SUDAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

COLLEGE OF GRADUATE STUDIES

COLLEGE OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY

MEDICAL IMAGE ENHANCEMENT USING GENETIC ALGORITHM

تعزيز الصور الطبية بإستخدام الخوارزمية الجينية

□

CASE STUDY: GLAUCOMA IMAGE

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قال الله تعالي :

(قَالُوا سُبْحَانَكَ لَا عِلْمَ لَنَا إِلَّا مَا عَلَّمْتَنَا إِنَّكَ أَنْتَ الْعَلِيمُ الْحَكِيمُ).

سورة البقرة، الآية (٣٢)

DEDICATION

I dedicate this work to:

My all family ..

My professors.

ACKNOWLEDGEMENT

My Huge respect to all whom gave me the possibility to complete my research. For Sudan university of science and technology - faculty of computer science and information technology.

My special thanks to my supervisor, Dr.Howida Ali Abdelghader Ahmed whose gave me full guides to complete this project.

All thanks and appreciation to my mother, my brothers and my sisters.

ABSTRACT

Image enhancement is to process an image so that result is better than original image for specific application. Medical image processing is a hard task in hand. Most of the medical images have very low contrast or full of noise and the challenge is to sharpen them and make them easier in processing. By using genetic algorithm (GA) which is a general method for solving problems and it was the most powerful techniques for sampling a large solution space noise were reduced and the contrast of medical image has increased so resulted image become more readable, more helpful and it can be extracted other features were been hidden. The resulted image was better when it compared to the original image. The goodness of image are determined by measuring the quality of both original and resulted image using quality assessment parameters which include Mean Square Error, Peak Signal to Noise Ratio and Structural Similarity Index Measure and then compare between them. Here two samples of image are used to doing three experiments using various selection operators. The quality Assessment parameters MSE, PSNR and SSIM for original image were recorded respectively as:

(0.0969650, 13.7615, 0.48947). And for enhanced image were respectively recorded as: (0.0066085, 50.7350, 0.97743). The algorithm was compared with histogram and the value for original image was recorded as: (196.0396, 22.0371, 0.4896) and for enhanced image was recorded as (251.7672, 13.5116, 0.3370).

Then there were very differences between original image and enhanced image when using genetic algorithm. Hence that the goal is to have small value for MSE and big value for both PSNR and SSIM.

المستخلص

عملية تحسين الصور هي عملية معالجة الصور بحيث تكون الصورة النهائية أكثر وضوحاً مقارنة بالصورة الأصلية. معالجة الصور الطبية تعتبر من أصعب العمليات لان الصور الاصلية تحتوي عادة علي تشويشس أو انها غير واضحة وبالتالي يكمن التحدي في جعل الصورة الناتجة أكثر وضوحا. في هذا البحث تم استخدام الخوارزمية الجينية التي تعرف بمقدرتها علي إنشاء حل أمثل من بين مجموعة من الحلول غير المثلي ، كما انها تعتبر واحدة من افضل التقنيات التي تستخدم في حل المشاكل ذات الفضاء الواسع. وعليه كواحده من اهداف هذا البحث فقد تمت ازالة التشويش الموجود بالصورة الأصلية والذي يعبر عن الكرومسوم العشوائي بل وتمت زيادة وضوح الصورة الناتجة مما جعلها مناسبة أكثر لأغراض البحث الأخري. الصورة الناتجة أصبحت أفضل من الصورة الأصلية ، وتم تحديد ذلك عن طريق استخدام معاملات لقياس الجودة مثل (MSE,PSNR,SSIM) ، وقد تم رصد قيمها لصورة ما قبل التحسين مرتبة كالآتي:

(0.0969650 , 13.7615 , 0.48947)

وبعد التحسين رصدت القيم لنفس الصورة بنفس الترتيب كالآتي :

(0.0066085 , 50.7350 , 0.97743)

وتجدر الاشارة هنا الي أن الصورة يتم تحسينها كلما قلت قيمة MSR وزادت قيمة كل من PSNR وSSIM كما هو ملاحظ من القيم أعلاها. في هذا البحث استخدمت عينتان واحدة صورة للجلكوما والأخري صورة أشعة وذلك لإختبار فعالية الخوارزمية ، كما أن الاختبار قد تم باستخدام ثلاثة معاملات لاختيار الكروموسومات المثالية (وذلك لأغراض معرفة المعامل الأفضل). تمت مقارنة الخوارزمية

الجينية مع الــــــHistogram لمعرفة فعالية الخوارزمية فتم رصد المعلومات الاتية لمعاملات قياس الجودة للصورة الاصلية كالآتي:

(196.0396, 22.0371, 0.4896) .اما الصورة بعد التحسين فكانت معاملات قياس الجودة لها كالآتي: .(251.7672, 13.5116, 0.3370)

وعليه يوجد اختلاف كبير جدا بين الصورة قبل التحسين والصورة بعد التحسين عند استخدام الخوارزمية الجينية لان المطلوب هو الحصول علي اصغر قيمة للــMSE وأكبر قيمة لكل من PSNR و SSIM.

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

GA	Genetic Algorithm
RCGA	Real Coded Genetic Algorithm
IQM	Image Quality Assessment
MSE	Mean Square Error
PSNR	Peak Signal to Noise Ratio
SSIM	Structural Similarity Index Measure
EAs	Evolutionary Algorithms
TSP	Travelling Salesman Problem
RCPSP	Resource-Constrained Project Scheduling Problem

TABLE OF CONTENTS

CHAPTER ONE

INTRODUCTION

1.1 Preface

Image enhancement techniques are used to improve image quality or extract the fine details in the degraded images. It is to modify attributes of an image to make it more suitable for given task [14].

1.2 Problem Statement

Medical images are one of the fundamental images, because they are used in more sensitive field which is a medical field. They are ought to be understand because it may contain noise, it may be dark or so white or it may become blurred, so image enhancement will applied to enhance medical image especially in (GLAKOMA) image [6].

1.3 Research Importance

Glaucoma diagnosis depends only on radiograph which are captured by specialist. From this point we need to suppose scenarios which make image easier for visual interpretation to the doctors whom are not forced to do radiography more than one time which ensures timeserving to the doctors and patients, speed and accuracy in making decision.

1.4 Literature Review

1.4.1 Image Enhancement Using Genetic Algorithm

The proposed algorithm takes gray image (.png) and then apply genetic algorithm to provide more enhanced image. First it takes input gray .png image. Create Random Initial State: add noise in image by change their contrast and bit map value. Evaluation fitness is done through noisy section of image. This proposed method gives better result than all the other individual method. It reflexes an effort to understand how to de-noise image using genetic algorithm. It is observed that genetic algorithm can play role efficiently to analyze image [8].

1.4.2 Evolutionary Image Enhancement Using Multi-Objective Genetic Algorithm

The proposed method has been tested with benchmark images in image enhancement taken into consideration three objectives (intensity, entropy and number of edges). There is usually no single optimum solution, so decision makers are required to select a solution from a finite set by making a complete set of optimal solutions. The number of edges and intensity values are calculated with 'Sobel derivative' method. After evaluating fitness of all individual objectives (entropy, edge and intensity). Tournament selection and arithmetic crossover are applied overall the experimental result means that the proposed method is effective for image enhancement as achieved best results in terms of intensity, edges and entropy. It may be used some other type of images like biomedical images, satellite images etc [9].

1.4.3 Application of Genetic Algorithm for Image Enhancement and Segmentation.

The proposed enhancement techniques use various combinations of methods from these two categories: spatial domain methods and frequency domain methods. Spatial domain methods operate on pixels. These techniques are based on gray level mappings. In frequency domain method operates on the Fourier transform of an image, you simply compute the Fourier transform of the image to be enhanced then multiply the result by a filter and take the inverse transform to produce the enhanced image which it will be modified in the brightness, contrast or the distribution of the grey levels. As a consequence the pixels value (intensities) of the output image will be modified according to the transformation function applied on the input values. The result of enhancement will improve the clarity of the original image by removing the noise. So that it will be easier to analyze any image [10].

1.4.4 Contrast Enhancement using Real Coded Genetic Algorithm Based (RCGA) Modified Histogram Equalization for Gray Scale Images

The proposed method is RCGA. Here the crossover and mutation operators are applied directly to real parameter values without any string coding because of this, the RCGA is a step easier when compared to the binary coded genetic algorithm. The process of RCGA is briefed as follows:

- Initialize the control variable population and evaluate using the fitness function.
- Play the tournament between two solutions and place the better one in the mating pool.
- Use single point crossover and Calculate polynomial mutation [11].

The contrast of the resulted enhanced image is found to increase progressively and the subsequent increase in the contrast has not introduced any unwanted artifacts in the enhanced image [11].

1.4.5 Image Brightness Enhancement of Natural and Unnatural Images Using Continuous Genetic Algorithm

The proposed algorithm used the modified continuous genetic algorithm by:

1) Capture natural digital images.
2) Initializing the population.
3) Calculate fitness function.
4) Sort the fitness function in descending order.
5) Obtain DNAs corresponding to sorted fitness function.
6) Content enhance process to display the best image corresponding to DNA.
7) Mating.
8) Mutation.
9) Go to step 3 and repeat.

The results for processed natural and unnatural images were enhanced in brightness during the successive iterations [12].

1.5 Research Hypotheses

The research hypothesizes are:

1) Using genetic algorithm is proven to be the most powerful optimization technique in a large solution space.
2) Prove the possibility of using GA in image enhancement.
3) Using genetic algorithm will enhance the image in good manner.
4) Medical image enhancement using GA will increase the probability of success diagnosis.
5) The time consumed in enhancement processing is minimal.

1.6 Research Objectives

The main objectives of this research are to:

1) Increase research in medical image area.
2) Increase the ability of enhancing medical image for glaucoma patients.
3) Increase the enhancing time of processing because it is considered a very sensitive area (medical area).
4) Improve the visual quality of an image. Contrast increment, elimination of noise and enlightenment of details.
5) Genetic algorithms are growing fast and it will definitely help to solve various complex image processing and it is unusual to use it for image enhancement [8].

1.7 Research Methodology

1.7.1 Genetic Algorithm

Genetic Algorithms encode a potential solution to specific problem on a simple chromosome like data structure and apply recombination operators to these structures so as to preserve critical information.

1.7.2 Matlab Software

Matlab is considered as solution of image processing problem. The power that MATLAB brings to digital image processing an extensive set of functions for processing multidimensional arrays. The image processing toolbox is a collection of functions that extend the capability of the MATLAB numeric computing environment [2].

1.8 Research Framework

The steps of program can be illustrated in points below for enhancing the medical image using genetic algorithm:

1) Uploaded original image.
2) Convert original to grey image.
3) Determining the image edges.
4) Add noise to gray image in order to create random population.
5) Choose the selection method for GA.
6) Gray image and noisy image is crossed over (Recombined).
7) Mutation is done randomly when there is no best result done by crossover.

1.9 Research Scope

1) The scenario is done only for grey scale image.
2) Contrast of medical image and noise removal are done using GA.
3) The type of noise which used is Salt and Pepper noise.
4) The proposed algorithm is compared with histogram algorithm.

1.10 Research Contents

The present thesis is organized in four sections. First section named introduction, it describes the introduction, problem statement, research importance, literature review, research hypothesis, research objective, research methodology and research scope. Second section named, digital image processing, it describes image processing task, digital image representation, digitizing image, image types, medical image processing, the quality of the medical image, image enhancement, image noise, image restoration, enhancement performance parameters, image segmentation. Third section named genetic algorithm, it describes overview of genetic algorithm, theory of genetic algorithm, a simple genetic algorithm, genetic algorithm flow chart, genetic algorithm options and genetic algorithm applications. Fourth section named practical result it describes description of data, steps of processing, factors taken onto consideration and experiments of results. Last section named discussion of results it describes results in details, figures of resulted samples, labels of samples, plotting quality parameters, discussion of results and conclusion & recommendation.

CHAPTER TWO

DIGITAL IMAGE PROCESSING

2.1 Image Processing Task

Image processing and pattern recognition has been studied extensively in computer science [1]. Image processing task may be accomplished in steps below:

1) Acquiring the image: Digital image produced from a paper envelope. This can be done using either a camera, or a scanner [4].
2) Preprocessing: This is step taken before the major image processing task. The problem here is to perform some basic tasks in order to render the resulting image more suitable for the job to follow. In this case it may involve enhancing the contrast, removing noise, or identifying regions likely to contain the postcode [4].
3) Segmentation: Here the postcode is extracted; in other words it is the process which done by extract from the image that part of it which contains just the postcode [4].
4) Representation and Description. These terms refer to extracting the particular features which allowed differentiating between objects. It is done by looking for curves, holes and corners which allowed distinguishing the different digits which constitute a postcode [4].
5) Recognition and interpretation. This means assigning labels to objects based on their descriptors (from the previous step), and assigning meanings to those labels. So identifying particular digits, and interpreting a string of four digits at the end of the address as the postcode [4].

2.1.1 Digital Image Representation

Digital image processing refers to process digital image by means of a computer. Image processing takes image as input, process it and produces the output. The image can be defined as an array, or a matrix, square pixel arranged in rows and columns [12].

2.1.2 Digitizing Image(Sampling)

An image may be continuous with respect to the x- and y-coordinates, and also in amplitude converting such an image to digital form requires that the coordinates, as well as the amplitude, be digitized. Digitizing the coordinate values is called sampling; digitizing the amplitude values is called quantization. Thus, when x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image [2].

2.1.3 Image Types

Image types include:

1) Binary Images

Each pixel is just black or white. Since there are only two possible values for each pixel, the needs are only for one bit per pixel. Such images can therefore be very efficient in terms of storage [4].

2) Gray-scale Images

Gray-scale image is a data matrix whose values represent shades of gray. When the elements of a gray-scale image are of class uint8 or uint16, they have integer values in the range [0, 255] or [0, 65535], respectively. If the image is of class double or single, the values are floating-point numbers. Values of double and single gray-scale images normally are scaled in the range [0, 1], although other ranges can be used [2].

3) Indexed Images

The image has an associated colour map, or colour palette, which is simply a list of all the colors used in that image. Each pixel has a value which does not give its colour, but an index to the colour in the map. It is convenient if an image has 25 colors or less, the index values will only require one byte to store. Some image file formats allow only colors or fewer in each image.[4].

4) Truecolor Images

Truecolor image also named RGB images (Red, Green, and Blue). It is stored as an m-by-n-by-3 data array that defines red, green, and blue color components for each individual pixel. Truecolor images do not use a palette. The color of each pixel is determined by the combination of the red, green, and blue intensities stored in each color plane at the pixel's location. Graphics file formats store RGB images as 24-bit images, where the red, green, and blue components are 8 bits each. This yields a potential of 16 million colors. The precision with which a real-life image can be replicated has led to the nickname "truecolor image." [2].

2.2 Medical Image Processing

The efforts on medical image enhancement have been focused mostly to improve visual perception of images that are unclear because of blur. Edges are the representations of the discontinuities of image intensity functions. For processing these discontinuities in an image a good edge enhancement technique is essential reduces complexity and makes the images look sharper than they really are [16].

2.3 The Quality Of The Medical Image

The quality of the medical image is as good as the clarity of the specific information sought for in the image by the observing physician. However, there is a need to define objective image quality features in order to assess the quality of the image produced by an imaging system or by processing techniques. The quality of the medical image depends on and assessed by three parameters: sharpness, contrast and noise [18]. The image quality assessment aims to use computational models so as to measure the image quality consistently with subjective evaluations [11].

2.4 Image Enhancement

Image enhancement technique is use to convert the original image into the better image. The input image can be from any image capturing device. There are various methods which can enhance the original image without losing its original good properties. Digital image enhancement techniques provide a multitude of choices for improving the visual quality of images [10]. Image enhancement refers to processing an image so that the result is more suitable for a particular application. Examples include: sharpening or de-blurring an out of focus image, highlighting edges, improving image contrast, or brightening an image and removing noise [8]. In image enhancement process one or more attributes of image are modified. The enhancement methods can broadly be divided into the following two categories:

2.4.1 Spatial Domain Methods

The term spatial domain refers to the image plane itself, i.e. aggregate of pixels of composing an image, and approaches in this category are based on direct manipulation of pixels in an image [31].

Spatial domain methods directly operate on pixels .These techniques are based on gray level mappings, and the type of mapping used for these technique are depends on the criterion chosen for enhancement [10].

2.4.2 Frequency Domain Methods

In frequency domain methods, the image is first transferred into frequency domain. For example the Fourier transform of the image is computed. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values [7].

2.5 Image Noise

Noise is an important factor that influences image quality which is mainly produced in the processes of image acquirement and transmission. Noise reduction is necessary for us to do image processing and image interpretation so as to acquire useful information that we want. Because the working status of image transmitter is influenced by varied of factors, such as the environment of image acquired, different noises can be dealt with in different ways. Through the analysis of image spectrum, its difference can help us to choose different methods to do noise reduction while the information of the image is reduced to be the most [29].

Image noise is generally regarded as an undesirable by-product of image capture. Although these unwanted fluctuations became known as "noise" by analogy with unwanted sound they are inaudible and such as dithering. There are many types of noise which includes [30]:

1) Gaussian noise.
2) Salt-and-pepper noise.
3) Poisson noise.
4) Speckle noise.

2.6 Image Restoration

This may be considered as reversing the damage done to an image by a known cause, it may include: removing of blur caused by linear motion, removal of optical distortion and removing periodic interference [4]. The distortion in image can be modeled as noise or blur or a degradation function. Unfortunately all images are more or less blurry. This is due to the reason that there is a lot of interference in the camera as well as in the environment. Blurring of an image can be caused by many factors such as movement during the capture process, using wide angle lens, using long exposure times, etc [19].

The field of image restoration (sometimes referred to as image deblurring or image deconvolution) is concerned with the reconstruction or estimation of the uncorrupted image from a blurred and noisy one. Essentially, it tries to perform an operation on the image that is the inverse of the imperfections in the image formation system [21]. Some image restoration techniques are:

1) Median filter

The median filter is used to remove the salt and pepper noise. It has capability with considerably less blurring than linear smoothing filters of the similar size. In other words median filtering is a widely used and very important technique of filtering and best known for its excellent noise reduction ability from the images. By the filtering it keeps the edges while removing the noise. This makes the image not to blur as other smoothing methods [22].

Fig 2.1 De-noise image using median filter

2) Adaptive filter

Adaptive filter is type of linear filter that has transfer function controlled by variable parameter. Adaptive filter use the color and gray space for removal of impulsive noise in images. All processing is done on the basis of color and gray space. Adaptive filter are used to remove the effect of speckle noise. This can provide the best noise suppression results and better preserve edges, thin lines and image details and yield better image quality in comparison to other filters [20].

3) Linear filter

In linear filter each pixel is replace with linear combination of its neighbors. Image processing operations are implemented with linear filter include sharpening, smoothing and edge enhancement. In linear filter output change linear with input. With the help of linear filter we can easily remove the noise from the image. This filter can be implemented on salt and pepper noise and Gaussian noise. [22].

2.7 Enhancement Performance Parameters

It includes the parameters which used to estimate the degree of enhancement of resulted image when we compare it to the original image.

2.7.1 Mean Square Error (MSE)

The MSE is the cumulative square error between the encoded and the original image defined by [20]:

$$\text{MSE} = \frac{1}{mn} \sum_{0}^{m-1} \sum_{0}^{n-1} \text{II} \int(i,j) - g(i,j)\text{II}^2 \quad \ldots\ldots\ldots\ldots\ldots (2.1)$$

Where:

f is original image.

g is uncompressed image.

m,n represent dimension of image.

i,j represent the index of the row and column

Thus MSE should be as low as possible for effective compression.

2.7.2 Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio between maximum possible power of a signal and the power of distorting noise which affects the quality of its representation. It is defined by [31]:

$$PSNR = 20\log 10 \frac{MAXf}{\sqrt{MSE}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.2)$$

Where:

$MAXf$ is a maximum signal value that exists in our original image.

“known to be good” image.

$\sqrt{MSE}$ is root mean square error.

2.7.3 Structural Similarity Index (SSIM)

Structural similarity index is a measure based on the assumption that human visual system is adapted to extract structural information from the field of view. Therefore, the change of structural information between distorted and original image could be a good approximation of perceived image distortion [24].

$$SSIM(x,y) = \frac{(2\mu x\ \mu y + C1)(2\sigma xy + C2)}{(\mu x2 + \mu y2 + C1)(\sigma x2 + \sigma y2 + C2)} \quad \ldots\ldots\ldots\ldots(2.3)$$

Where:

It means to compute local statistics μ_x, σ_x and σ_{xy} in a small window that is pixel-by-pixel moved over the entire image and the results are then averaged.

2.8 Image Segmentation

Image segmentation is the most difficult task in image processing. The original image is partitioned into different pieces for better analysis. The most difficult task in image segmentation is parameter selection. The goal of image segmentation is to cluster pixels into image regions. Applications of image segmentation include: segmentation is used for image recognition such as Face recognition, Medical imaging such as diagnosis, and agricultural imaging such as irrigation, crop and Traffic control systems as identifying objects in a moving scene for object-based video compression [10]. Here are some segmentation techniques:

1) **Thresholding Technique**

Thresholding technique is based on image space regions i.e. on characteristics of image. Thresholding operation convert a multilevel image into a binary image, it choose a proper threshold T, to divide image pixels into several regions and separate objects from background. Any pixel (x, y) is considered as a part of object if its intensity is greater than or equal to threshold value, else pixel belongs to background [23].

2) **Segmentation Based on Edge Detection**

This method attempts to resolve image segmentation by detecting the edges or pixels between different regions that have rapid transition in intensity are extracted [1, 5] and linked to form closed object boundaries. The result is a binary image [2]. Based on theory there are two main edge based segmentation methods- gray histogram and gradient based method [23].

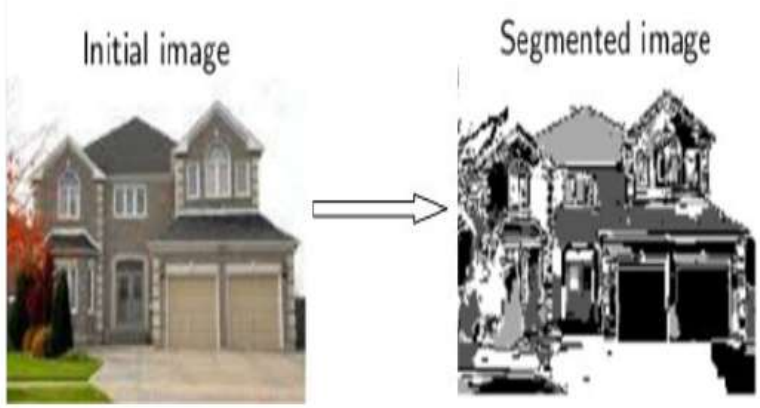


Fig 2.2 Image Segmentation

2.9 Summary

This chapter has presented the scientific background of the research in terms of handling the basic concepts relating to the research topic such as: image processing, image types, and image enhancement and segmentation techniques.

CHAPTER THREE

GENETIC ALGORITHM

3.1 Overview Of Genetic Algorithm

GAs was invented by John Holland in the 1960s and was developed by Holland and his students and colleagues at the University of Michigan in the 1960s and the 1970s. In contrast with evolution strategies and evolutionary programming, Holland's original goal was not to design algorithms to solve specific problems, but rather to formally study the phenomenon of adaptation as it occurs in nature and to develop ways in which the mechanisms of natural adaptation might be imported into computer systems [5].

Genetic Algorithm (GA) is a global optimization algorithm derived from evolution and natural selection. Although genetic algorithm cannot always provide optimal solution, it has its own and it is a powerful tool for solving complex problems [13].

3.2 Theory Of Genetic Algorithm

In spite of the easiness of describing and programming GA but their behavior can be complicated, and many open questions exist about how they work and for what types of problems they are best suited. Much work has been done on the theoretical foundations of GAs (see, e.g., Holland 1975; Goldberg 1989a; Rawlins 1991; Whitley 1993b; Whitley and Vose 1995) [5].The traditional theory of GAs (first formulated in Holland 1975) assumes that, at a very general level of description, GAs work by discovering, emphasizing, and recombining good "building blocks" of solutions in a highly parallel fashion. The idea here is that good solutions tend to be made up of good building blocks - combinations of bit values that confer higher fitness on the strings in which they are present [5].

3.3 A Simple Genetic Algorithm

Given a clearly defined problem to be solved a simple GA works as follows [16]:

1) Start with a randomly generated population of N chromosomes.
2) Calculate the fitness value of function of each chromosome x in the population.
3) Repeat until N offsprings are created.
4) Probabilistically select a pair of chromosomes from current population using value of fitness function.
5) Produce an offspring by using crossover and mutation operators.
6) Replace current population with newly created one.
7) Go to step 2.

3.4 Genetic Algorithm Flowchart

Here is a flow chart illustrate how genetic algorithm work. It firstly began by defining fitness function which is written in a way that can help finding the best solution. Then random population must be created in order to use it with the original one to find another best solution, before the operation of creation a best solution the evaluation of each population is done (Based on fitness function) to select which population will participate at new generation. Then crossing over the selected solution is done to create a best solution. If here were no change on solution using crossover then mutation is done. All best new solutions are used instead of old one and check if they satisfy fitness function and so on.

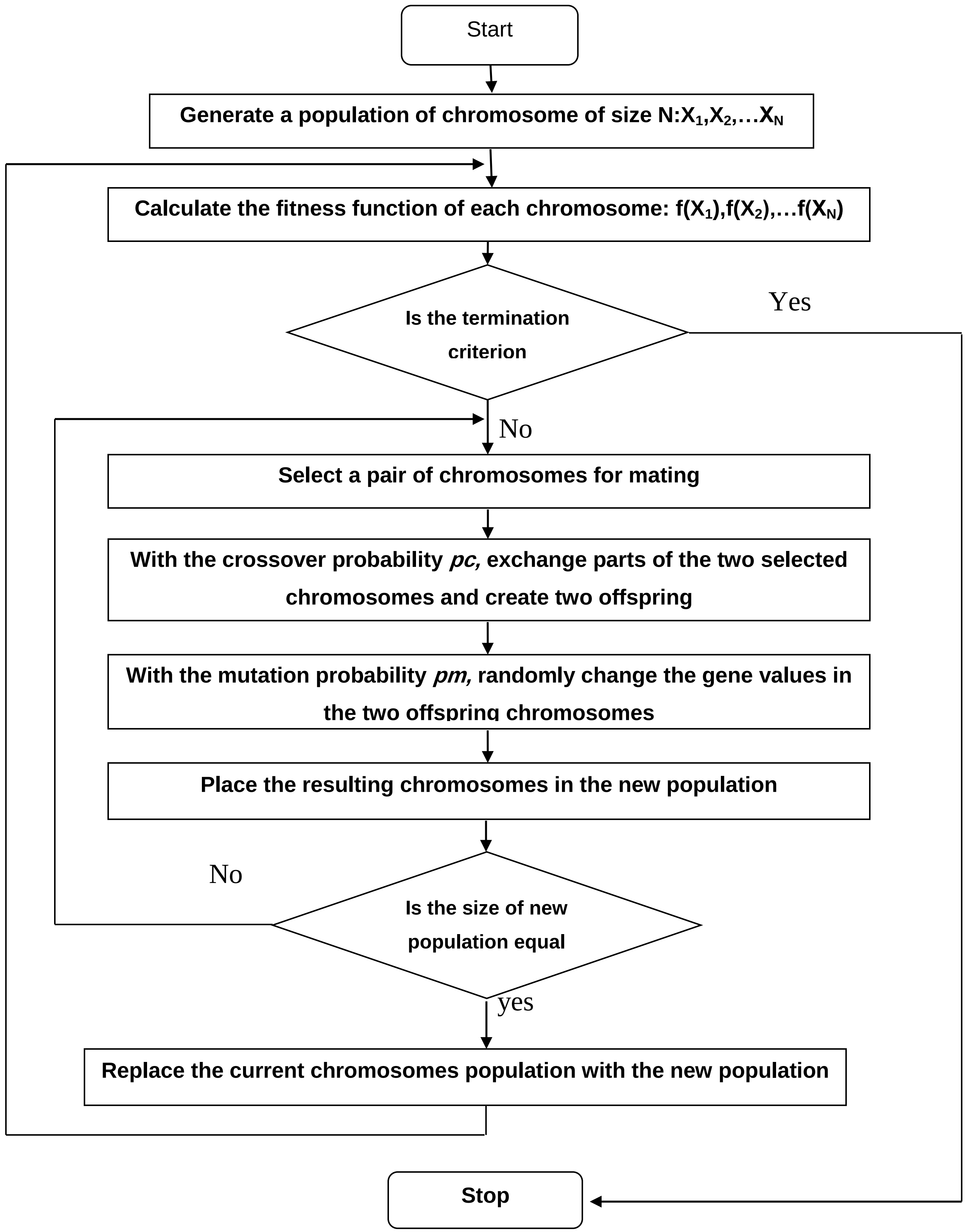


Fig 3.1 Genetic Algorithm Flowchart [32]

3.5 Genetic Algorithm Options

Genetic Algorithm Has options must be specify like:

3.5.1 Population

GAs search for the possible optimal solution without having knowledge about the search spaces. Usually in GAs, the initial population consists of entirely random strings (chromosomes). The parameters needed in defining a genetic algorithm for a specific problem are [10]:

1) The population size: The number of chromosomes in each generation that means population size provides how many chromosomes are in population (in one generation). Some problems have very large solution spaces (i.e. many variables, with a large range of permissible values for those variables).
2) Initial population: Enables you to specify an initial population for the genetic algorithm.

3.5.2 Fitness Scaling

Fitness gives main pressure for convergence of evolution process. It is calculated by the evaluation function. The scaling function converts raw fitness scores returned by the fitness function to values in a range that is suitable for the selection function [8].

3.5.3 Selection

Evolutionary Algorithms (EAs) involve a search from a ‘population’ of solutions, not from a single point like traditional optimization techniques. Each iteration of an EA involves a competitive selection that weeds out poor solutions. The solutions with high ‘fitness’ value are chooses for the next generation. You can specify the function that performs the selection in the selection function field. Selection methods types is like stochastic uniform, Uniform, Shift linear, Roulette, Tournament, Rank and Custom (Enables you to write your own selection function) [9].

This operator selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce [5].

3.5.4 Crossover

Crossover means exchange of genetic material to form children. Once selection has chosen fit individuals, they must be randomly altered with hope of improving their fitness for the next generation. In crossover, two individuals are chosen to swap segments of their code, to produce offsprings [9]. It is also defined as a genetic parameter which will combines two chromosomes (can also be called as parents) to produce a new chromosome (also called offspring). The result of crossover will give the new chromosome may be better than both of the parents if it takes the best characteristics from each of the parents. Crossover occurs during evolution according to a user-definable crossover probability. The new offspring will have some properties from one parent and some properties from other parent. Crossover types like: scattered, single point, two points, intermediate, heuristic, arithmetic, custom (Enables you to write your own crossover function) [10].

3.5.5 Mutation

Mutation can be takes place after the crossover gets performed. This is to prevent falling all solutions in population into a local optimum of solved problem.

The mutation depends on the encoding as well as the crossover. Then when we are encoding permutations, mutation could be exchanging two genes. Mutation changes the new offspring randomly. Mutation types like gaussian, uniform, adaptive feasible and custom (Enables you to write your own Mutation function) [10]. For example, the string 00000100 might be mutated in its second position to yield 01000100. Mutation can occur at each bit position in a string with some probability, usually very small (e.g., 0.001) [5].

3.5.6 Stopping Criteria

The algorithm repeats itself but stops after a predetermined stopping criteria are met which include [12]:

1) Generations: specifies the maximum number of iterations the genetic algorithm performs.
2) Time limit: specifies the maximum time in seconds the genetic algorithm runs before stopping.
3) Fitness limit: if the best fitness value is less than or equal to the value of Fitness limit, the algorithm stops.

3.6 Genetic Algorithm Applications

3.6.1 Travelling Salesman Problem

Travelling Salesman Problem (TSP) is well known in operation research for minimized travelling cost/ distance. TSP has to visit n cities. The objective is to select the sequence in which the cities are visited in such a way that total travelling time is minimized [28].

3.6.2 Genetic Algorithm For Construction Resource Scheduling

Construction project resource scheduling problems have been interesting and challenging subjects of extensive research for several decades in the optimization study area in order to put them in practical application. The generalized model of the resource scheduling is valuable in that it can be incorporated into the advanced computational methods of commercial project management software for practical applications. The problems have different versions, depending on the objective functions such as:

1) The minimization of project duration.
2) The minimization of the total project cost.
3) The maximization of the net present value of cash flows.
4) The resource levelling problem.

The objective of the resource-constrained project scheduling problem (RCPSP) is to allocate the available resources to activities in order to find the shortest duration of a project network within the constraints of precedence relationships [26].

3.6.3 Genetic Algorithm To Estimate Parameters To Calibrate a water Quality Model

They used nonlinear regression to search for parameters that minimize the least square error between the best fit model and the data. They found that the GA works better than more traditional techniques plus noted the added advantage that the GA can provide information about the search space, enabling them to develop confidence regions and parameter correlations. Some other work related to water quality includes using GAs to determine flow routing parameters [26].

3.7 Other Genetic Algorithm Applications

There are many applications which GA used to solve them it may include [26]:

1) Solving ground water management problems.
2) Managing groundwater supplies.
3) Fit parameters of a model to optimize pumping locations and schedules for groundwater treatment.
4) Classification and prediction of rainy day versus non-rainy day.
5) Estimate the parameters in a third order Markov model.
6) Determining the type of underground rock layers.
7) Determining the source of air pollutants.

3.8 Summary

This chapter has detailed the theory of genetic algorithm, the options of it, and the application of genetic algorithm.

CHAPTER FOUR

PRACTICAL EXPERIMENTS

4.1 Digital Image Processing

Image processing involves changing the nature of an image in order to [4]:

1) Improve its pictorial information for human interpretation.
2) Render it more suitable for autonomous machine perception.

4.2 Description Of Data

Data are taken by specialist from various resources which include (Internet and Kush Hospital) for research purpose.

They are three samples of image which includes: Gal(1), Gal(2) and one X-Ray image (Hand).

Here the three images are dissimilar and this considered as an advantage of proposed algorithm and proves the ability of GA for dealing with various size of image.

Table 4.1 Description of Data

Sample No	Original Image	Width (Columns)	Height (Rows)
Sample One	Gal(1).jpg	1411	1411
Sample Two	Hand.jpg	1459	1076
Sample Three	Gal(2).jpg	1200	820

4.3 Steps Of Processing

The processing steps for enhancing image are:

1) Image uploaded from the path which you select.
2) Original image is converted to grey image.
3) You must determine the edges of image, to pass it for the GA optimizer which it will use them to reconstruct the image.
4) Adding noise to gray image (Salt & Pepper noise) and adjacent their contrast to create random initial population. All these done in order to examine the ability of the algorithm.
5) GA optimizer is used. Then the resulted image is de-noised and has contrast high when we compare it with gray.
6) Before enhancement is begun user must choose the selection method for GA. Here Roulette wheel, Tournament and Rank selection are used in order to know which of them give best result. All previous steps are shown in figure 4.1.
7) Gray image and noisy image is crossed over (Recombined) together in order to select fittest pixels based on fitness function. The syntax of the fitness function is:

$$alpha = en2/\mathrm{sqrt}(\ en1^2 + en2^2\ ) \quad \ldots\ldots(4.1)$$

$$en1 = 0.5 * sum(sum(g.* (T - I)^2)) \quad \ldots\ldots(4.2)$$

$$en2 = 0.5 * sum(sum(TX^2 + TY^2)) \quad \ldots\ldots(4.3)$$

Where:

I=input image

T=threshold image.

g = (Ix.^2+Iy.^2).^ (pow/2)

T-I =Pixels creation

Tx=pixels on X-axis

Ty=pixels on Y-axis

8) Mutation is done when there is no best result done by crossover. With probability 0.05.
9) Number of iteration is taken as stopping criteria (it is differed from one image to another) and results are figured out using the cost of fitness function and number of iteration (at iteration 100).
10) For Image Quality Assessment (IQM): Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and (SSIM) Structural Similarity Index which were used as parameters for assessing image quality.

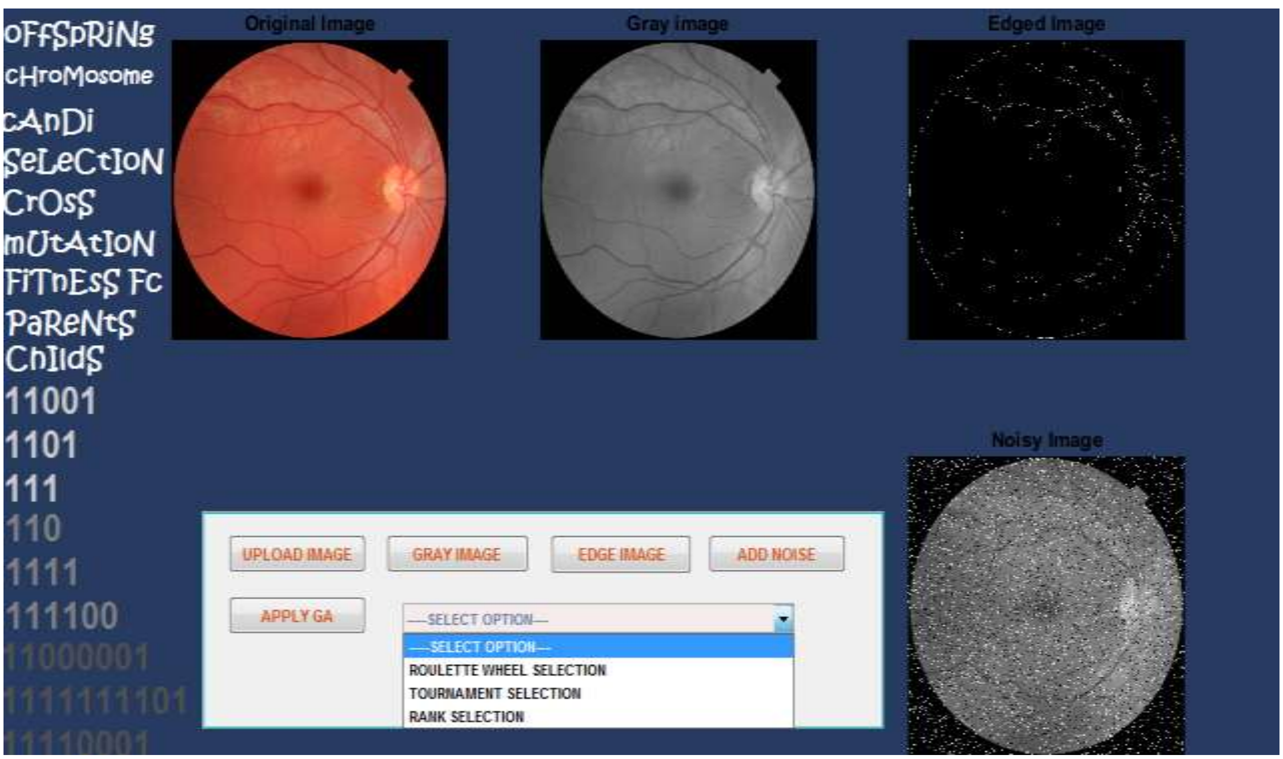


Fig 4.1 Module Implementation

4.4 Factors Taken Onto Consideration

1) Number of iteration

It is a number of generation that genetic algorithm need to work. Here the algorithm was used a two value at (80 and 100).

2) Density of noise

It is the number of white and black pixels which are added to make image noisy. The algorithm was used a two value (0.02 & 0.09). The default value of salt & pepper noise is 0.05).

Table 4.2 Factors Taken Onto Consideration Using GA

Results	Number Of Iteration	Noise Density
Expermint1	80	0.02
Expermint2	100	0.02
Expermint3	100	0.09

4.5 Experiments Using Genetic Algorithm

The experiments include using all selection operators in order to examine which will give me suitable value of each (MSE,PSNR and SSIM), and then make decision based on these values.

4.5.1 Experiment One

Table 4.3 Exp1 - Quality Assessment Value for Gal (1) Using GA

Sample One	MSE	PSNR	SSIM
Original image Value	0.0969650	13.7615	0.48947
Roulette Wheel Selection Value	0.0066085	50.7350	0.97743
Tournament Selection Value	0.0066008	50.6904	0.97754
Rank Selection Value	0.0066093	50.9910	0.97742

Table 4.4 Exp1 - Quality Assessment Value for Hand Using GA

Sample Two	MSE	PSNR	SSIM
Original image Value	0.071304	19.4282	0.56215
Roulette Wheel Selection Value	0.0079857	48.7639	0.96812
Tournament Selection Value	0.0079857	48.6766	0.96811
Rank Selection Value	0.0079864	48.6099	0.96811

4.5.2 Experiment Two

Table 4.5 Exp2 - Quality Assessment Value for Gal(1) Using GA

Sample One	MSE	PSNR	SSIM
Original image Value	0.097693	10.9272	0.49052
Roulette Wheel Selection Value	0.0066144	49.3604	0.97734
Tournament Selection Value	0.0066145	48.2867	0.97734
Rank Selection Value	0.0066139	50.3096	0.97735

Table 4.6 Exp2 - Quality Assessment Values for Hand Using GA

Sample Two	MSE	PSNR	SSIM
Original image Value	0.072348	15.3183	0.5602
Roulette Wheel Selection Value	0.0079878	48.8476	0.96808
Tournament Selection Value	0.0079891	48.3001	0.96806
Rank Selection Value	0.0079903	48.4199	0.96804

4.5.3 Experiment Three

Table 4.7 Exp3 - Quality Assessment Values for Gal(1) Using GA

Sample One	MSE	PSNR	SSIM
Original image Value	0.20369	5.2408	0.082917
Roulette Wheel Selection Value	0.0066145	48.4378	0.97734
Tournament Selection Value	0.0066136	49.8903	0.97736
Rank Selection Value	0.0066144	48.6322	0.97734

Table 4.8 Exp3 - Quality Assessment Value for Hand Using GA

Sample Two	MSE	PSNR	SSIM
Original image Value	0.15816	7.0074	0.13716
Roulette Wheel Selection Value	0.0079888	48.581	0.96807
Tournament Selection Value	0.0079889	48.5432	0.96807
Rank Selection Value	0.0079885	48.9722	0.96807

4.6 Experiments Using Histogram

Genetic algorithm here compared with histogram in order to assess our proposed algorithm.

4.6.1 Factors Taken onto Consideration Using Histogram

Factor affect on result is noise density.

Table 4.9 Factors Taken Onto Consideration

Results	Noise Density
Expermint1	0.02
Expermint2	0.09

4.6.2 Experiment One

Table 4.10 Exp1 - Quality Assessment Value for Gal (1) Using Histogram

Sample One	MSE	PSNR	SSIM
Original Image Values	**196.0396**	**22.0371**	**0.4896**
Enhanced Image Values	**251.7672**	**13.5116**	**0.3370**

Table 4.11 Exp1 - Quality Assessment Value for Hand Using Histogram

Sample Two	MSE	PSNR	SSIM
Original Image Values	241.5343	21.7563	0.5607
Enhanced Image Values	215.7698	7.1403	0.2190

4.6.3 Experiment Two

Table 4.12 Exp2 - Quality Assessment Value for Gal (1) Using Histogram

Sample One	MSE	PSNR	SSIM
Original Image Values	196.0396	15.4989	0.0826
Enhanced Image Values	253.488	13.8598	0.0744

Table 4.13 Exp2 - Quality Assessment Value for Hand Using Histogram

Sample Two	MSE	PSNR	SSIM
Original Image Values	241.5343	15.1974	0.1386
Enhanced Image Values	254.9994	16.6825	0.1078

4.7 Summary

This chapter contained three main parts, part one explain the parameters which took onto consideration, part two explain the experiments when genetic algorithm was used for enhancing, part two explain the experiments when histogram are used.

CHAPTER FIVE

DISCUSSION OF RESULTS

5.1 Results

The values of quality assessment parameters (MSE,PSNR and SSIM) are recorded for all selection operators at all experiments for all samples .

5.1.1 Quality Assessment Parameters of Sample One Using Various Selection Operators

5.1.1.1 Mean Square Error

The MSE value when Roulette Wheel selection are used is at Exp1(0.0066085) , for Tournament selection the best value at Exp1(0.0066008) and for Rank selection the best value at also at Exp1(0.0066093). That means Exp1 give best results of MSE. See table below.

Table 5.1 MSE for Sample One Per All Experiments

MSE for Sample One	Exp1	Exp2	Exp3
Roulette Wheel	0.0066085	0.0066144	0.0066145
Tournament	0.0066008	0.0066145	0.0066136
Rank	0.0066093	0.0066139	0.0066144

5.1.1.2 Peak Signal to Noise Ratio

The PSNR value when Roulette Wheel selection are used is at Exp1(50.7350) , for Tournament selection the best value at Exp1(50.6904) and for Rank selection the best value at also at Exp1(50.9910). That means Exp1 give best results of PSNR. See table below.

Table 5.2 PSNR for Sample One Per All Experiments

PSNR Value Sample One	Exp1	Exp2	Exp3
Roulette Wheel	50.7350	49.3604	48.4378
Tournament	50.6904	48.2867	49.8903
Rank	50.9910	50.3096	48.6322

5.1.1.3 Structural Similarity Index Measure

The SSIM value when Roulette Wheel selection are used is at Exp1(0.97743) , for Tournament selection the best value at Exp1(0.97754) and for Rank selection the best value at also at Exp1(0.97742). That means Exp1 give best results of PSNR. See table below.

Table 5.3 SSIM for Sample One Per All Experiments

SSIM Value Sample One	Exp1	Exp2	Exp3
Roulette Wheel	0.97743	0.97734	0.97734
Tournament	0.97754	0.97734	0.97736
Rank	0.97742	0.97735	0.97734

The conclusion from (Table 5.1, Table5.2 and Table5.3) was that: The best result of enhancement for sample one given in Exp1.

5.1.2 Quality Assessment Parameters Of Sample Two Using Various Selection Operators

5.1.2.1 Mean Square Error

The MSE value when Roulette Wheel selection are used is at Exp1(0.0079857) , for Tournament selection the best value at Exp1(0.0079857) and for Rank selection the best value at also at Exp1(0.0079864). That means Exp1 give best results of MSE. See table below.

Table 5.4 MSE for Sample Two Per All Experiments

MSE for Sample Two	Exp1	Exp2	Exp3
Roulette Wheel	0.0079857	0.0079878	0.0079888
Tournament	0.0079857	0.0079891	0.0079889
Rank	0.0079864	0.0079903	0.0079885

5.1.2.2 Peak Signal to Noise Ratio

The PSNR value when Roulette Wheel selection are used is at Exp2(48.8476) , for Tournament selection the best value at Exp1(48.6766) and for Rank selection the best value at also at Exp3(48.9722). That means Exp1 give best results of PSNR. See table below.

Table 5.5 PSNR for Sample Two Per All Experiments

PSNR for Sample Two	Exp1	Exp2	Exp3
Roulette Wheel	48.7639	48.8476	48.581
Tournament	48.6766	48.3001	48.5432
Rank	48.6099	48.4199	48.9722

5.1.2.3 Structural Similarity Index Measure

The SSIM value when Roulette Wheel selection are used is at Exp1(0.96812) , for Tournament selection the best value at Exp1(0.96811) and for Rank selection the best value at also at Exp1(0.96811). That means Exp1 give best results of SSIM. See table below.

Table 5.6 SSIM for Sample Two Per All Experiments

SSIM for Sample Two	Exp1	Exp2	Exp3
Roulette Wheel	0.96812	0.96808	0.96807
Tournament	0.96811	0.96806	0.96807
Rank	0.96811	0.96804	0.96807

5.1.3 Sample One Best Value of Various Selection Operators

Here we need to know which selection operators are best for enhancement processing.

Table 5.7 Best Selection operator Value for Sample One

Sample One	MSE	PSNR	SSIM
Roulette Wheel	0.0066085	50.7350	0.97743
Tournament	**0.0066008**	**50.6904**	**0.97754**
Rank	0.0066093	50.9910	0.97742

The best selection operator for enhancing the sample one is Tournament Selection which give best MSE, PSNR and SSIM at all experiment. See the table above (The best value written in **bold**).

5.1.4 Sample Two Best Value of Various Selection Operators

Table 5.8 Best Selection operator Value for Sample Two

Sample Two	MSE	PSNR	SSIM
Roulette Wheel	**0.0079857**	48.8476	**0.96812**
Tournament	0.0079857	48.8659	0.96811
Rank	0.0079864	**48.9722**	0.96811

But here the best selection operator for enhancing the sample two is not static

See the table above (The best value written in **bold**).

5.2 Comparing Genetic Algorithm With Histogram

5.2.1 Sample One

Table 5.9 Comparing GA with Histogram For Sample One

Quality Parameters Value	Original Value	GA	Histogram
MSE	196.0396	0.0066008	251.7672
PSNR	22.0371	50.6904	13.5116
SSIM	0.4896	0.97754	0.3370

5.2.2 Sample Two

Table 5.10 Comparing GA with Histogram For Sample Two

Quality Parameters Value	Original Value	GA	Histogram
MSE	241.5343	0.0079857	215.7698
PSNR	21.7563	48.9722	7.1403
SSIM	0.5607	0.96812	0.2190

5.3 Algorithm Time Consumed Using GA

The processing time using GA for enhancing image is calculated per second for computer has descriptions below:

(Windows 7 Ultimate 32-bit (6.1,build 7601, Dual- Core-CPU, 3072 MB RAM.

Table 5.11 Time Consumed on Processing Using GA

Time Of Processing Per Seconds	Sample One	Sample Two
Experiment One	20.810877	19.936467
Experiment Two	26.884714	24.409643
Experiment Three	26.992179	24.653948

5.4 Algorithm Time Consumed Using Histogram

The processing time using Histogram for enhancing image is calculated per second for computer has descriptions below:

(Windows 7 Ultimate 32-bit (6.1,build 7601, Dual- Core-CPU, 3072 MB RAM).

Table 5.12 Time Consumed on Processing Using Histogram

Time Of Processing Per Seconds	Sample One	Sample Two
Experiment One	0.513951	0.441739
Experiment Two	0.531475	0.470414

5.5 Figures Of Resulted Samples Using GA

Comparison of original image with enhanced image is done in order to assess the algorithm for all samples.

5.5.1 Sample One Outputs Using GA

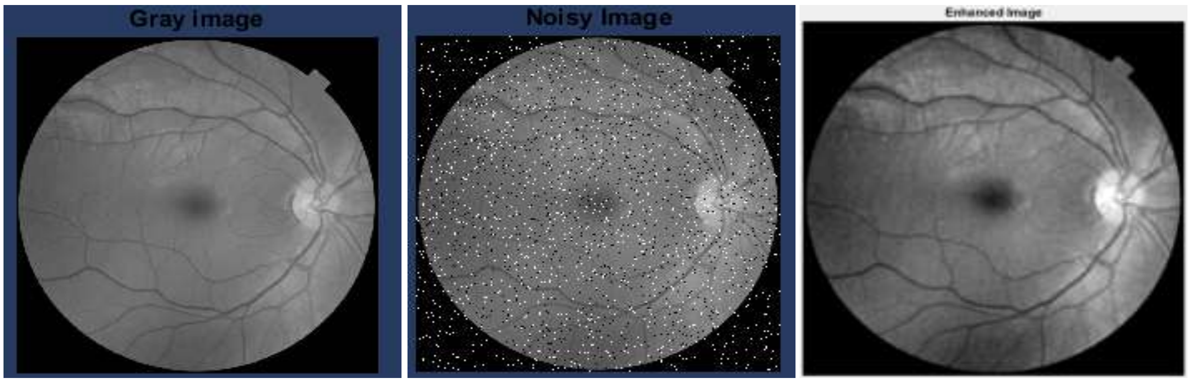


Fig 5.1 Sample One Output Using GA

5.5.2 Sample Two Outputs Using GA

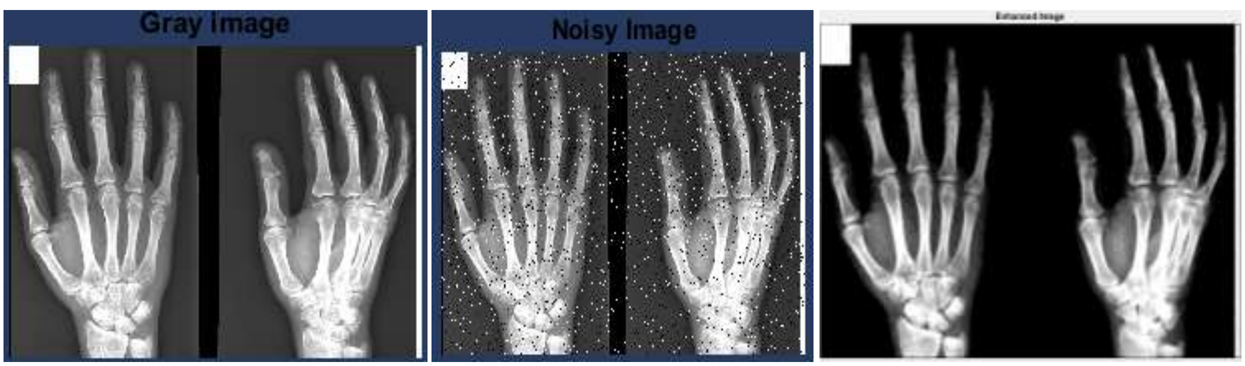


Fig 5.2 Sample Two Output Using GA

5.6 Figures Of Resulted Samples Using Histogram

Original image and enhanced image were compared using histogram.

5.6.1 Sample One Using Histogram

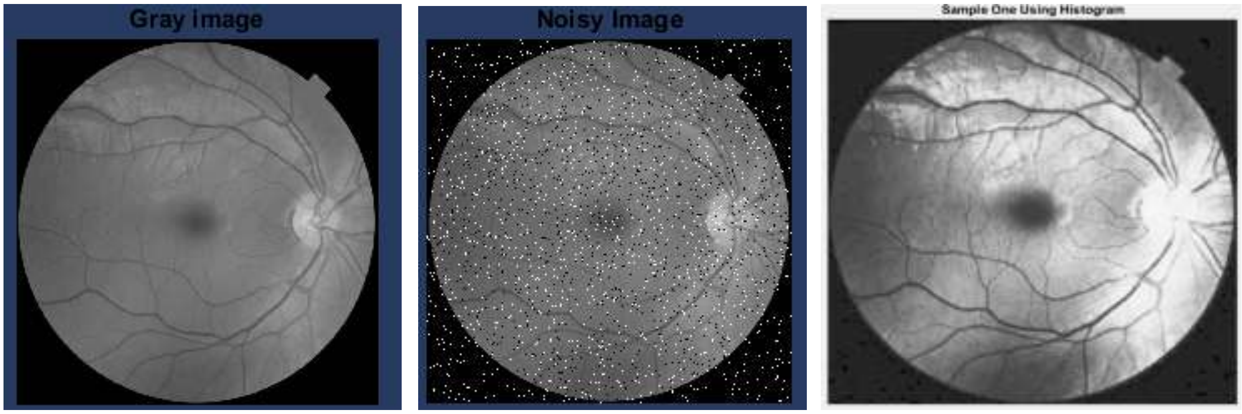


Fig 5.3 Sample One Output Using Histogram

5.6.2 Sample Two Using Histogram

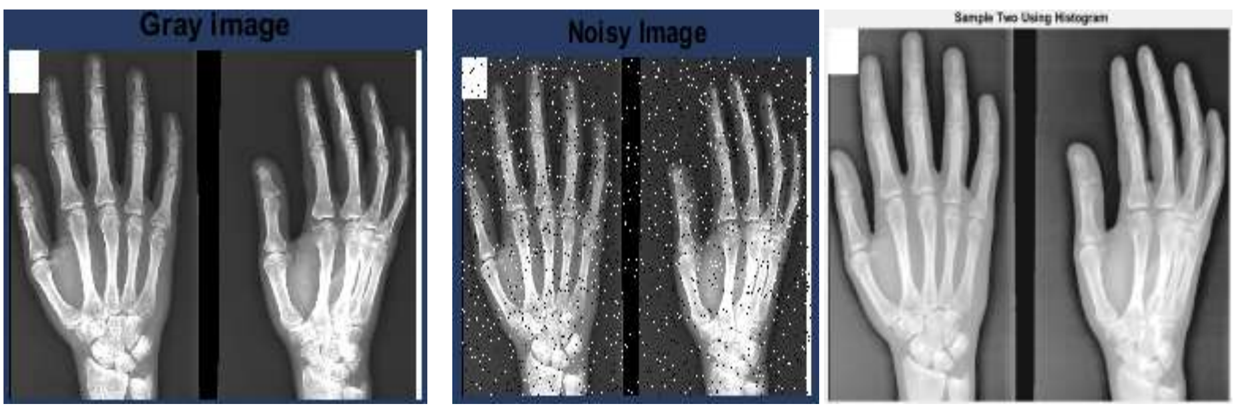


Fig 5.4 Sample Two Output Using Histogram

5.7 Labels Of Samples

The objective function of this program is to maximize the fitness function at each iteration (by increasing the contrast and decreasing the noise). Here the fitness cost (value) which was calculated after passing all parameters to GA optimizer, and then plotted with the number of iteration.

At each iteration the value of fitness function was calculated using pixels values, any pixels that not satisfies the fitness function were discarded.

At vertical direction the values of cost function were normalized, by multiplication the values of fitness function - which are resulted when the fitness function are applied - by the number of iteration plotted horizontally with the number of iteration (generation) which used to give the resulted image. As seen at the first iterations the value of the fitness was very small (that means the contrast was less and there were more noise) when the number of iteration was increased then the fitness function (values) became very high and the image was became very well. See Figures below.

5.7.1 Sample One Label

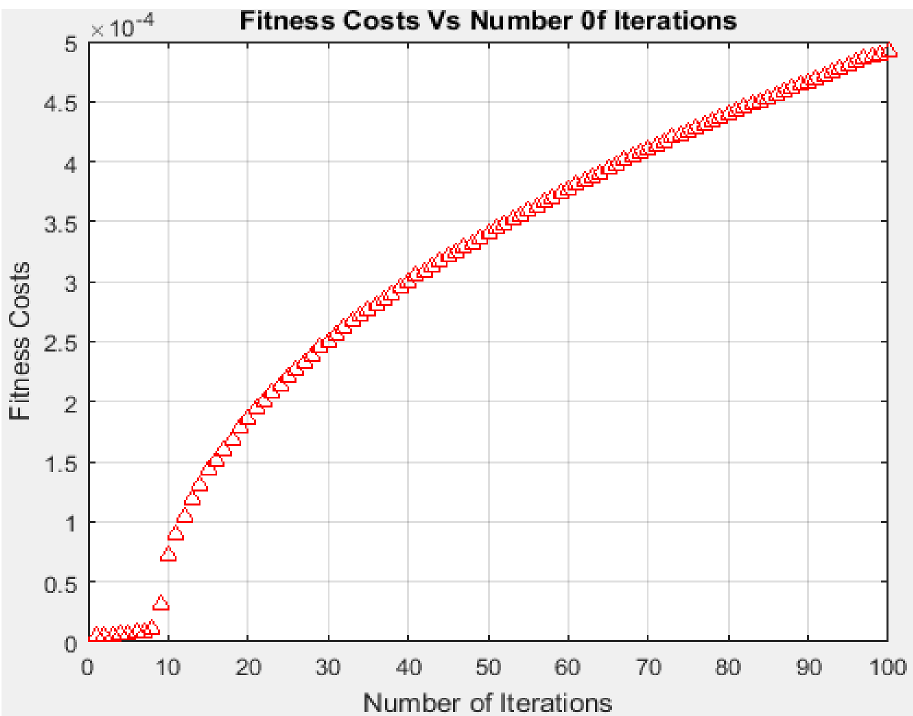


Fig 5.5 Sample One Fitness Value

5.7.2 Sample Two Label

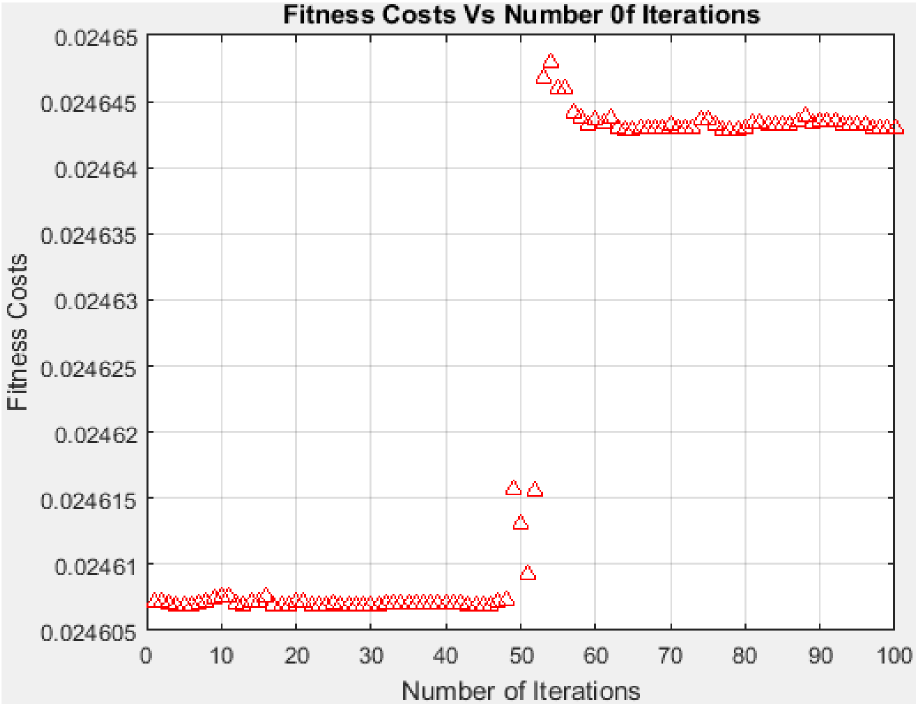


Fig 5.6 Sample Two Fitness Value

5.8 Plotting Quality Parameters

5.8.1 Quality Parameters for Sample One Using GA

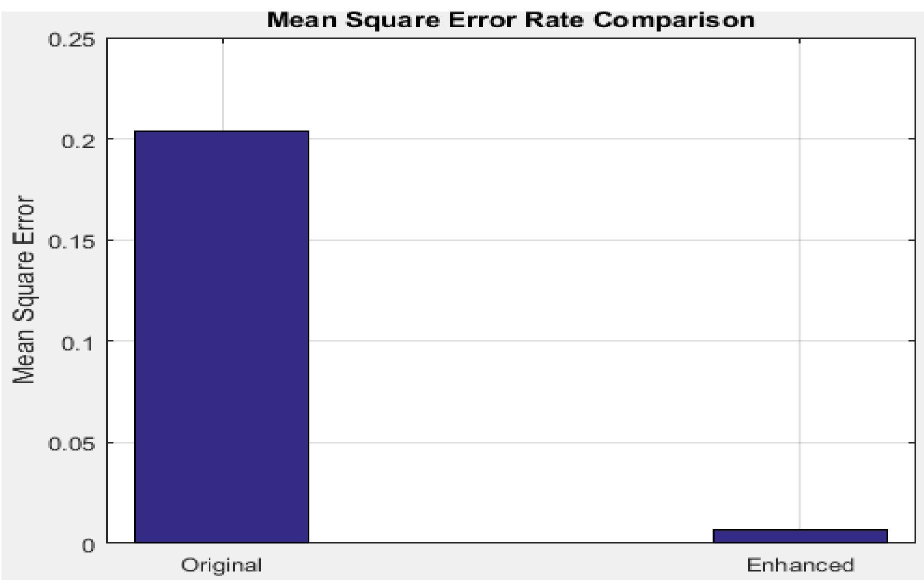


Fig 5.7 MSE for Sample One

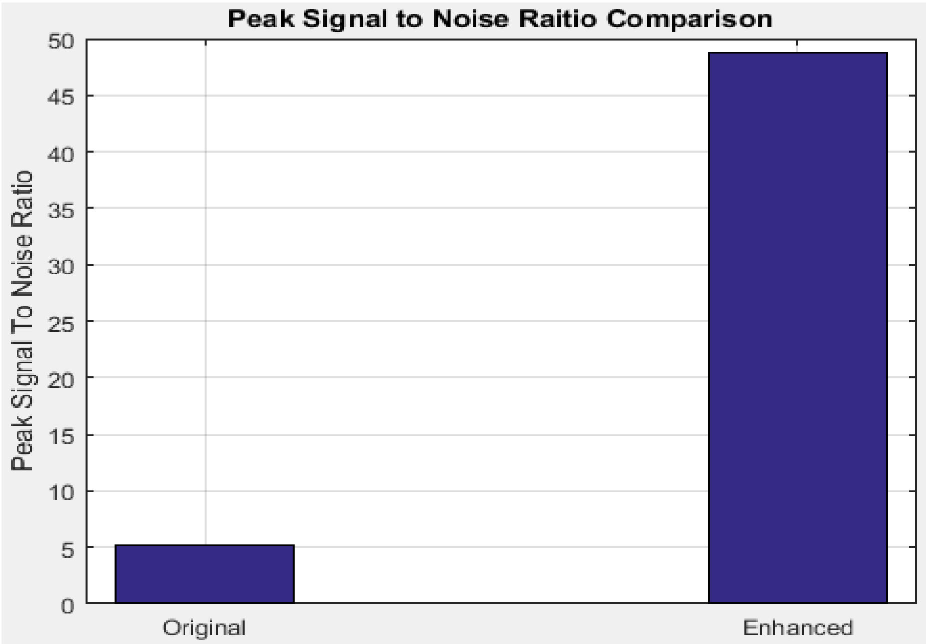


Fig 5.8 PSNR for Sample One

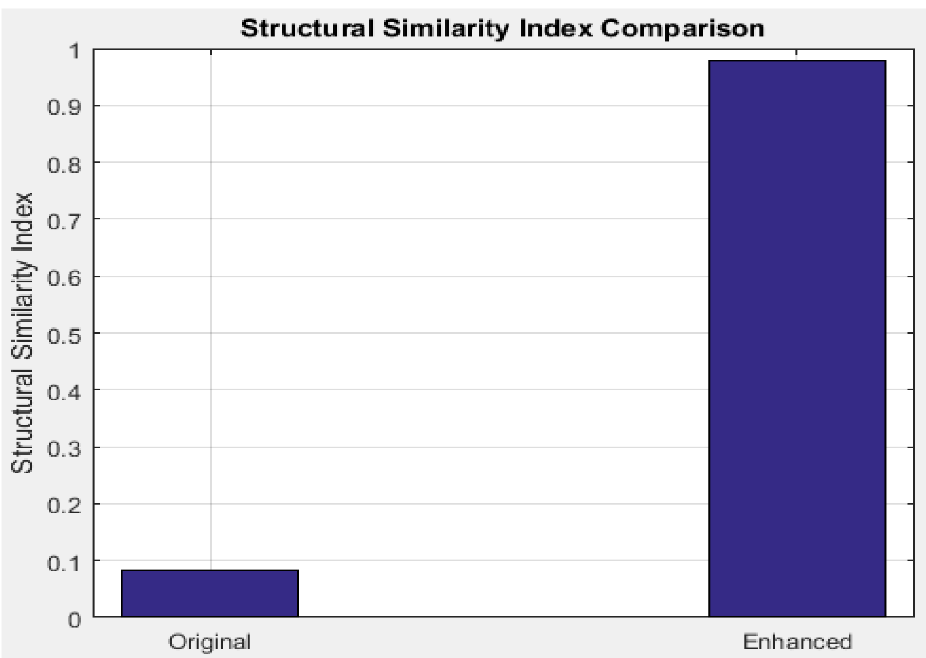


Fig 5.9 SSIM for Sample One

5.8.2 Quality Parameters for Sample Two Using GA

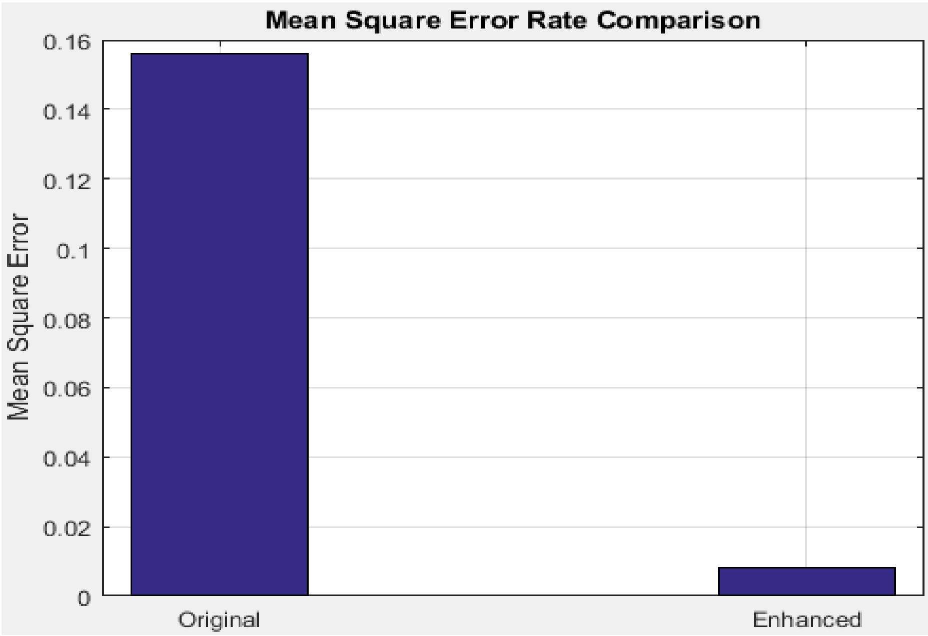


Fig 5.10 MSE for Sample Two

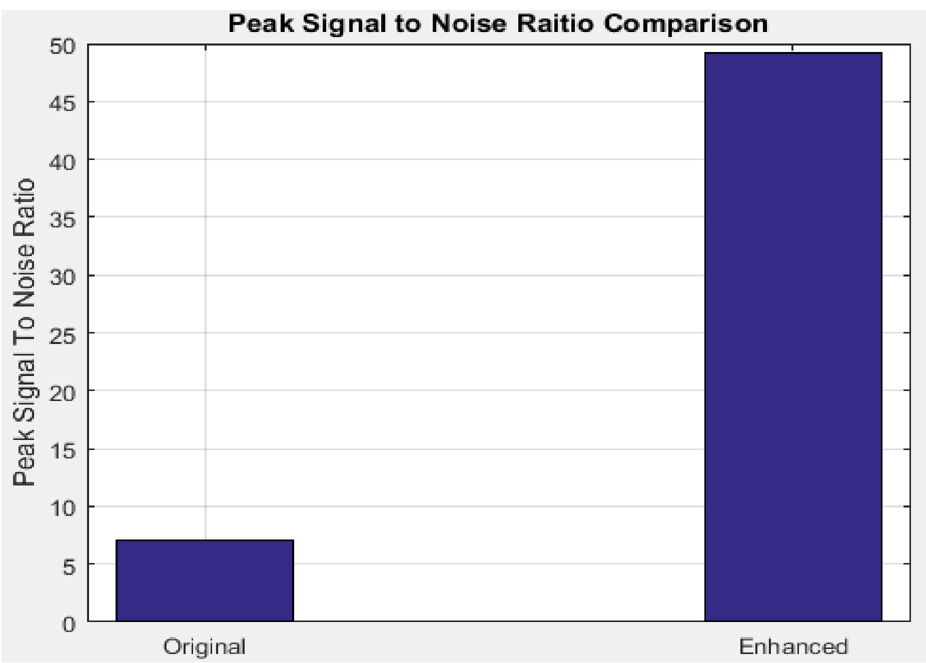


Fig 5.11 PSNR for Sample Two

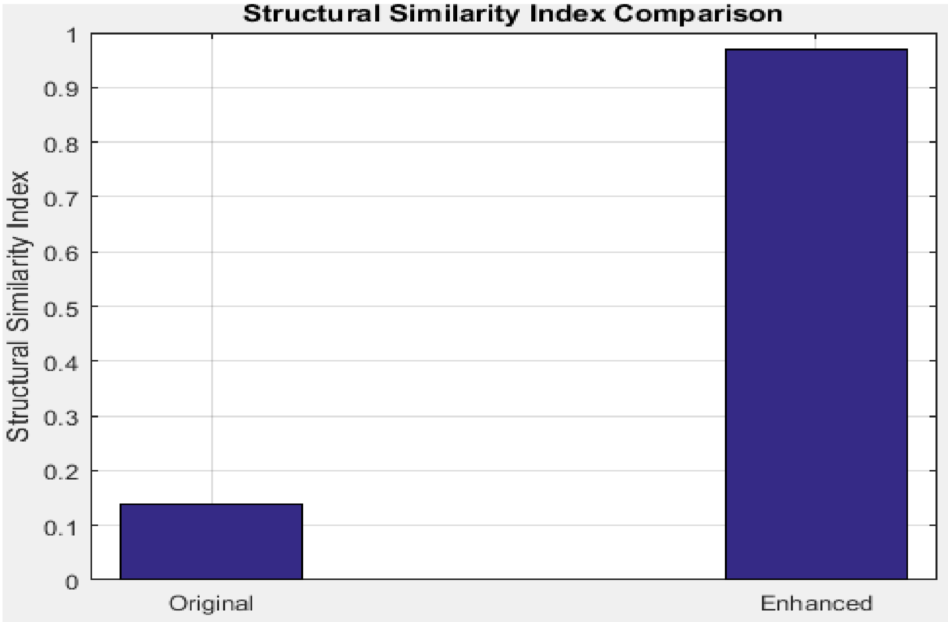


Fig 5.12 SSIM For Sample Two

5.9 Discussion Of Results

After doing all experiments and examine the ability of GA to doing enhancement the values for MSE, PSNR and SSIM for enhanced image gave best values when it compared to original image for three selection operators.

The algorithm is applied for Sample one (colored image which are transferred to gray with size 1114 ×1114) and also applied to sample two (Gray image with size 1459 × 1076) in order to examine the ability of GA Can it deal with various types of image and various sizes of image or not. The algorithm gives best results for both image and that are considered as an advantage of the project.

For Sample one tournament Selection gave best result for three parameters (MSE, PSNR and SSIM) in all experiments. For sample two roulette Selection and tournament selection gave best result for MSE at all experiments, but for (PSNR) and (SSIM) the Rank selection and roulette selection gave best value for all experiments respectively. At figure(5.1) and figure(5.2) There was comparison of two chromosomes for GA (Gray image and noisy image) and after applying GA the resulted image was been Enhanced image. Histogram are used to assure the ability of GA for enhancing more than other algorithm, and the resulted image which was enhanced using GA are better than others which was enhanced using histogram. See figure(5.3) and figure(5.4). At last GA was proved that it can deal with many types of images to do the process of enhancing. There were no any experiments done to examine the program at phone.

5.10 Conclusion & Recommendation

5.10.1 Conclusion

Genetic algorithm was proven to give an excellent enhancing in medical image for both types of image RGBs images and X-ray images for various size of them .And it gives a very accurate results for all quality parameters which are used to assessed the image.

5.10.2 Recommendation

1) We recommended using other techniques for enhancing Galucoma image.
2) Use algorithm to enhance blurred image because blurring will make the overall image not clear.
3) Use algorithm to enhance colored image because the diagnosis of glaucoma may often done directly for colored image.

5.11 Summary

This chapter contains results of experiments using genetic algorithm and results using histogram, comparing genetic algorithm with histogram, figures of resulted samples using genetic algorithm and histogram and labels of resulted image.

REFERENCES

[1] Jiawei Han and Micheline Kamber. 2006. “Data Mining:Concepts and Techniques”. Diane Cerra. United States of America.

[2] Rafael C. Gonzalez, Richard E. Wood, Steven L. Eddin. 2009.”Digital Image Processing Using Matlab”. A Division of Gatesmark,® LLC. United States of America.

[3] Vipin Kumar. 2009. “Multimedia Data Mining A Systematic Introduction to Concepts and Theory”. Taylor & Francis Group, LLC. Minneapolis, Minnesota, U.S.A.

[4] Alasdair McAndre. “AnIntroduction to Digital Image Processing with Matlab”. School of Computer Science and Mathematics.Victoria University of Technology.

[5] Mitchell Melanie. 1999. “An Introduction to Genetic Algorithms”. Massachusetts Institute of Technology. Cambridge, Massachusetts - London, England.

[6] Raman Maini,Himanshu Aggarwal.2010.”AComprehensive Review of Image EnhancementTechniques”. JOURNAL OF COMPUTING. 2(3).8-9.

[7] H. K. Sawant, Mahentra Deore. “A Comprehensive Review of Image Enhancement Techniques”. International Journal of Computer Technology and Electronics Engineering (IJCTEE) .1(2).39-44.

[8] Ms,Shivangini ,Shrivastava., Mr. Arvind Upadhyay . 2014. “Image Enhancement Using Genetic Algorithm”, International Journal of Engineering Research & Technology (IJERT),3(5), 1768 -1772.

[9] Dhirendra Pal Singh, Ashish Khare . 2014 .”Evolutionary Image Enhancement Using Multi-Objective Genetic Algorithm” .J.K. in *Image*, Graphics and Signal Processing, INDIA, MECS , 61-67.

[10] Miss. Komal R. Hole1, Prof. Vijay S. Gulhane, Prof. Nitin D. Shellokar. 2013. “Applic-ation of Genetic Algorithm for Image Enhancement and Segmentation”. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2(4), 1342-1346.

[11] P. Babu, V. Rajamani. 2014. “Contrast Enhancement using Real Coded Genetic Algorithm Based Modified Histogram Equalization for Gray Scale Images”. In Department of Computer Applications, PSNA College of Engineering and Technology, Dindigul,(India), 24-32.

[12] Chaahat, Madhu Bahl, Parveen Lehana. 2013. “Image Brightness Enhancement of Natural and Unnatural Images Using Continuous Genetic Algorithm”. International Journal of Advanced Research in Computer Science and Software Engineering, 3(9), 948-959.

[13] Cheng Guo, Xiaoyong Yang. 2011. “A Programming of Genetic Algorithm in Matlab7.0”. Modern Applied Science, www.ccsenet.org/mas. Vol. 5,(1). 230-235.

[14] Miss. Komal.R. Hole, Nitin D. Shellokar.2013. "Application of Genetic Algorithm for Image Enhancement and Segmentation". International Journal of Advanced Research in Computer Engineering & Technology (IJARCET).2(4).1342-1346.

[15] Karithikeyan Sakthivel,Rengarajan Narayanan.2015. "An automated detection of glaucoma using histogram". Int J Ophhalmol,WWW.IJO.cn.194-200.

[16] Mantas Paulinas, Andrius Ušinskas.2007."a survey of genetic algorithms Applications For Image Enhancement and Segmentation". Information Technology and Control .36(3).278-284.

[17] B.Lakshmi, G.Lingaiah, S.S.Madhavi.2012." An Enhanced Approach for Medical EDGE ImageEnhancement using Genetic Algorithm". IJCST.3(1).270-274.

[18] Instructor Prof.D.Cavouras.Medical Image Processing.Electronic EngineerB.sc.M.sc.ph.D.Cavouras@teiath.gr).

[19] Er.Jyoti Rani, Er.Sarabjeet Kaur.Volume 4, Issue 1, January 2014.International Journal of Advanced Research in Computer Science and Software Engineering.

[20] Shilpa Rani Mtech ,Sonika Jindal, Bhavneet Kaur." A Brief Review on Image Restoration TechniquesShilpa". International Journal of Computer Applications (0975 – 8887).150(12).1-4.

[22] Mathri thakur, Shilpa Chadury.Volume 14 Number 4 – Aug 2014.Image Restoration Based On Deconvolution by Richardson Lucy Algorithm. International Journal of Engineering Trends and Technology (IJETT).

[23] L.Aurdal,"Image Segmentation beyond thresholding", Norsk Regnescentral, 2006.

[24] M. Kudˇelka Jr. Image Quality Assessment. Institute of Information Theory and Automation.(94-99). 224-5.

[25] Hongo Hirano Bldg, Hongo, Bunkyo-ku,. 2006. Guidelines for Glaucoma. Japan Glaucoma Society.

[26] Jin-Lee Kim. INTEGRATED GENETIC ALGORITHM AND ITS APPLICATIONS FOR CONSTRUCTION RESOURCE OPTIMIZATION. Proceedings of the 2010 Winter Simulation(1-8).

[27] Sue Ellen Haupt, Randy L. Haupt. GENETIC ALGORITHMS AND THEIR APPLICATIONS IN ENVIRONMENTAL SCIENCES. Utah State University, Logan, UT(1-8).

[28] Kirtiwant P Ghadle _ , YogeshMMuley. Travelling salesman problem with MATLAB programming. Journal homepage. 2(3) .(258-266).

[29] Chi Chang-yan, Zhang Ji-xian, Liu Zheng-jun.STUDY ON METHODS OF NOISE REDUCTION IN A STRIPPED IMAGE. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.(213-216).

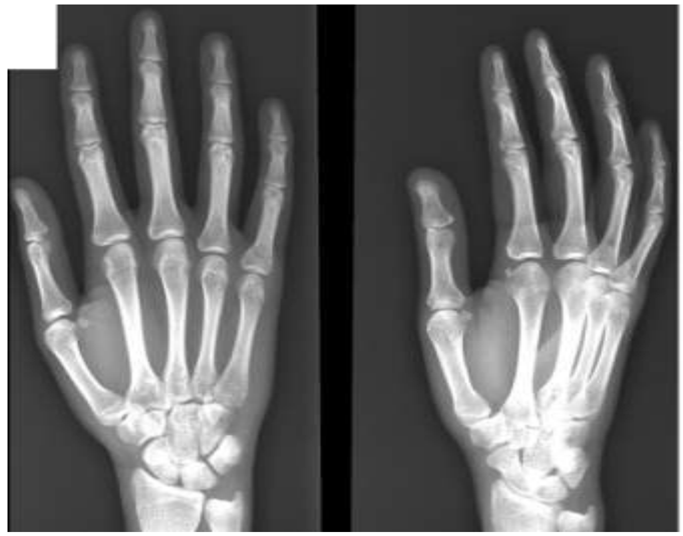
[30] Pawan Patidar, Manoj Gupta. Image De-noising by Various Filters for Different Noise. International Journal of Computer Application.9(4).(45-50).

[31] Leelavathi H P , Ram Manohar Nisarg. Comparative Study of Frequency Vs Spacial Domain for Multi Sensor Image Fusion. International Journal of Innovative Research in Science,Engineering and Technology.3(7).(14242-14249).

[32] MICHAEL NEGNEVITSKY,Artificial Intelligence, A Guide to Intelligent Systems, second edition(435).

APPENDIX

Sample One Gal(1).jpg



Sample Two Hand.jpg

Sample Three Gal(2).jpg