$$\text{Cost} = f(\text{chromosome}) = f(p_1, p_2, \dots, p_{N\text{var}}). \dots \quad (3.3)$$

The cost function is written as the negative of the elevation in order to put it into

The form of a minimization function:

$$F(x, y) = -\text{elevation at } (x, y). \dots \quad (3.4)$$

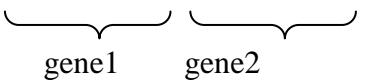
The user must decide which variables of the problem are most important. Too many variables bog down the GA (Randy L., Haupt, & sue Ellen Haupt. 2004).

3.4.2 Variable Encoding and Decoding

Since the variable values are represented in binary, there must be a way of converting continuous values into binary, and vice versa. Quantization samples a continuous range of values and categorizes the samples into no overlapping sub ranges.

Then a unique discrete value is assigned to each sub range. The difference between the actual function value and the quantization level is known as the level that allows a maximum error equal to the quantization level.

The GA works with the binary encodings, but the cost function often requires continuous variables. Whenever the cost function is evaluated, the chromosome must first be decoded. An example of a binary encoded chromosome that has N_{var} variables, each encoded with $N_{gene} = 10$ bits (Randy L., Haupt, & sue Ellen Haupt. 2004).

Chromosome: 11110010010011011111 0000101001

 gene1 gene2

3.4.3 The Population

The GA starts with a group of chromosomes known as the population. The Population has N_{pop} chromosomes and is an $N_{pop} \times N_{bits}$ matrix filled with random ones and zeros.

3.4.4 Selection

(Randy L., Haupt, & sue Ellen Haupt. 2004) they describe the selection process as a time to play matchmaker. Two chromosomes are selected from the mating pool of N_{keep} chromosomes to produce two new offspring. Pairing takes place in the mating population until $N_{pop} - N_{keep}$ offspring are born to replace the discarded chromosomes. Pairing chromosomes in a GA can be as interesting and varied as pairing in an animal species. We'll look at a variety of selection methods, starting with the easiest.

3.4.5 Mating (Crossover)

Usually the mating described as the creation of one or more offspring from the parents selected in the pairing process. The genetic makeup of the population is limited and usually it's depending on the current members of the population. (Randy L., Haupt, & sue Ellen Haupt. 2004).

3.4.5.1 Crossover techniques

In literature there are many techniques have been used for crossover and are relatively applied different data structures to store themselves. Therefore the following five points describe some of them.

1. One-point crossover

A single crossover point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. The resulting organisms are the children:

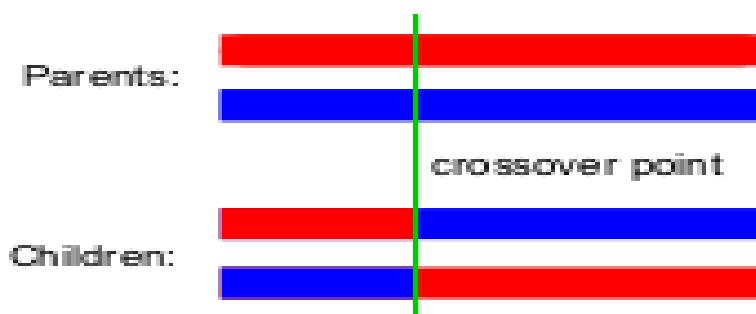


Figure (3.17) one point crossover (Randy L., Haupt, & sue Ellen Haupt. 2004).

2. Two-point crossover

Two-point crossover calls for two points to be selected on the parent organism strings. Everything between the two points is swapped between the parent organisms, rendering two child organisms:

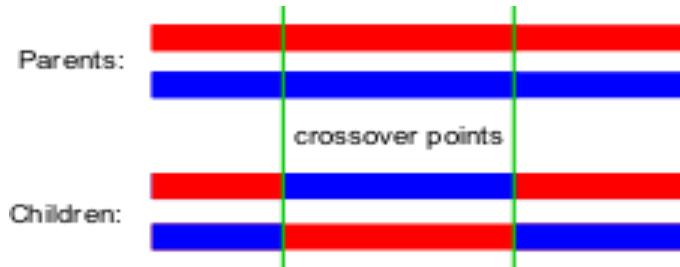


Figure (3.18) two point's crossover (Randy L., Haupt, & sue Ellen Haupt. 2004).

3. Cut and splice

Another crossover variant, the "cut and splice" approach, results in a change in length of the children strings. The reason for this difference is that each parent string has a separate choice of crossover point.

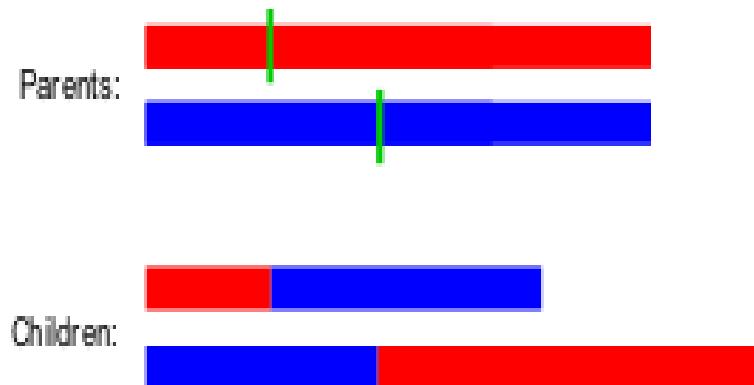


Figure (3.19) Cut Splice Crossover (Randy L., Haupt, & sue Ellen Haupt. 2004).

4. Uniform Crossover and Half Uniform Crossover

The Uniform Crossover uses a fixed mixing ratio between two parents. Unlike one- and two-point crossover, the Uniform Crossover enables the parent chromosomes to contribute the gene level rather than the segment level. If the mixing ratio is 0.5, the offspring has approximately half of the genes from first parent and the other half from second parent, although cross over points can be randomly chosen as seen below:

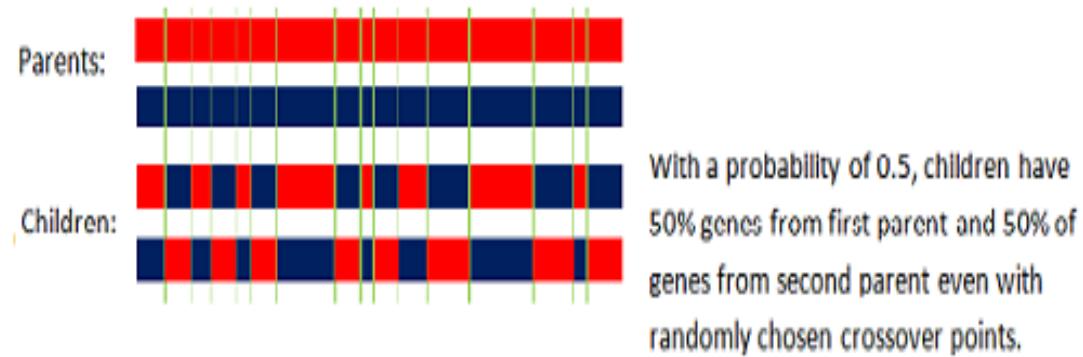


Figure (3.20) Uniform Crossover (Randy L., Haupt, & sue Ellen Haupt. 2004).

The Uniform Crossover evaluates each bit in the parent strings for exchange with a probability of 0.5. Even though the uniform crossover is a poor method, empirical evidence suggest that it is a more exploratory approach to crossover than the traditional exploitative approach that maintains longer schemata. This results in a more complete search of the design space maintaining the exchange of good information. Unfortunately, no satisfactory theory exists to explain the discrepancies between the Uniform Crossover and the traditional approaches. (P.K. Chawdhry, 1998)

In the Uniform crossover scheme (UX) individual bits in the string are compared between two parents. The bits are swapped with a fixed probability, typically 0.5.

In the Half Uniform crossover scheme (HUX), exactly half of the no matching bits are swapped. Thus first the Hamming distance (the number of differing bits) is calculated. This number is divided by two. The resulting number is how many of the bits that do not match between the two parents will be swapped.

5. Three parent crossover

In this technique, the child is derived from three parents. They are randomly chosen. Each bit of first parent is checked with bit of second parent whether they are same. If same then the bit is taken for the offspring otherwise the bit from the third parent is taken for the offspring. For example, the following three parents:

parent1 1 1 0 1 0 0 0 1 0

parent2 0 1 1 0 0 1 0 0 1

parent3 1 1 0 1 1 0 1 0 1

Produces the following offspring:

Offspring is 1 1 0 1 0 0 0 0 1 (S.N.Sivanandam, & S.N.Deepa, 2008).

The most common form of mating involves two parents that produce two offspring. A crossover point is randomly selected between the first and last bits of the parents' chromosomes. First, parent1 passes its binary code to the left of that crossover point to offspring1. In a similar manner, parent2 passes its binary code to the left of the same crossover point to offspring2. Next, the binary code to the right of the crossover point of parent1 goes to offspring2 and parent2 passes its code to offspring1. Consequently the offspring contains portions of the binary codes of both parents. The parents have produced a total of $N_{pop} - N_{keep}$ offspring, so the chromosome population is now back to N_{pop} . (Randy L., Haupt, & sue Ellen Haupt. 2004)

The first set of parents includes chromosomes 3 and 2 and has a crossover point between bits 5 and 6. The second set of parents includes chromosomes 3 and 4 and has a crossover point in binary number system namely bits 10 and 11. This process is known as simple or single-point crossover as shown in figure (3.21) (Janne K., & Jarmo T., 2004; George Bebis, Sushil L., & Sami F., 1999).

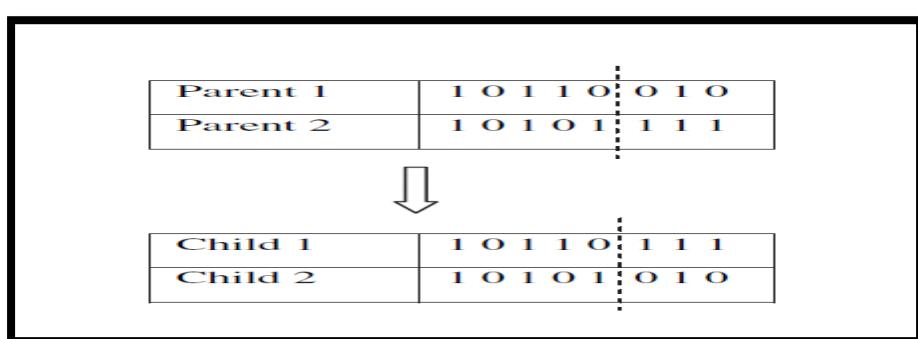


Figure (3.21) first point crossover.

3.4.6 Mutations

The GA uses the mutations for altering a certain percentage of the bits in the list of chromosomes in order to increase the algorithm's freedom to search outside the current region of variable space. So mutation can be regarded as the second way for GA to explore a cost surface.

Therefore the process of mutation can produce traits not in the original population and keeps the GA from converging too fast before sampling the entire cost surface. Usually the single point used in mutation process changes the 1's to the 0's, and vice versa. In mutation process the points are randomly selected from the $N_{pop} \setminus N_{bits}$ total number of bits in the population matrix (Randy L., Haupt, & sue Ellen Haupt. 2004).

CHAPTER FOUR

Proposed Model for Handwritten Character Recognition

4.1 Overview

4.2 Input Image

4.3 Preprocessing Module

4.4 Feature Extraction Module

4.5 Genetic Algorithm Module

4.6 Identify the Recognize Character Module

4.7 Encoding

4.8 Fitness Evaluation

Chapter four

Proposed Model for Handwritten Character Recognition

4.1 Overview

Figure 4.1 presents the architecture of the proposed model, which consists of six modules, these are: Preprocessing Image, Feature Extraction Using Wavelet, Comparison Using Genetics Algorithm, Access Stored Database, and Identifying Recognized Character. The proposed model based on pattern recognition for converting a digital image contains document features into readable/modified text.

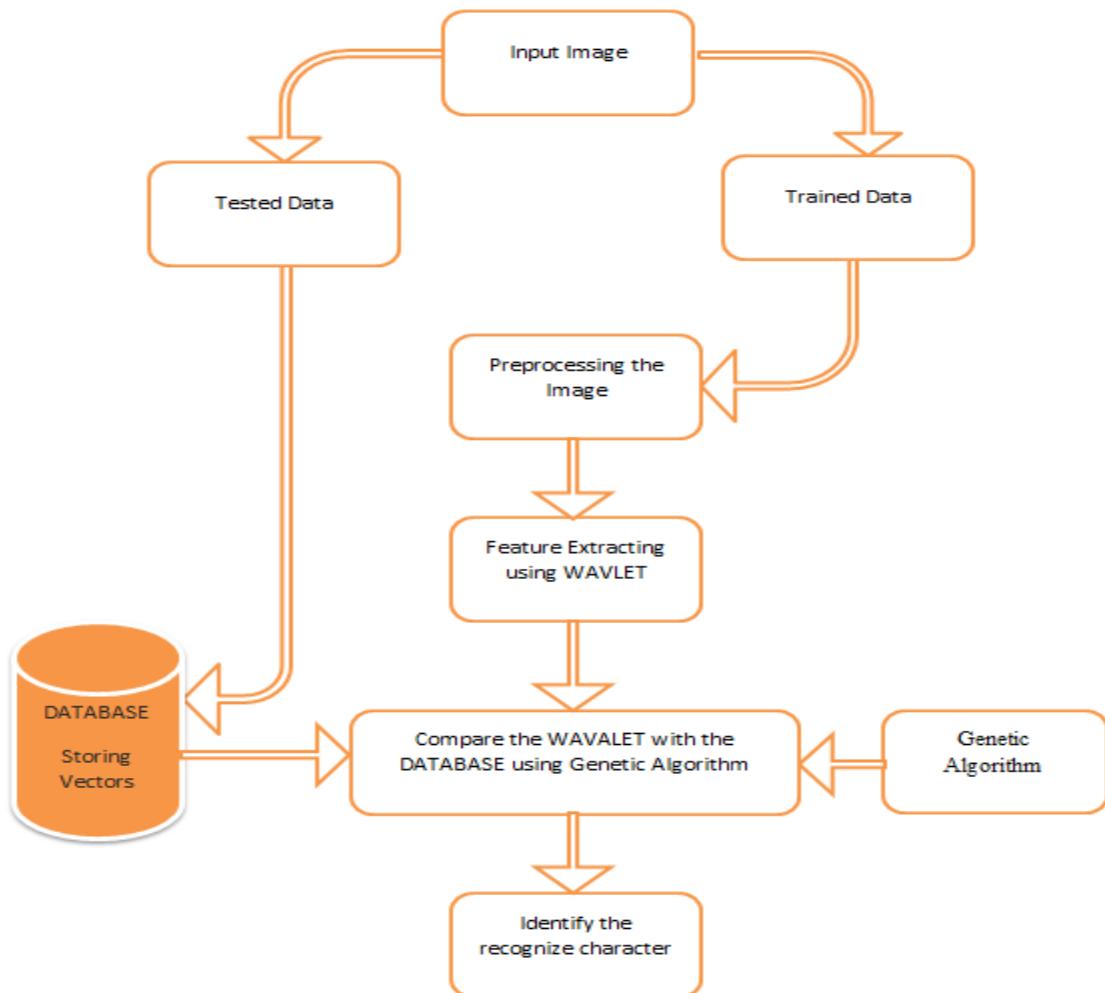


Figure (4.1) Architecture of the Proposed Model

4.2 Input Image

The input image consists of both trained and tested images, so that if the input image is trained it will be entered to preprocessing module, but if the input image tested it will be saved in the database.

4.3 Preprocessing Module

There are two techniques used in this phase, Denoising image and thinning filter. The proposed method in image Denoising is median filter, and thinning filter. In addition to that, the preprocessing stage process the input data (image) to produce output data (enhanced image) that is used as input to another stage (feature extraction). The importance of the preprocessing is preparing the digital image to be in suitable shape for the feature extraction and recognition stage. The images (samples) were first scanned using a scanner. These scanned images were colored images; the size of the samples was not defined and differs from one image to another since the digits were written in different handwriting styles by different people. There are many steps in the preprocessing stage which are shown in the figure (4.2).

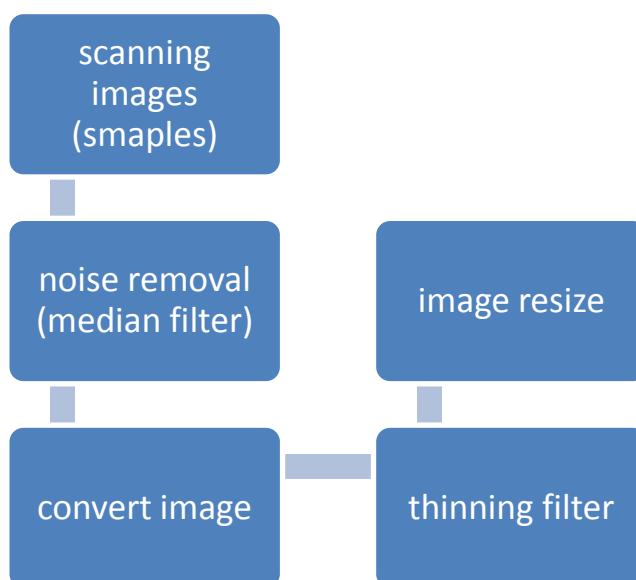


Figure (4.2) Preprocessing Stage

4.3.1 Scan Image Sampling

Image scanning is a reading pixel of an image from high to lower and from left to right, as array of two dimension (width, height). Then store the feature extraction as vector and then build the Database after wavelet transform.

4.3.2 Noise Removal using Median Filter

The median filter performance increases denoise. Further with larger image and as the size of the kernel increases, the details and the edges becomes obscured. The standard median filter does not take into account the variation of image characteristics from one point to another. The behavior of the adaptive filter changes is based on a statistical characteristic of the image inside the filter region defined by the $m \times n$ rectangular window adaptive filter as the size of the rectangular window.

(a) Z_{min} =Minimum gray level value, (b) Z_{max} =Maximum gray level value
 (c) Z_{med} =Medians of gray level, (d) Z_{xy} =Gray levels at coordinate, (e) S_{max} = Maximum allowed size of the flowchart of adaptive median filtering based on two levels is shown in figure (4.3) replaced with the median performance which degrades when the spatial noise variance of the S_{xy} takes place (Sarita Dangeti, 2003).

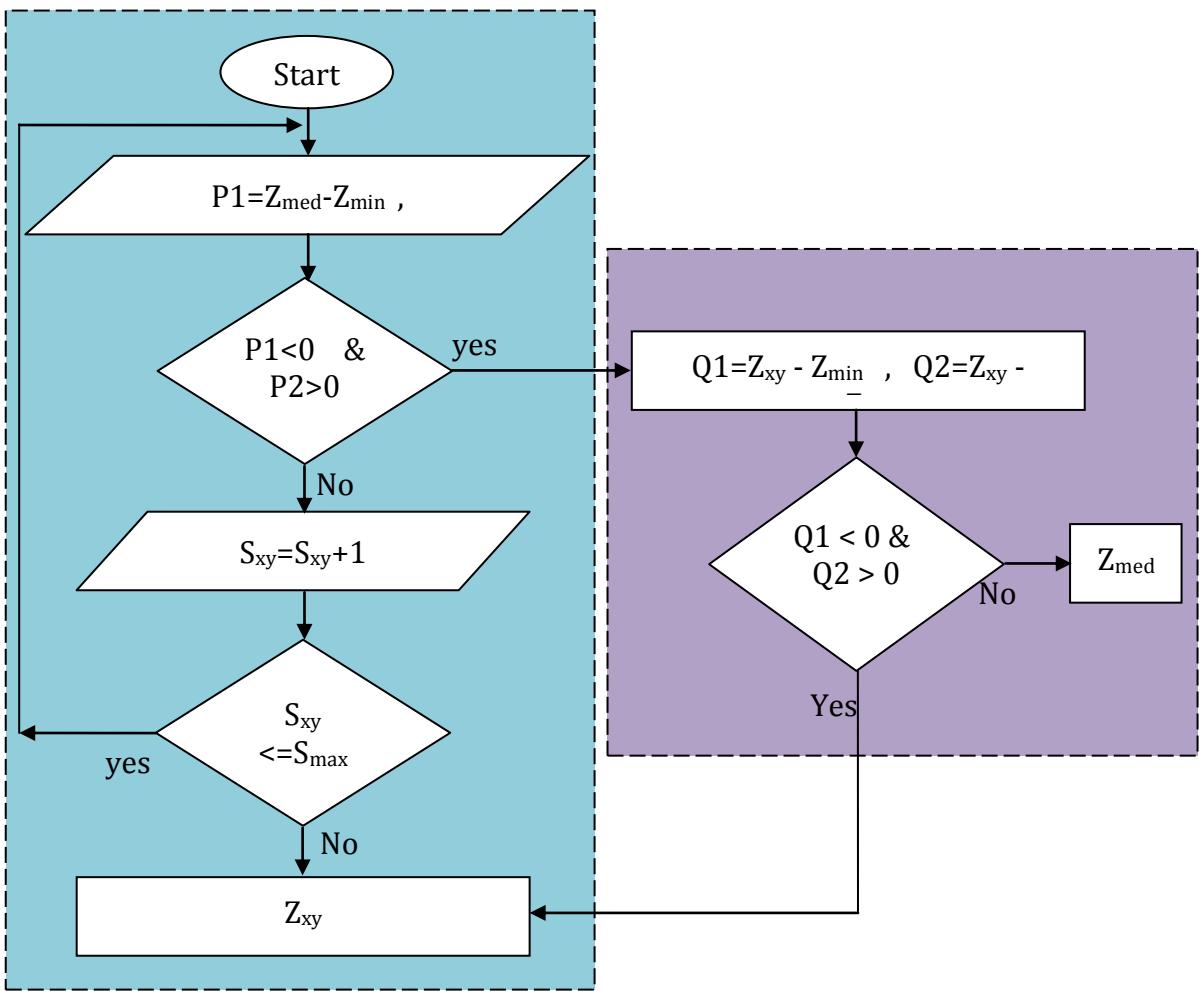
**Level 1****Level 2**

Figure (4.3) Median filter

Where,

P_1 first level,

Q_1 is the second level

Z_{min} minimum gray level value in S_{xy}

Z_{med} medium of gray level value in S_{xy}

Z_{max} maximum of gray level value in S_{xy}

Z_{xy} gray level at coordinate (x, y)

Smax maximum allowed size of Sxy

Level P

1: Compute $P1 = Z_{med} - Z_{min}$

2: Compute $P2 = Z_{med} - Z_{max}$

3: if $P1 > 0$ and $P2 < 0$ then

4: go to Level Q

5: else

6: increase window size

7: end if

8: if window size $\leq S_{max}$ then

9: repeat level P

10: else

11: output Z_{xy}

12: end if

Level Q

1: Compute $Q1 = Z_{xy} - Z_{min}$

2: Compute $Q2 = Z_{xy} - Z_{max}$

3: if $Q1 > 0$ and $Q2 < 0$ then

4: output Z_{xy}

5: else

6: output Z_{med}

7: end if

The adaptive median filtering algorithm works in two levels, denoted by LEVEL1 and LEVEL2.

The application of AMF provides three major purposes: to denoise images corrupted by salt and pepper (impulse) noise; to provide smoothing of non- impulsive noise, and also to reduce distortion caused by excessive thinning or thickening of object boundaries. The values Z_{\min} and Z_{\max} are considered statistically by the algorithm to be ‘impulse like’ noise components, even if these are not the lowest and highest possible pixel values in the image.

The purpose of LEVEL1 is to determine when the median filter output Z_{med} is impulse output or not.

If LEVEL1 does find an impulse output then that would cause it to branch to LEVEL2. Here, the algorithm then increases the size of the window and repeats LEVEL1 and continues until it finds a median value that is not an impulse or the maximum window size is reached, the algorithm returns the value of Z_{xy} .

Always the algorithm outputs a value, the window S_{xy} is moved to the next location in the image. The algorithm is then reinitialized and applied to the pixels in the new location. The median value can be updated iteratively by using only the new pixels, thus reducing computational overhead. (Subhojit S. et al., 2012).

4.3.3 Convert Image

Image is entered by reading its contents, and then this content of information is converted to more reliable form of data such as binary form after taking wavelet transform. The binary image is best form of data to calculate the chromosome that is for recognition stage.

4.3.4 Thinning Filter

Thinning filter is used to give clearer image and then this reflects accurate information that is given from image. Thinning filter used with image processing techniques as supporting method for good information features.

4.3.5 Resize the Image

One of important method in the proposed system is used to resize the image which applied to each cropped character to fit the characters of trained data. The image resize method has number of rows and columns to resize the image and preserve the aspect ratio.

4.4 Feature Extraction Module

The literature survey found many researches used many different wavelet functions. In this thesis the Meyer wavelet transformation is proposed to extract features handwriting characters. A binary form of selected wavelet first sub-band is computed. In extraction procedure, image, which maybe attacked, is pre-filtered by combination of median and thinning filters to increase distinction information. The result of the wavelet is feature vectors which in our case study is a chromosome of (3422) bits when using a Meyer wavelet.

4.5 Genetic Algorithm Module

Genetic algorithms are optimization techniques for problems. They optimize the desired property by generating hybrid solutions from the presently existing solutions. These hybrid solutions are added to the solution pool and may be used to generate more hybrids. These solutions may be better than the solutions already generated.

All this is done by the genetic operators, which are defined and applied over the problem. We already have a set of graphs generated from data for any character. The use of genetic algorithm is to classify such handwriting text and to generate the printed text. These may happen to match the character better than the existing others characters in database.

Hence genetic algorithms are a good optimizations technique. (Rahul KALA et al., 2010; Mantas Paulinas, & Andrius, 2007). Figure (4.4) presents the life cycle of using the genetic algorithm for character recognition.

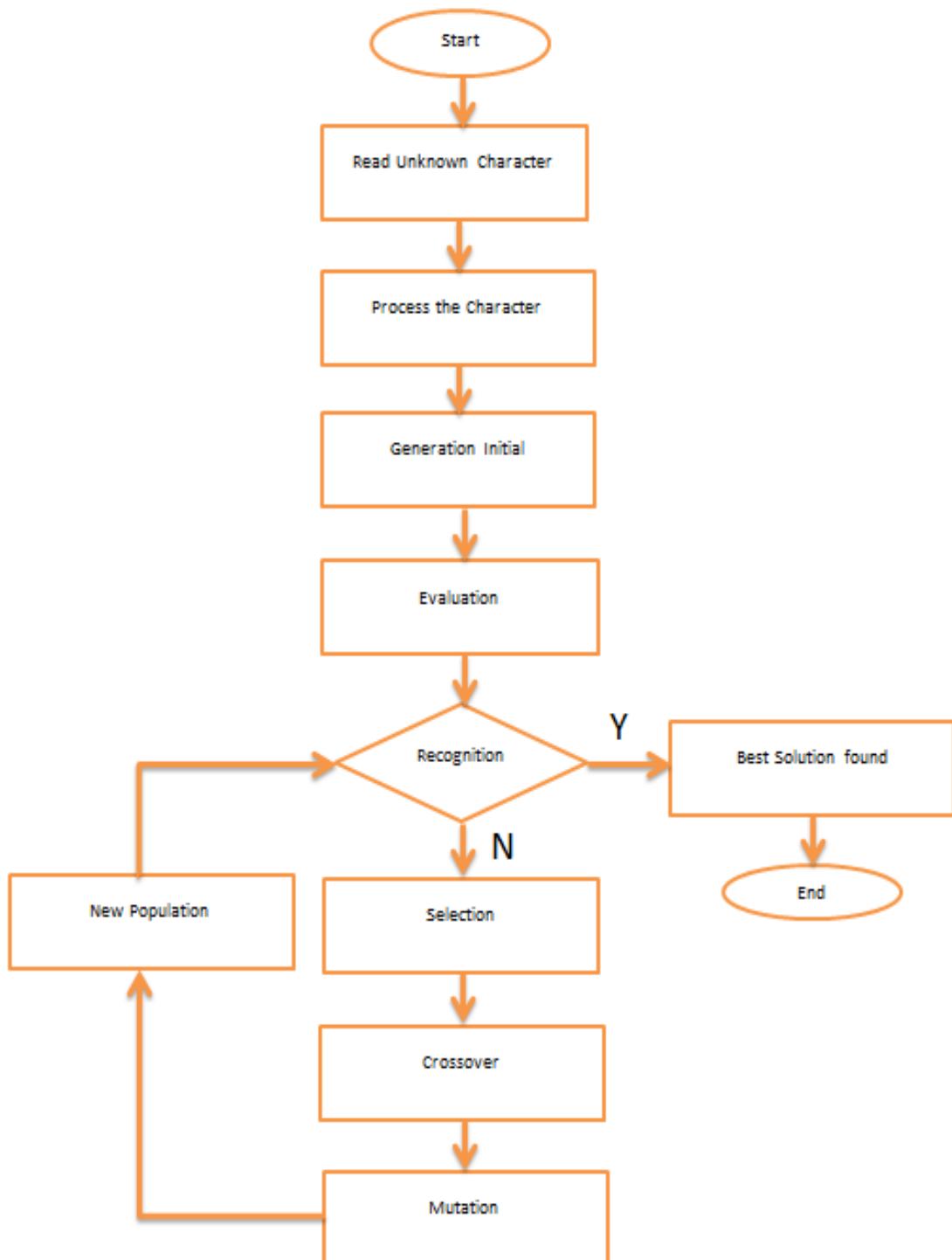


Figure (4.4) Life cycle of the Genetic Algorithm

4.6 Identify the Recognize Character Module

The identification and recognize character by using Wavelet Transform-Genetic method depends on the information that is taken from wavelet transform as featuring stage and then this block of information used as population of chromosomes to build the data base that is used in next stage to recognize the character by using genetic algorithms .

4.7 Encoding

A simple binary encoding scheme was also used to represent solutions in the space of coefficients. Each chromosome contains 3422 bits.

Since have a methodology to estimate the maximum value of each fitness function. Two-point crossover and point mutation were used.

4.8 Fitness evaluation

We evaluate fitness of individuals by computing the matching between the chromosome and database. After the coefficients have been obtained by decoding the chromosome corresponding to the best solution in the population, apply the Eq. (4.1) in order to predict the character of the chromosome into the chromosomes in database. Then, we compute the maximum matching between tested chromosome and between the chromosomes in database. The fitness function equation is shown below (Randy L., Haupt, & sue Ellen Haupt. 2004):

And the recognition rate is:

$$RC = \frac{\text{Number of matching bits}}{\text{number of total bits}} \quad \dots \quad (4.2)$$

$$\text{Error} = 1 - \text{RC} \dots \quad (4.3)$$

CHAPTER FIVE

Implementation of the Proposed Model

5.1 Overview

5.2 The main Module

5.3 Preprocessing Module

5.4 Feature Extraction Module

5.5 Genetic Algorithm Module

5.6 Experimental Results

Chapter Five

Implementation of the Proposed Model

5.1 Overview

In this Thesis, the design of the model has been implemented which is based on two techniques, one of these techniques has been used in feature extraction, and other has been used in recognition. The design has based on off-line image which contains English phrases in both writing and typing methods. The Implementation consists of many modules that will be described in the next sections

5.2 The main module

Figure (5.1) presents the pseudo code of main module and figure (5.2.) presents the main form design using MATLAB application.

```

Begin
    Initialization: population of chromosome.

    Input data: Image reading.

    Select: windowing of interesting area.

    Cropping: Windowing each beginning and ending of detecting of drawing
    Character.

    CharCR=1: N (N the number of total image character in selected area).

    Smoothing: CharSM = CharCR(xi+xi+1)/2.

    Wavelet transform:CharF=dwt2(CharSM).

    Genetic algorithms:CharR=max(fittnes(CharF)).

End

```

Figure (5.1) the pseudo code

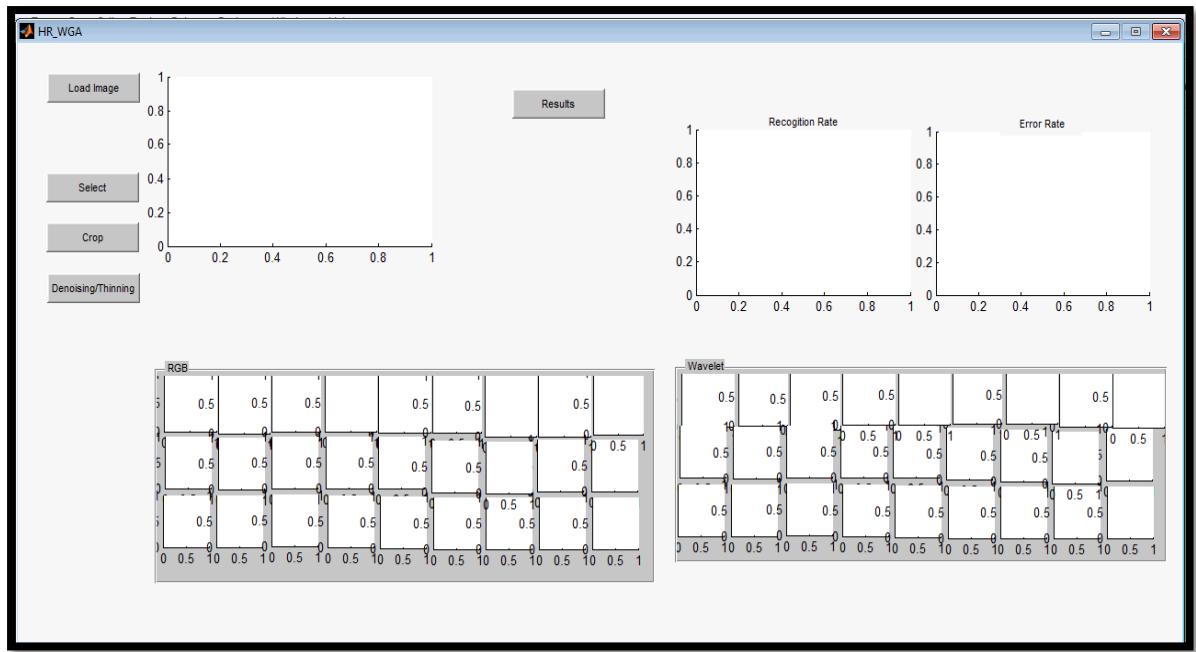


Figure (5.2) GUI of Proposed Model

5.2.1 Loading an Image Model

By using a dialog box for opening files, the files in this case are used, to explore type of image such as (jpg, png, bmp) these types are used to be processed later.

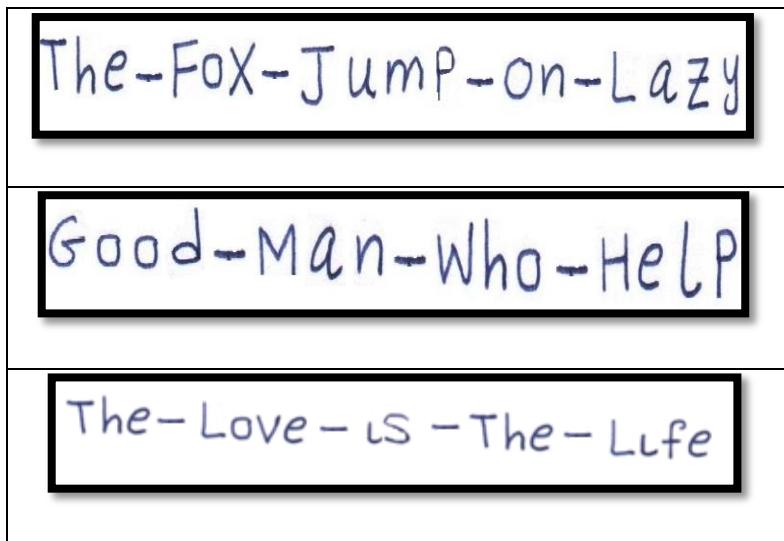
The command statement to open the dialog box for browsing image has been used to return a value and this value contains the image file and path of this image. Later will used this value in variable (I) to display the image in place of image inside form.

Also, these files (images) contain phrases and each file is considered as a sample of different person's style on writing different phrase, and this array of image is determined in equation below:

$$I_{arr} = \sum_1^n \sum_1^m I(x, y)$$

Where x =the number of pixels in horizontal direction, and y the number of pixels in vertical direction. In addition to that, other images contain a typing style of some various fonts, as shown in table (5.1).

Table (5.1) Images Contain Handwriting Style



5.2.2 Image Initialization Model

There are two functions, have been applied, one of these functions is used to select which part of an image is focused as an important region as described in equation below:

$$I_{sel} = \sum_1^n \sum_1^m I_{arr}(x, y)$$

Figure (5.3) shows the function is used for cropping the part which has been selected, and dividing the selected region to blocks.

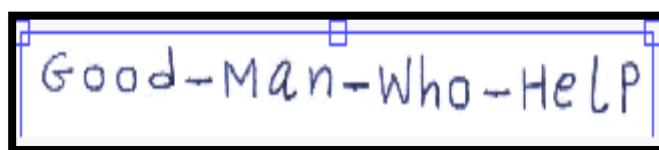


Figure (5.3) Region Selection of Part Image

Each block represents the character, as described in equation below:

$$I_{crop(k)} = \sum_1^n \sum_1^m \sum_1^k I_{sel}(i, j, k)$$

Where: The k is determined by the number of selected characters over the selected parts.

The second function represents the cropped images, which select each part of characters, image by detection the top-left and down-right points and these will result in a rectangle Surrounding each character represent in image. The GUI will be shown in as shown in figure (5.4).

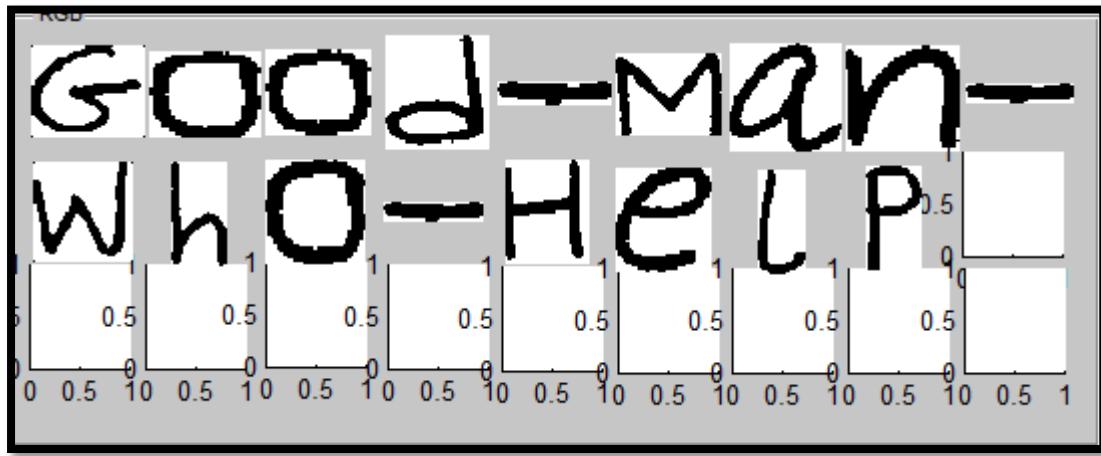


Figure (5.4) Cropping of Selected Part of Image

Each cropped character has its own figure which helps to be processed separately, and later will process each of these characters alone.

5.3 Preprocessing Module

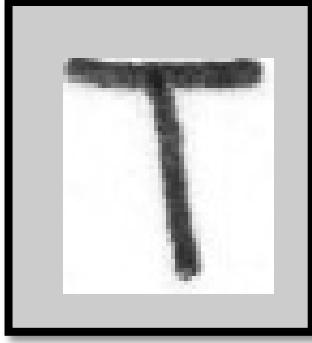
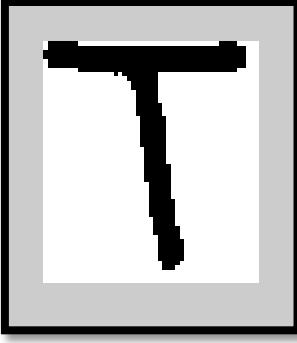
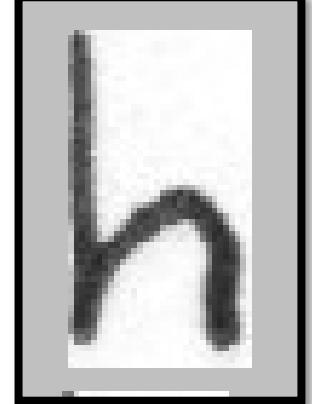
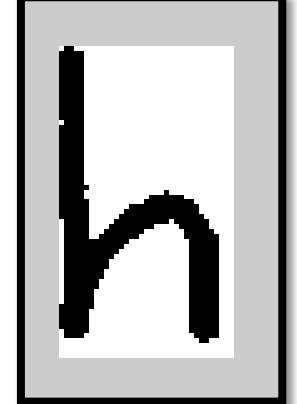
The preprocessing module consists of three model, these are Convert an image to grayscale, Denoising an image, and Resize, these three models will be described in the next subsections.

5.3.1 Convert an image to grayscale Module

In this step, when loading an image, the enhancement of an image needed to remove the noise (in case if the image has included) or applying some kind of filters, then need to convert the image to grayscale as shown in table (5.2).

$$I_{gray} = \begin{cases} 1 & \text{if } I_{crop}(x, y) \geq threshold \\ 0 & \text{if } I_{crop}(x, y) < threshold \end{cases}$$

Table (5.2) Converting a Character Images to Grayscale and B/W

Image without grayscale	Image with grayscale and B/W
	
	

5.3.2 Denoising an image Model

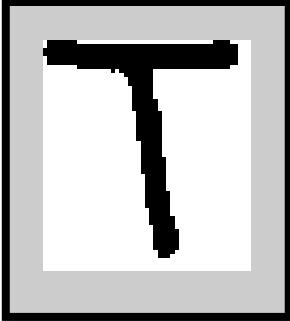
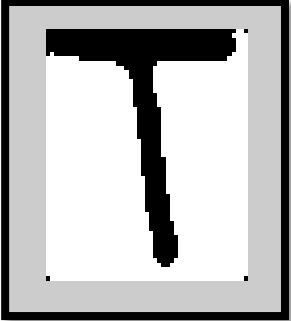
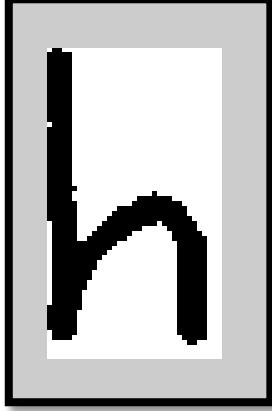
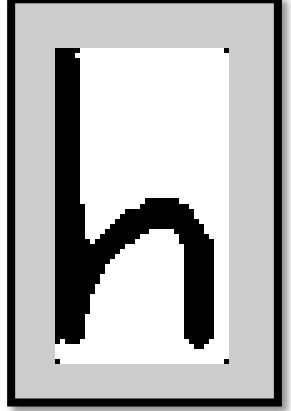
By applying a median filter which has been described in details in previous chapter (3), we can remove the noise which helps more in training and testing characters. The equation below describes the Denoising.

$$i_{denosing} = medianFilter(i_{gray})$$

Where filter are represents a type of median filter of samples of each sequential cropped image.

The table (5.3), show denoised images.

Table (5.3) Noised and Denoised Character Images

Character Image with noise	Character Image Applied Median filter
	
	

5.3.3 Resize Model

During implementation of our model and analysis, we've noted that the vectors have been of varieties when searching the training data to find matched character, this was considered as a challenge. Then need reshape both the data (trained and tested) for all the vectors of characters to be of same size as in equation below.

$$i_{resized\ (n,m)} = \sum_{y=1}^n \sum_{x=1}^m i_{denosing}(x, y)$$

Where

Height of source image = x

Width of source image = y,

Height of target image = 18

Width of target image = 16

Then,

$$\text{source ratio} = \frac{\text{source width}}{\text{source height}} = \frac{y}{x}$$

$$\text{target ratio} = \frac{\text{target width}}{\text{target height}} = \frac{16}{18}$$

$$\text{scale width} = \frac{\text{source width}}{\text{target width}} = \frac{y}{16}$$

$$\text{scale height} = \frac{\text{source height}}{\text{target height}} = \frac{x}{18}$$

$$\text{resize width} = \frac{\text{source width}}{\text{scale width}} = \frac{y}{16}$$

$$\text{resize height} = \frac{\text{source height}}{\text{scale height}} = \frac{x}{18}$$

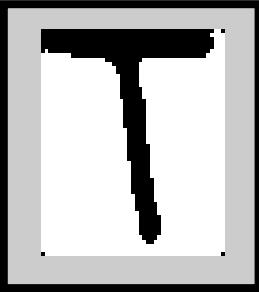
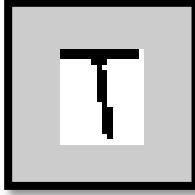
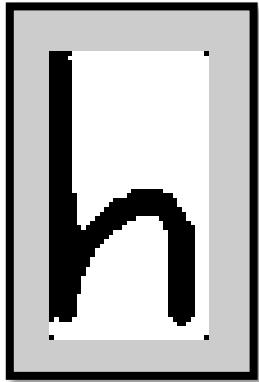
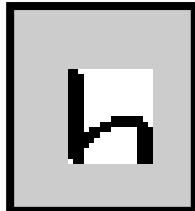
$$\text{crop left} = \frac{\text{resize width} - \text{target width}}{2} = \frac{\frac{y}{16} - 16}{2} = \frac{y - 256}{32}$$

$$\text{crop top} = \frac{\text{resize height} - \text{target height}}{2} = \frac{\frac{x}{18} - 18}{2} = \frac{x - 324}{36}$$

The input image may have different size and that because it has different size of character and type of image, in addition to these, the resolution of image, which affects the recognition results.

Therefore, in this proposed model application becomes resized function for each character (18x16) of each character image. The Table (5.4) shows the resized character image.

Table (5.4) Normal and Resized Character Image

Normal Size of Image	Resized Image
	
	

5.4 Feature Extraction Module

As mentioned in our model proposal, one of the important techniques implemented in this model is the use of Meyer Wavelet for character feature extraction.

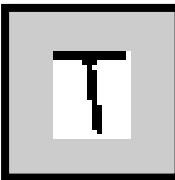
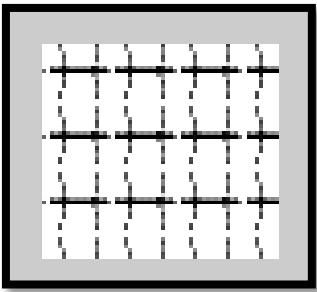
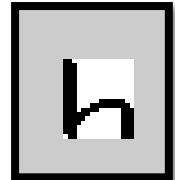
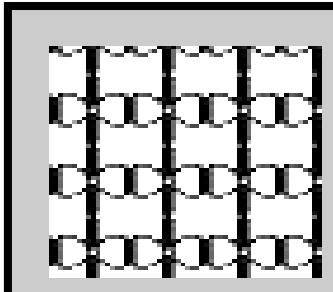
It is important to note the significance of the concept of features proposed in this model for improving the recognition accuracy. The computational complexity involved with extracting (3422), these features is used to counts of distances or counts of white or black pixels with certain characteristics existing within the bounding box of each character.

The wavelet transforms image if taken from final state:

$$i_{wld(n,m)} = \sum_1^n \sum_1^m i_resize(x, y)$$

When applying a Meyer wavelet to last image of preprocessing for character image sized (18x16), we've got (3422) vectors for each character image. In table (5.5) a drawing of Meyer wavelet generated when applied to character.

Table (5.5) Feature extraction stage for both characters (T and h)

Image of Character	Meyer wavelet applied to Image	Part of Vector
		1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
		0 0 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 1 1

5.5. Genetic Algorithm Module

The genetic algorithm is used to compare the chromosome of text characters, this must be recognition, with the data base of the persons and giving the more approximates for this chromosome to write the recognition text as printed words. The genetic algorithm is a techniques used to recognition with features taken from preprocessing as image reading and feature extraction using wavelet transform.

The feature extracted is the base structure of genetic algorithm because is used as the chromosomes of character building the database and must be used as knowledge base to compare with testing text that needs to know the handwriting of known person.

Firstly must initialize the population of chromosome as initial data feature and this is used as zero element.

Ch1= [00000000000000000000000000000000]

Ch2= [00000000000000000000000000000000]

Ch54= [00000000000000000000000000000000]

The updated chromosomes is calculated from the features is output from steps of wavelet transform and these chromosomes are compared with database chromosome and take the maximum fitness function to give the correct characters as final results are printed text.

The fitness function is calculated as matched binary digits that being chromosome and the number of matching character is giving the final decision of character. The correct character is taking the maximum value of matching of chromosome (maximum recognition rate) If there are many values maximum, this may give an error in recognition of character.

The crossover is used with two point techniques as shown in figure (5.5).

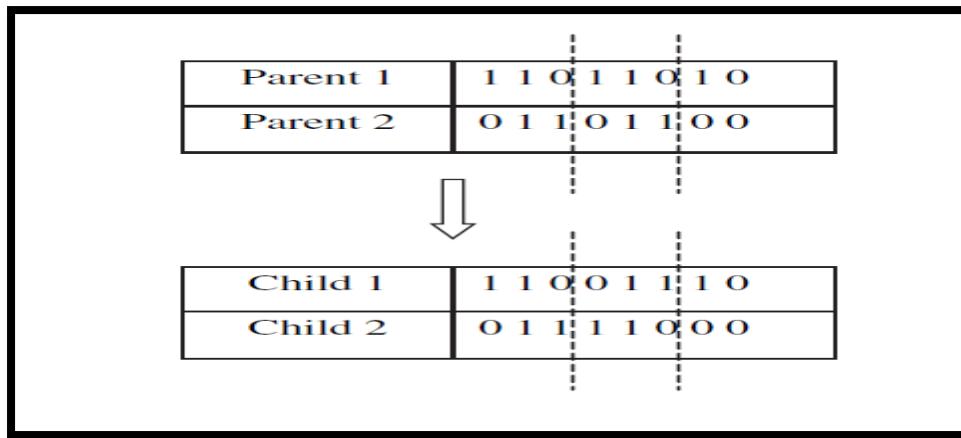


Figure (5.5): Two point crossover.

5.6 Experimental Results

There are many kind of results we've get through the design of proposed work, so, we will categorized the results by types of writing style (typing and handwriting), then each part of category of writing style is divided into two types of character (small and capital letter). Finally, we've tested the design application by writing samples containing both characters (small and capital letters).

Sample dataset of training contains (3) samples and these samples have (54) for all small and capital alphabets characters instead of these data having vector format which is (3422) vectors. Samples of handwriting character are shown in table (5.6), and trained data shown in figure (5.1).

Table (5.6) Training Dataset

sample 1	
Sample 2	

In recognition step, the character will be recognized by extract features of current browsed image. After getting the feature vector of character which is (3422) of vectors, the search function has been applied and makes the connection with database. For the search function needs to bring all vector data of all trained characters from database one by one to be compared with current vector of handwritten character.

These steps of recognize stage have been described as below.

First Step: Building Database

The database has been designed containing fields as (character_name and Feature_Vector), where the character_name field has been used to save the label of the character and retrieve it in recognition stage, and feature_vector has been used to save the feature vector from feature extraction stage and retrieve this data in recognition stage.

Second Step: Feature Extraction

In this step the feature vector which is present in 1's and 0's with their positions are taken for the required character depending on the process of output data.

Third step: Matching Process

In this step the features: ((1's) with their positions) of the required characters are focused to find the best matched (best accuracy) obtained from database as explained in first step.

The Recognition rate was inspected in letters of the Latin alphabetic characters written by person. The inspection was for the uppercase and lowercases (A-Z and a-z) separately as shown in table (5.6), since the first has more right-angled straight strokes than the curved ones as shown in figure (5.6).

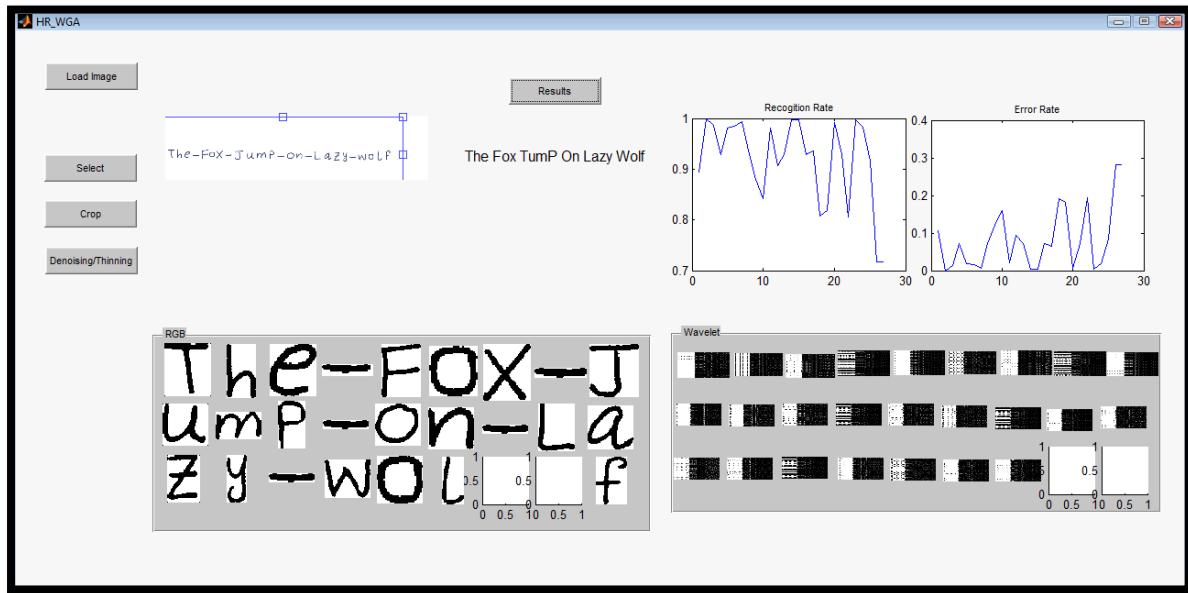


Figure (5.6) test of recognition prase1 "The Fox Jump on Lazy Wolf".

In addition to that, the recognition rate of each recognition time has been taken in consideration.

The chromosome bit string from the chromosome generation function is used to recognize a character by computing the fitness value of an unknown character with each English character in the database and comparing it with fitness value of data base characters. The highest fitness value is used as recognition result. The fitness value is calculated by using formula as the described below:

$$\text{fitness value} = \sum_{i=1}^{3422} |(S_i) = (L_i)| * W_i$$

Where

S is the chromosome bit string in database, L is the chromosome bit string for unknown character, and W is the weight of each chromosome bit string which is of fixed value as (1).

Where: Y-axes= the recognition rate and X-axes=Input character position.

The other test of proposed design application has processed different handwritten phrases of different persons which including the phrase “The love is the Live”, Instead of that, the chromosome generation function has been applied to recognize each character by comparing the fitness value of an unknown current character with all English characters in the database. The phrase “The love is the Live” is shown in figure (5.7).

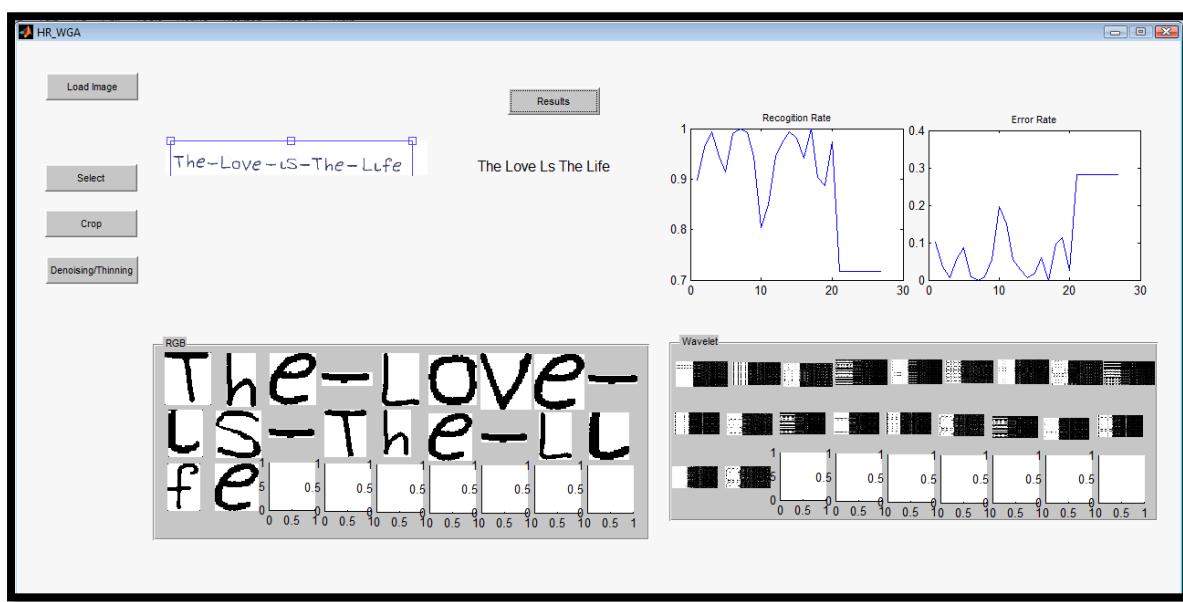


Figure (5.7) test of recognition prase2 "The Love is The Life".

To find best accuracy of proposed design application, test the application by processing other handwritten phrase image as shown in figure (5.8).

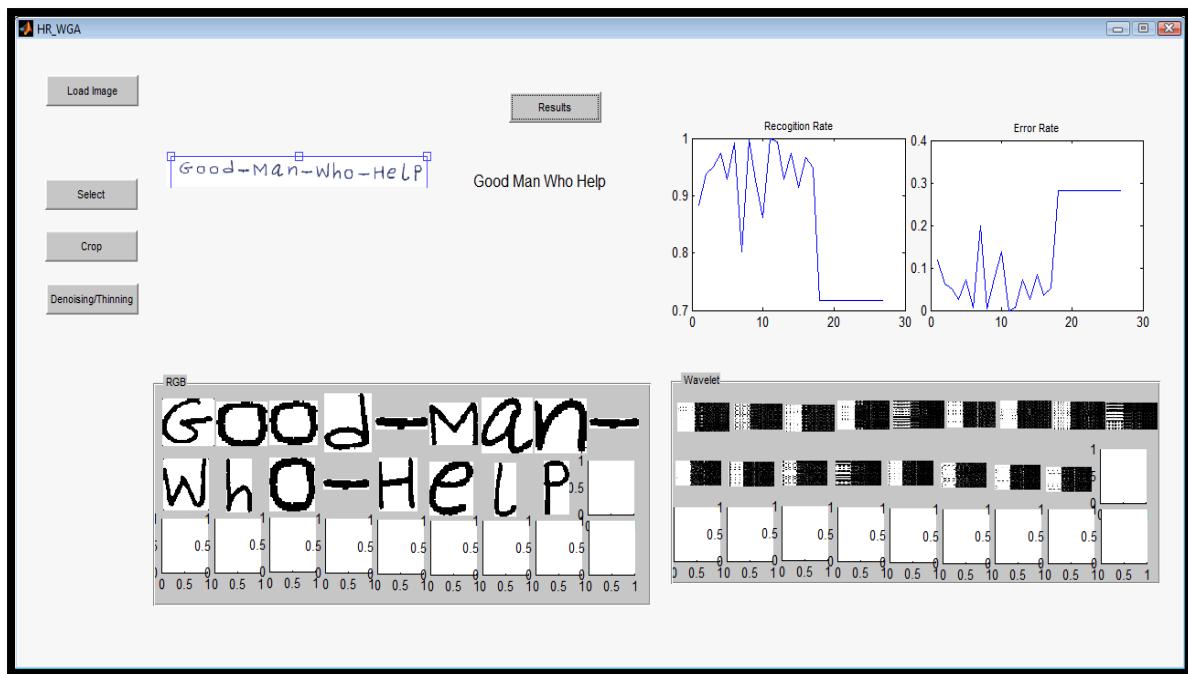


Figure (5.8) test of recognition phrase3 "Good Man Who Help".

The recognition rate has been calculated from equation shown below

$$Error_{rate} = 1 - \frac{Number\ of\ Matched\ bit\ string\ of\ chromosome}{Total\ number\ of\ bit\ string}$$

Figures (5.9, 5.10, and 5.11) showing the Recognition rate and Error rate for three different phrases ("The Fox Jump on Lazy Wolf", "The Love is The Life", and "Good Man Who Help").

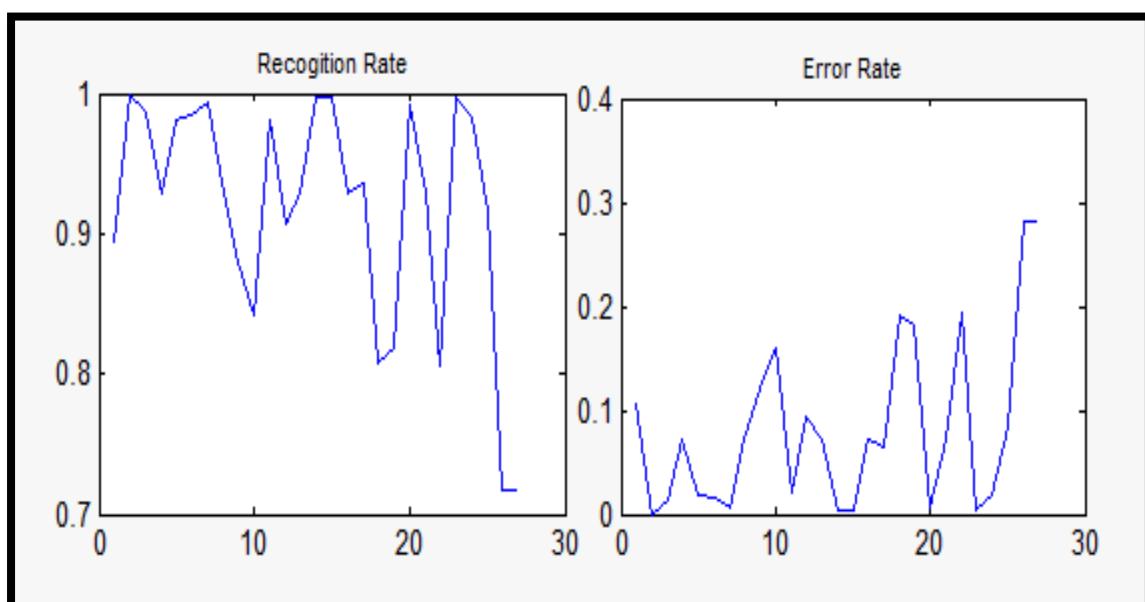


Figure (5.9) recognition rate and Error rate of phrase1 "The Fox Jump on Lazy Wolf".

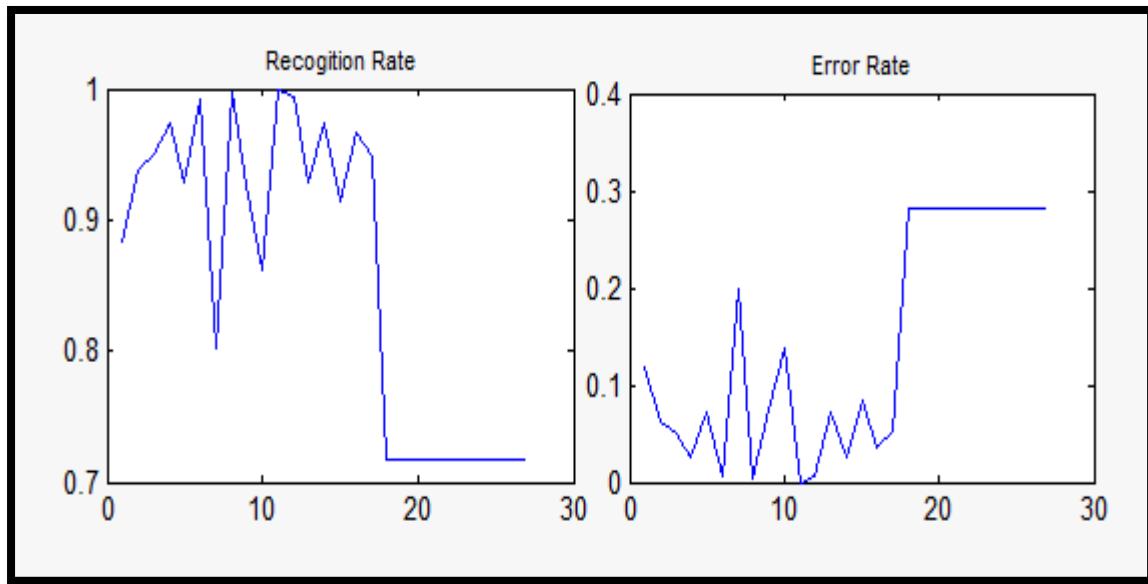


Figure (5.10) recognition rate and Error rate of phrase2 "The Love is The Life".

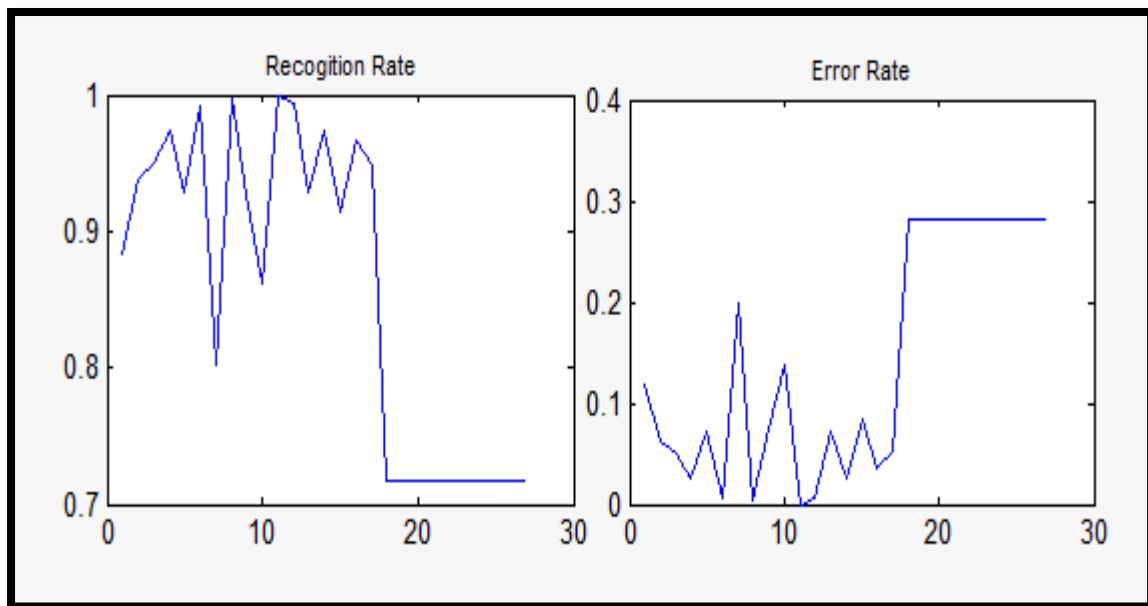


Figure (5.11), recognition rate and Error rate of prase3 "Good Man Who Help".

The recognition rate for the three samples sentences in table (5.1), based on the training dataset in table (5.6), is calculated by using the equation shown in table (5.7):

$$RC = \frac{\text{number of correct character}}{\text{total number of character of text}}$$

$$\text{Error} = 1 - RC$$

Table (5.7) Recognition rate of the text samples

The text samples	Recognition Rate	Error Rate
1-The Fox Jump on Lazy Wolf	0.95	0.05
2-The Love is The Life	1	0
3-Good Man Who Help	1	0

The recognition rate of the model is calculated as mean of recognition rate of the samples.

$$RCM = \text{mean } (RC)$$

$$RCM = 0.95 + 1 + 1 / 3 = 0.98$$

The error rate of the systems is calculated as mean of error rate of the samples.

$$Errorm = \text{mean } (\text{Error})$$

$$Errorm = 0.05 + 0 + 0 / 3 = 0.016$$

Finally, the goal of the work is to design a complete modular off-line recognition of handwriting character recognition text. This design has been dealing with both styles in the upper and lower cases of Latin script letters. The proposed design has applied a Meyer Wavelet Transform-based as a feature extractor. The model has been trained on a handwritten sample of (54) characters of one individual, and tested using one handwritten sample of the same individual for the three sentences.

CHAPTER SIX

Conclusion and Future Work

6.1 Conclusion

6.2 Future work

Chapter Six

Conclusion and Future Work

6.1 Conclusion

This thesis presents a model for character recognition using two modules, the wavelet function, which is the Meyer wavelet, and the genetic algorithm module. The following points can be concluded in this thesis:

1. The Meyer wavelet is applied in feature extraction phase to get a (3422) vector for each character in both training and testing method.
2. The genetic algorithm has been applied in recognition, which is used to search the matched vectors by finding best fitness of whole database (capital and small letters).
3. The implemented model was trained on a sample of (54) characters, handwritten by one individual , and tested using three sentences written by the same individual .

6.2 Future Work

The following points are recommended for future work, in order to get more benefits of using Genetic algorithms together with Wavelet Functions.

1. Extending this research to handle other languages such as Arabic language.
2. Developing the proposed model for applying figures recognition instead of character recognition by assuming that image is including phrases and figures or tables.
3. Applying another type of Genetic Algorithm such as SSGA or RGA for recognition.
4. The model needs to be tested on a publically available handwritten character dataset in order to evaluate its recognition performance.
5. Using neural network and Genetic Algorithm as an inference engine.

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