User Aid-based Evolutionary Computation for Optimal Parameter Setting of Image Enhancement and Segmentation

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.
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Abstract

Applications of imaging and image processing become a part of our daily life and find their crucial way in real-world areas. Accordingly, the corresponding techniques get more and more complicated.

Many tasks are recognizable for a image processing chain, such as, filtering, color balancing, enhancement, segmentation, and post processing. Generally speaking, all of the image processing techniques need a control parameter setting. The better these parameters are set the better results can be achieved. Usually, these parameters are real numbers so search space is really large and brute-force searching is impossible or at least very time consuming. Therefore, the optimal setting of the parameters is an essential requirement to obtain desirable results. Obviously, we are faced with an optimization problem, which its complexity depends on the number of the parameters to be optimized and correlation among them.

By reviewing the optimization methods, it can be understood that metaheuristic algorithms are the best candidates for these kind of problems. Metaheuristic algorithms are iterative approaches which can search very complex large spaces to come up with an optimal or close to optimal solution(s). They are able to solve black-box global optimization problems which are not solvable by classic mathematical methods.

The first part of this thesis optimizes the control parameters for an eye-illusion, image enhancement, and image thresholding tasks by using an interactive evolutionary optimization approach. Eye illusion and image enhancement are subjective human perception-based issues, so, there is no proposed analytical fitness function for them. Their optimization is only possible through interactive methods. The second part is about setting of active contour (snake) parameters. The performance of active contours (snakes) is sensitive to its eight correlated control parameters which makes the parameter setting problem complex to solve. In this work, we

have tried to set the parameters to their optimal values by using a sample segmented image provided by an expert. As our case studies, we have used breast ultrasound, prostate ultrasound, and lung X-ray medical images. The proposed schemes are general enough to be investigated with other optimization methods and also image processing tasks. The achieved experimental results are promising for both directions, namely, interactive-based image processing and sample-based medical image segmentation.

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To All Human Rights Activists

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List of Acronyms

CG Computer Graphic

DE Differential Evolution

GP Genetic Programming

IEC Interactive Evolutionary Computation

IGA Interactive Genetic Algorithm

IO Interactive Optimization

MRI Magnetic Resonance imaging

Chapter 1

Introduction

A picture worth thousand words. – Japanese proverb in "New York Times, May 16, 1914"

If we take a close look around us, we can see variant applications of images in our daily life. In any area of expertise, we have to deal with images everyday. We all appreciate better quality in images and it makes our tasks much easier. This is the main reason behind all the efforts to achieve more in this field. There have been many efforts to improve image quality and other characteristic in an image in order to help professionals in their technical tasks. Nowadays, most of the images are digital; and digital image processing techniques are among the popular methods of improving images or elaborating more on some features in images to help out the users in different fields. Performance of all these techniques are highly dependent on their control parameters. Setting these parameters is difficult and needs good knowledge of image processing. In the current work, I have proposed a new approach to optimal parameters setting of image processing techniques without requiring any prior knowledge. By the proposed approach, any professional can obtain the optimal settings for control parameters corresponding to a specific image processing algorithm, ranging from image filtering to image understanding.

1.1 Motivation

Images and pictures have been a part of human being's life since the creation. If we go back in history, we can see the trace of images in caves. Cavemen used to draw objects on cave's walls. Ever since there has been plenty of changes in images. Nowadays, we see digital images every where. Applications of digital images are so diverse and almost in any field, the trace of digital imaging can be seen. To name some applications, we can mention, medical, engineering, criminology, film making, astrology, security, military, among many others.

When there is an image, the very first thing that crosses our mind is the qual-

ity. For sure, quality can affect the image impact in any field of applications. The better the quality the easier it is to work with. There have been many attempts to improve image qualities. That is why, we see high definition images every where nowadays. But beside capturing improvements, many works have also been conducted on improving images quality through programming and digital image processing techniques. Digital image processing techniques are not limited to image quality enhancement. They are used for many different purposes based in different applications. There is a long list of digital image processing techniques. Among many others, we can mention color correction, contrast enhancement, image enhancement, image morphing, color balancing, interpolation and image recovery, image registration, image recognition, image segmentation, thresholding, and image understanding.

A digital image can be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial coordinates, and the amplitude of f is the intensity or gray level of the image at that point (pixel). The amplitude of f are all finite and discrete quantities. Digital image processing techniques, work on these quantities to come up with a desired outcome. So, digital image processing is the process of working on these quantities with a computer and changing them around or selecting some desired ones in order to reach better images for a special application. Generally speaking, the performance of these techniques are dependent on some control parameters settings. In order to have a good result, these parameters should be set to optimal values, which are image-oriented values. The setting of parameters is not an easy task and it is a time consuming trail. It also requires a well knowledge of digital image processing. But, professionals in different fields do not have free time for that, and often do not have the image processing knowledge. The only thing that all professionals can share is the professional eye which can provide some sample gold images to work with them.

This gives us an idea that instead of trying to tune the parameters of digital image processing techniques for professionals, let them do it themselves using their own eyes, let say judgments. For sure, they have a better judgement in their own fields. On the other hand, it saves a lot of time and cost to tune the parameters. I give them the tools of tuning which user does not need any prior knowledge in digital image processing. The only thing, the user need is providing feedback on set of images or providing some sample images.

The search space for these parameters are from continuous values and some times there are a set of correlated parameters. The correlation makes the parameter setting problem more complex. Now, we are facing an optimization problem which can not be solved through straight forward classical methods. The current problem has not a well-defined mathematical objective function, so it is not solve able by classic methods. Usually the main approach for solving these problems is using metaheuristic algorithms.

Metaheuristic approaches can solve complex global optimization problems efficiently (including non-convex and/or nonlinear problems) which makes them a good choice for our parameters optimization. There are many different approaches which are classified as metaheuristics, such as, memetic algorithm, differential evolution, genetic algorithms, hill climbing, particle swarm, simulated annealing, and etc.

By using the metaheuristic algorithm, we are able to make a bond between optimization and digital image processing methods. By this way, any professional can use this approach to set the parameters optimally for their desired usage. This approach enables all people to use image processing procedures with out having deep knowledge about the procedures. Image processing techniques are complex and usually need a deep knowledge of programming and a strong mathematical background. But by using the proposed approach, the only thing which user needs

is a pair of eyes for providing subjective judgments (feedback). In problems with more than four parameters the direct subjective judgement can not be applied and instead, the gold image from a professional can be used to train the program.

1.2 Scope and Objectives

The proposed approach is an interactive algorithm which adjusts the image processing parameters to optimal values, based on user's feedbacks. People perceptions are different and the positive point of this approach is the fact that, it optimizes the parameters based on any individual perception. For example, some people may prefer bright images and some may prefer dark ones, thus this approach can set the parameters in a desired way based on their feedbacks. It enables users to lead the program so they may reach their desired goal. In professional fields, this advantage is really important since only a professional eye can find the target in the images and can direct the program in a way to elaborate more on those targets. This is really important when it is being applied to medical images. Identifying special organs or tissue or other features in medical images needs enough knowledge and expertise and usually is done manually by expert physician as a phase in treatment planning or diagnosis. But, a manual segmentation of images is time consuming. Only, the trained eyes of professional doctors can find region of interest (ROI) in these images, using the proposed approach enables them to elaborate more on those features. Untrained eyes may enhance a medical image in a different way and make it useless for experts.

The proposed approach in this thesis can be used in variant fields by professionals for different applications. In this work, I have focused more on medical image processing and tackled some problems in this field of image processing. The reason for that, is the face that images in this category are more challenging and there

are many useful variant applications for them. Nowadays, diagnostics are mostly dependent on digital images which can be found almost in any medical center. Usually medical images are noisy and applying image processing procedures to them are not effective. There are some challenging tasks in medical image processing like segmentation which is really hard and alot of research is being done on them. Optimizing parameters in these challenging fields make it a good candidate for our case studies in the current research.

For the current research, Differential Evolution (DE) algorithm has been utilized as an optimizer, but the proposed approach is general and this algorithm can be replaced by any other metaheuristic optimization algorithm. The main concept is optimizing the parameters through metaheuristic optimization methods. The reason for choosing DE algorithm is that, it is the-state-of-the-art algorithm and is proven to be one of the best algorithms among all population-based methods. I have also worked on some of the digital image processing techniques including: thresholding, enhancement, and segmentation, but these techniques can be replaced by any other image processing tasks. The only issue is to model the procedures in a way that they can be optimized based on user feedbacks, interactively or sample-based.

1.3 Outline of the thesis

Chapter 2 presents a background review on optimization in general and in particular it explains the DE algorithm. It also elaborates more on some digital image processing techniques which have been used in this work.

Chapter 3 explains the interactive evolutionary-based parameter setting. The results are provided and discussed in this chapter.

Chapter 4 describes the proposed sample-based evolutionary parameter setting.

This chapter is about segmentation in medical image processing and its parameter setting. It presents the comprehensive results for experimental verifications on ultrasound prostate, ultrasound breast, and lung X-ray images.

Chapter 5 presents the conclusion, contribution, and future work direction.

Chapter 2

Background Reviews

2.1 Optimization

Before saying anything about optimization, it is better to know what exactly optimization means. If we look up this word from the dictionary, it is defined as the act of achieving maximum efficiency. In mathematics, it is defined as a mathematical technique for finding a maximum or minimum value of a function of several variables subject to a set of constraints. The simplest example of optimization is to try to minimize or maximize a real function by choosing the values of variables from an allowed set of candidates.

All optimization problems are not straight-forward problems that can be solved through mathematical methods. Specially, when it comes to engineering problems, in most cases we have to deal with non-linear equations and the variables are correlated mixed type, so the conventional mathematical procedures can not be used. The approach for solving these problems is mostly the iterative approach, such as population-based algorithms. The algorithm checks the candidate solution iteratively to converge to the best solution. The problem with iterative methods is that sometimes the computational complexity is really high and it takes a long time for the program to converge to a solution. Specially, when it comes to large search spaces, the complexity gets higher. There is a special class of iterative approach which is called metaheuristic algorithm.

A metaheuristic algorithm is a computational method which optimizes a problem by trying to improve the candidate solution accuracy iteratively. This approach can search very large spaces of candidate solutions; that is why it can be used for combinatorial problems, which are NP-complete problems. In these kind of problems, the search-space of candidate solutions grows exponentially as the size of the problem increases. As I will explain later the search space for our problems are continues, and variables are correlated. Among all the metaheuristic optimization

approaches, I have chosen the DE. But the proposed approach to optimize the parameters in image processing procedures is not limited to just this method of optimization and any other metaheuristic method can be investigated to replace the DE.

DE algorithm was introduced by Ken Price's to solve the Chebychev polynomial fitting problem and this problem was posed by Rainer Storn [Price et al. 2005]. This algorithm was an amazing new approach for perturbing the population of the vectors (individuals) by using vector differences . DE does not use the gradient of the problem and works on multi-dimensional real-value functions which are not necessarily continuous or even differentiable.

DE is a simple, effective, and robust population-based optimization algorithm. I selected it since it offers a fast convergence rate and capability of working directly with real numbers which are the values for our parameters in image processing techniques.

The main idea behind DE is a scheme for generating trial vectors. Basically, for every vector in the population (called target vector), DE selects two other vectors randomly, then, subtracts them and adds the weighted difference to a randomly chosen third vector (called the base vector) to produce a mutant vector. Then, for every vector in the mutant population, it uses a user-determined value, called Crossover rate (Cr), to control the fraction of parameter values which are copied from the mutant and target vector to the trial vector. Finally, for the selection step, if the trial vector has an equal or lower fitness value (for a minimization problem) than that of its target vector, it replaces the target vector in the next generation; otherwise, the target vector retains unchanged at least for one more generation. These steps are repeated for every vector in the population to produce the next new population.

Algorithm 1 presents pseudocode of the classical Differential Evolution (DE)

[Rahnamayan 2007]. Three main operators (mutation, crossover, and selection) are given in lines 5-6, 7-13, and 15-19, respectively.

As it can be seen in the algorithm. DE is consist of four main parts. At first the population is randomly generated. Then the mutation happens. In mutation three members of the population are randomly selected and then a weighted difference of two of them is added to the third one which produces V_i. Next step is crossover. Depending on the crossover rate, each value in the vector can be selected from the noise vector (V) or the main vector (X) after this the trial vector (U) is ready for the last step. The last step is selection which is through evaluation of the trial vector. If the trail vector improves the solution for the problem then it will replace the main agent in the population otherwise it will be discarded.

2.2 Digital image processing

No matter where we live or what we do, we have to deal with images in our daily life. Almost all of us have had a camera at some point in our life. But images are not only those which are taken by people to save the moments. Nowadays, images are an integrated part of science and industries. So, it seems reasonable if people try to improve in image processing field, ranging from quality enhancement to image understanding.

In general, image processing is any form of processing for which the input is an image and the output can either be an image or set of extracted characteristics or parameters related to the image. Image processing usually refers to digital image processing, but optical and analog image processing are also possible.

Nowadays, there is not any area of technical endeavor which is not influenced by digital image processing. The areas of application of digital image processing are so varied and diverse that some sort of organization is desirable in attempting

Algorithm 1 Differential Evolution (DE) [Rahnamayan 2007]. P_0: Initial population, N_p: Population size, V: Noise vector, U: Trial vector, D: Problem dimension, BFV: Best fitness value so far, VTR: Value-to-reach, NFC: Number of function calls, MAX_{NFC}: Maximum number of function calls, F: Mutation constant, $rand(0,1)$: Uniformly generated random number, C_r: Crossover rate, $f(\cdot)$: Objective function, P': Population of the next generation.

```
Generate uniformly distributed random population P_0
while ( BFV > VTR and NFC < MAX_NFC ) do
  //Generate-and-Test-Loop
  for i = 0 to N_p do
    Select three parents X_a, X_b, and X_c randomly from current population
    where i ≠ a ≠ b ≠ c
    //Mutation
    V_i ← X_a + F × (X_c − X_b)
    //Crossover
    for j = 0 to D do
      if rand(0,1) < C_r then
        U_{i,j} ← V_{i,j}
      else
        U_{i,j} ← X_{i,j}
      end if
    end for
    //Selection
    Evaluate U_i
    if (f(U_i) ≤ f(X_i)) then
      X'_i ← U_i
    else
      X'_i ← X_i
    end if
  end for
  X ← X'
end while
```

to capture the breadth of this field. We can only mention some among many others, to show the broad range of image processing , including, image processing in medical imaging, astrology, aviation, computer vision, military application, security purposes, industries, universities and etc. It is quite obvious that digital image processing plays an important role in technology and industry. Due to the fact that most of this work has contributed to medical image processing. It is better to know more about medical imaging.

Medical imaging is the technique and process used to create images of the human body and organs. These images are for clinical purposes and help physicians in diagnostics or treatment planing process. There are different techniques to acquire these images such as: Radiography, Magnetic Resonance imaging (MRI),Thermography, Ultrasound, Tomography, and etc. Usually medical images have a higher level of noise in comparison to other images. This characteristic make medical images complicated to work with and they can be good candidates for our work since they are challenging tasks. Although, the current work can be applied to any kind of digital images and it is not limited to medical images only.

There are lots of digital image processing techniques. In this work, I have studied on some of them and tried to optimize their parameters. In the following sub sections, I introduce these techniques that have been utilized in our case studies.

2.2.1 Image Enhancement

Image enhancement is one of the most interesting areas of digital image processing. Basically, the idea behind the enhancement techniques is to bring out the details in an image which are obscured, or simply to emphasis some features of interest in an image. A familiar example of enhancement is increasing the contrast in an image to make it look better. It is important to mention that enhancement is a very subjective area of image processing.

The main objective of image enhancement is to process an image in order to achieve a result which is more suitable than the original image for a specific application. The word specific is very important, because it shows that these techniques are problem oriented. Meaning that, different techniques of enhancement can be used for different purposes. Regardless of the method used, however, image enhancement is one of the most interesting and visually appealing areas of image processing.

Image enhancement is completely subjective. When an image is processed for visual interpretation, the viewer can judge how well a particular method works. Visual evaluation of image quality is a highly subjective process, which makes the definition of a good image an elusive standard by which to compare the results. This nature of image enhancement leads us to use interactive optimization techniques to set the parameters for this specific method. This technique will be explained in the next chapter.

There are different techniques for image enhancement such as contrast smoothing, sharpening, contrast enhancement, contrast stretching, histogram processing, histogram equalization, and etc. The one that I have used for our work is a matlab *imadjust* function which adjust image intensity values or colormap.

2.2.2 Image Thresholding

Image thresholding is a method of image segmentation which applies to grayscale or color images. Thresholding is a challenging task and many techniques have been introduced to offer a global technique that can be applied to all kinds of images but because of the nature of images which are different,there is no a universal method. Thresholding segments an image into two classes (background and foreground, for bi-level thresholding) of black and white pixels based on the threshold value. The pixels greater than that value will be in white class and pixels lower than that value

will be in the black class.

Many methods are introduced for thresholding. One of the most famous ones is the Otsu method which tries to optimize threshold level by separating the black and white subsets so that their combined spreads is minimal (Nobuyuki Otsu (1979)). This technique is among the well-known techniques being proposed till now. That is why, I have compared our approach results with Otsu method's.

The key parameter in the thresholding process is the selection of the optimal threshold value. Several different methods for choosing a threshold value exist; it can be selected by trial and error process (which is very time consuming) , or a thresholding algorithm which can compute a value. I have used an Interactive Optimization (IO) method to set the thresholding value which will be explained later in chapter 3, but this approach can be applied to all kinds of images because it works based on the user's feedbacks so the user can manage the parameter settings to go towards a desired goal.

2.2.3 Image Segmentation

Segmentation is a process which subdivides a digital image into multiple segments that are sets of pixels. The goal of segmentation is to simplify or change the representation of an image into something which is more meaningful and easier to analyze. The level to which the subdivision is carried out depends on the problem being solved. Meaning that segmentation should stop when the object of interest in an application have been isolated. Image segmentation is typically used to locate objects and boundaries in images such as lines, curves, etc.. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

Image segmentation algorithms generally are based on one of the two basic properties of intensity values, discontinuity, and similarity. In the first category,

the approach is to partition an image based on abrupt changes in intensity, such as the edges in an image. The principal approaches in the second category are based on partitioning an image into regions that are similar according to a set of predefined criteria. Thresholding, region growing, and region splitting and merging are examples of methods in this category. I will explain more the segmentation and it's methods in chapter 4.

Chapter 3

Interactive Evolutionary-based Parameter Setting

3.1 Introduction

In this chapter, the main concept of Interactive Evolutionary Computation (IEC) will be introduced and surveyed. Then, the proposed interactive-based image processing methods are explained in detail. At the end of this chapter the experiment results for several case studies will be presented.

3.2 Interactive Evolutionary Computation (IEC): A background review

IEC or aesthetic-selection is a general term for methods and algorithms of evolutionary computation that gets human feedback for evaluation of the results. Usually human evaluation is necessary when the form of fitness function is not known or it is not possible to make a mathematical function for it. Example of these problems can be visual appeal or attractiveness; as in [Dawkins 1986]. Another example can be that, the result of optimization should fit a particular user preference, for example, taste of coffee or the color set of the user interface.

When, there is not any form of fitness function and no mathematical model can be defined for the problem then using the interactive evolutionary algorithm is reasonable. In this case, the user chooses or selects the best candidates in the generated population. Based on the user's feedbacks, the next generation can be generated. This method is widely used for problems which are related to human's perception one way or another and because there is no mathematical model for that, the only solution is to get the feedback from the user. In fact, user replaces the responsibility of the object function (for assigning the fitness value) and selection in an evolutionary process.

The main problem with this method is user fatigue which can affect the final

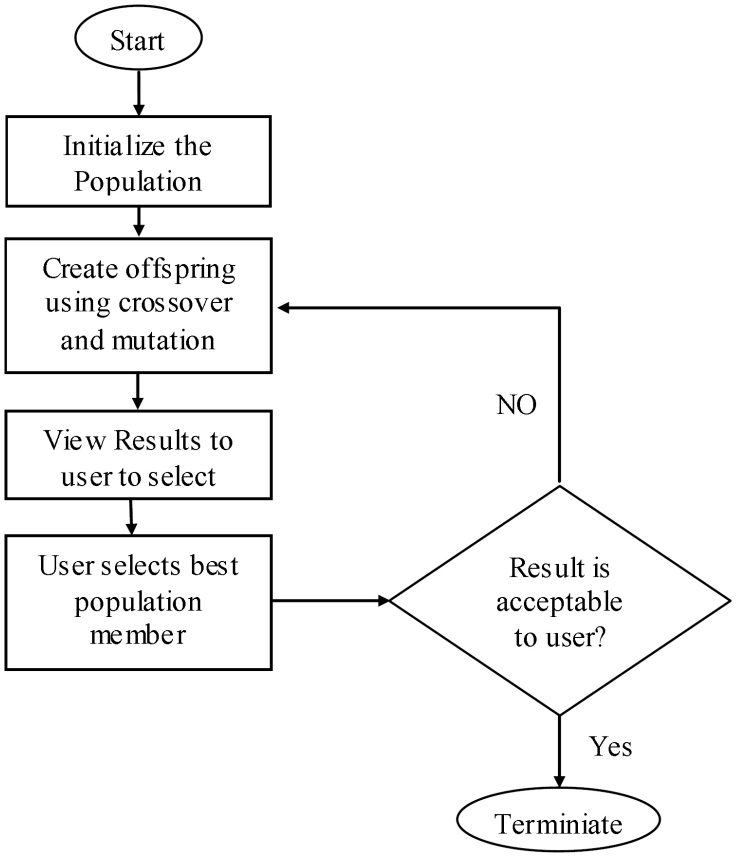

Fig. 3.1: General schematic of an IEC algorithm

result. If the problem consists of too many parameters and computation time and iterations are too long then it makes the user tired and the user's response can be degraded. To overcome this problem, the interactive evolutionary algorithm should be designed in a way that it tries to solve low dimensional problems which needs a small population size and small number of user feedbacks. Figure 3.1 presents a general schematic of an IEC.

Most of the works which have been conducted using IEC, are involved with human perception, such as, movies, images, tastes, music and art. It can also

be seen in engineering applications where there is no mathematical model for the problem.

To have a better idea about Interactive Evolutionary, methods I present a short survey in the following subsection.

3.2.1 Applications of IO methods in Graphics and Art Designs

IEC was introduced by Dawkins in 1986 [Dawkins 1986], [Dawkins 1988]. He utilized an L-system which tries to model the development of a plant in a mathematical way. He was able to create several insect-like Computer Graphic (CG) shapes by selecting the output of program subjectively. Many of other researchers have followed his footsteps to create CG shapes [Smith 1991], [McCormack 1993], [Ochoa 1998]. There are many other works on 2-D CG, based on mathematical approaches as follows: [Greenfield 1998], [Greenfield 2000],[Ito and Ishizaki 1999], [Raynal et al. 1999], [Unemi 2000]. Beside 2-D graphic shapes, IEC can also be used to render 3-D graphics, like animal graphic rendering [Graf and Banzhaf 1995]. Modeling moving objects can also be a good field for IEC such as, [Nguyen and Huang 1993], [Nguyen and Huang 1994] which are in airplane drawing and body design.

Genetic Programming (GP) can also be used to create CG shapes. In order to do so, linear and non-linear equations should be defined and the structure and parameters of these equations can be optimized by interactive approaches. There are interesting works which interacts with users to generate their desirable shape or concept of things [Iwasaki et al. 2000b], [Iwasaki et al. 2000a]. Mentioned researches are very interesting work about designing of a virtual aquarium, opened in Japan in 2001. They let the visitors to create their own 3-D fish by using an Interactive Genetic Algorithm (IGA). Visitors can choose the mathematical parameters

through IGA to create their own fish in the aquarium.

The IEC footprints can also be found in cartoon characters. One of the most famous examples of these characters is the Sims which has been produced by using evaluated CG based on mathematical equations [Sims 1991].

Lighting condition can affect 3-D CG drastically. The lighting-level can be judged by human vision, because choosing the best situation is a subjective task, positioning of lights and their colors can be enhanced through IEC to improve the 3-D design [Aoki and Takagi 1998].

All the mentioned projects up to now have been related to vision, but IEC is not limited to visual perceptions, it can be utilized interactively with other senses as well. Another interesting field of research for IEC is generating melodies and sounds [Biles 2000], [Onisawa et al. 2000], [Tokui and Iba 2000]. The first IEC-based music system was the sonomorphs. It has been developed based on the biomorph of Dawkins [Nelson 1993]. The user can choose the best melody by clicking on good or bad. It has also been used to create jazz melodies [Biles 1998].

Main problem of IEC-based approaches is human fatigue. If the process takes a long time, the user will get tired and this can affect the judgment and so the final outcome. The GenJam, a genetic algorithm-based jazz musician model, tries to fix this problem by giving the opportunity to evaluate melodies measure-by-measure instead of melody-by-melody meaning that the melody is being played and the user can give a real-time feedback on that phrase, and the fitness value will be assigned to that measure. This approach takes less time and can be more practical for human interaction-based approaches [Biles 1994]. There is a comprehensive but old survey paper [Takagi 2001] which covers many papers about IEC-based approaches. All the mentioned papers so far in this subsection - and many others with maybe more detailed explanations - can be found there.

There are other recent researches (2005-2011) about IEC and its applications

in graphics such as [Nishino et al. 2008] which tries to produce 3D graphic for cell phones or [Hastings et al. 2009] which is about designing computer graphics and animation . There are also some recent works in relation with music and sound design applications. An interesting research tries to compare a direct subjective approach with a physiological approach in music chord progression ([Fukumoto et al. 2010]). In [Sun et al. 2006], authors optimize the music choices based on user interactions. [Takagi and Ohsaki 2007] tries to utilize IEC in optimizin hearing aid fitting. More recent studies are summerized in Table 3.1 and Table 3.2 under variant categorizations.

There are many design fields that have been benefited by IEC approaches recently. There is a recent interesting paper about Persian rug pattern design [Dalvandi et al. 2010]. [Xiao-yan et al. 2010] is about curtain design. Another paper is related to make up face images [Arakawa and Nomoto 2005]. Even, the footprints of IEC can be found in food industry [M.Herdy 1997]. When it comes to a taste enhancement application, IEC approaches can play an important role since there is no mathematical model for human taste.

3.2.2 Applications of IO Methods in technology and engineering

The IEC boundaries are not limited to art and graphics design. Its applications can also be found in engineering design fields as well.

Image processing applications are one of the most interesting fields for IEC approaches. Extracting the affected areas or organs in medical images can be of a great value to physicians in their diagnosis and treatment planning. Only experts' trained eyes can evaluate these kinds of images. Developing programs for physicians to enhance their medical images through IEC-based approaches can be an inter-

esting field to follow by researchers. There is a research in designing image filters (noise removal) for MRI images and echo-cardiographic images [Poli and Cagnoni 1997]. There is another work on optimal image filters chain. Different combination of image filters can result different outputs in term of image quality, so finding the right combination can be done through human interactions. It is hard for amateurs to come up with the optimal order of image filters to enhance an image but it is easy even for non-expert users to choose the best image after being processed by different chained filters [Mutoh et al. 1998]. Combining interactive and non-interactive evaluations to speed up the optimization in image processing is another direction to tackle with the mentioned human fatigue problem [JakSa and Takagi 2003]. In [Katsuyama and Arakawa 2010] utilized IEC approach to set filter's parameters to reduce noise in color images. Another work tried to enhance the image quality through gamma correction. This work optimizes two parameters of gamma correction algorithms [Tokuda et al. 2007]. Reducing speckle noise in ultrasound images is another example of recent works [Morales et al. 2008]. More examples of recent papers in image processing are presented in Table 3.1.

Another recent attractive application of IEC is in controlling systems. Engineering applications of IEC has been started to appear with an insect-like six-legged robot design in 1992 [Lewis et al. 1992]. They have applied IEC to controlling the robot's leg movements system, the robot tries to learn walking gradually. Another project used the same approach to control an Eight leg robots movements [Gruau et al. 1996]. Another reserach has been conducted IEC to control obstacle avoidance by a small size robot [Dozier 2001]. There are some other recent papers in the same field, such as [Sato and Kubota 2009] which considers designing a robot, based on the user's preferences [Inoue and Miyagoshi 2007] which applies IEC in pet robot training.

As that mentioned before, the fingerprints of IEC can also be seen in engineering

design fields. Micromachine design or fabrication uncertainty cannot be modeled easily, but it is easy to human vision. A major problem for these cases is human fatigue due to large number of necessary evaluations. In order to solve this problem, human judgment can be utilized as a supervisory role to reduce the number of evaluations [Kamalian et al. 2005], [Kamalian et al. 2007]. An interesting paper [Inoue and Takagi 2008] is about architectural layout design. There are more recent miscellaneous applications for IEC which are summarized in Table 3.2.

Now, the applications of IO methods have been surveyed, I can present my approach. The next section presents our proposed approaches for eye illusion enhancement, image enhancement, and image thresholding.

3.3 Proposed Interactive-Based Image Processing

The main approach for all the following case studies is the same. The concept is to set the parameters for an image processing method by using an interactive evolutionary optimization algorithm. There is a user interface which receives the user feedback by pushing a button. User chooses the best candidate among four candidates which are shown on the screen. By using this approach, there is no need for fitness function and the user evaluation is used instead of that. So, the images can be directed toward what user prefers. Figure 3.2 illustrates an example of an interface which has been used in this work.

To the best of the author's knowledge, that is the first time which IEC is used in image thresholding and eye illusion applications.

The optimizer which was used in this work is a Differential Evolution algorithm. As it has been explained in the last chapter. The codes are implemented in Matlab.

Table 3.1: Recently published IEC papers

Category	Topic
Robotics	IEC for robot design support system [Sato and Kubota 2009]
	Behavior Evolution of Pet Robots with Human Interaction [Inoue and Miyagoshi 2007]
	Gait optimization of AIBO robot based on IEC [Eperjesi 2008]
	Interactive learning of consensus sequences in genetic programming for evolution of snake-like robot [Tanev 2007]
Graphics and Image processing	IEC-based mobile 3D graphics modeler [Nishino et al. 2008]
	Nonlinear denoising filter for images with IEC considering the subjective assessment [Arakawa and Nomoto 2008]
	Evolving colors in user interfaces by interactive genetic algorithm [Birtolo et al. 2009]
	A system for decorating QR code with facial image based on IEC and Case-Based Reasoning [Ono and Nakayama 2010]
	Software Environment for Research on Evolving User Interface Designs [Quiroz et al. 2007]
	Image quality enhancement support system by gamma correction using IEC [Tokuda et al. 2007]
	Interactive Genetic Algorithms for User Interface Design [Quiroz et al. 2007]
	Development and evaluation of a 3D graphics design system based on simulated human immune system [Nishino et al. 2007]
	Speckle Reduction Through Interactive Evolution of a General Order Statistics Filter for Clinical Ultrasound Imaging [Morales et al. 2008]
	Interactive Evolution of Particle Systems for Computer Graphics and Animation [Hastings et al. 2009]
	Color image interpolation for impulsive noise removal using IEC [Katsuyama and Arakawa 2010]
Music and Sound	Extended IEC using heart rate variability as fitness value for composing music chord progression [Fukumoto et al. 2010]
	Emotional Music Generation Using IGA [Zhu et al. 2008]
	A recommender system based on genetic algorithm for music data [Kim et al. 2010]
	Interactive Evolutionary Computation in music [Marques et al. 2010]
	Using Evolving Agents to Critique Subjective Music Compositions [Sun et al. 2006]
	Emotional Image and Musical Information Retrieval With Interactive Genetic Algorithm [Cho 2004]
	IEC-based Hearing Aid fitting [Takagi and Ohsaki 2007]
	Improvement of interactive EC fitting based on substitute evaluation using sound volume preference [Ohsaki 2009]
Design	(Interior Design) EMO-based architectural room floor planning [Inoue and Takagi 2009]
	(Software Design) Dynamic parameter control of interactive local search in UML software design [Simons and Parmee 2010]
	(Product Design) An improved evaluation method for interactive genetic algorithms and its application in product design [Yan et al. 2010]
	(Curtain Design) Grid-based knowledge-guided IGA and its application to curtain design [Xiao-yan et al. 2010]
	(Texture Design) A method of interactive texture design with IEC [Kagawa et al. 2008]
	(Rug Design) Exploring Persian Rug Design Using a Computational Evolutionary Approach [Dalvandi et al. 2010]
	(Outfit Color Design) An evolutionary fuzzy color emotion model for coloring support systems [Tokumaru and Muranaka 2008]
	(Flag Design) Constrained evolutionary art: Interactive flag design [Whigham et al. 2009]
	(Barcode Design) Barcode design by evolutionary computation [Ono et al. 2008]
	(Jewelry Design) Aesthetic evolutionary algorithm for fractal-based user-centered jewelry design [Wannarumon et al. 2008]

Table 3.2: Recently published IEC papers in miscellaneous areas

Category	Topic
Micromachines	Use of IEC with simplified modeling for computationally expensive layout design optimization [Kamalian et al. 2007]
Architecture	Layout algorithm for an EC-based room layout planning support system [Inoue and Takagi 2008]
3-D Sensation Modeling	A Method of Creating 3D Haptic Sensation Using Interactive Evolutionary Computation[Hiroaki et al. 2006]
Hearing Error	Simulating listener errors in using genetic algorithms for perceptual optimization [Baskent and Edwards 2007]
Geophysics	Interactive geophysical inversion using qualitative geological constraints [Chris and Peter 2007]
Artificial Environments	Proposal for a Framework for Optimizing Artificial Environments Based on Physiological Feedback [Hideyuki et al. 2005]
Database	An interactive evolutionary approach for content based image retrieval [Arevalillo-Herraez et al. 2009]
Gaming	The Seven Valleys: Capturing the Numinous in a 3D Computer Game Engine [Nelson 2008]
Synthesized Instruments	IEC Control of Synthesized Timbre [McDermott et al. 2010]
Text-to-Speech	Efficient and reliable perceptual weight tuning for unit-selection text-to-speech synthesis based on active IGA: A proof-of-concept [Alas et al. 2011]

3.3.1 Interactive-based Eye-illusion Image Enhancement

Eyes are one of the most important organs of the human being and we are all the reflection of what we have seen throughout our life. Eye illusion or vision illusion is an interesting topic which has been studied for many years and lots of illusive designs have been created as outcomes of these efforts. Everybody has seen at least one deceiving scene in their life. Figure 3.3 shows one of the famous eye illusion picture known as Bulging Checkerboard, the central bulge in the image is illusionary.

Illusion itself is a subjective issue since it is related to humans visual perception and it can vary from person to person. This characteristic makes the design process complex due to the fact that the final result should be illusive enough to deceive majority of people. A good procedure to achieve this goal is to collect the viewer's opinion and incorporate those ideas and feedbacks in the design to have a better

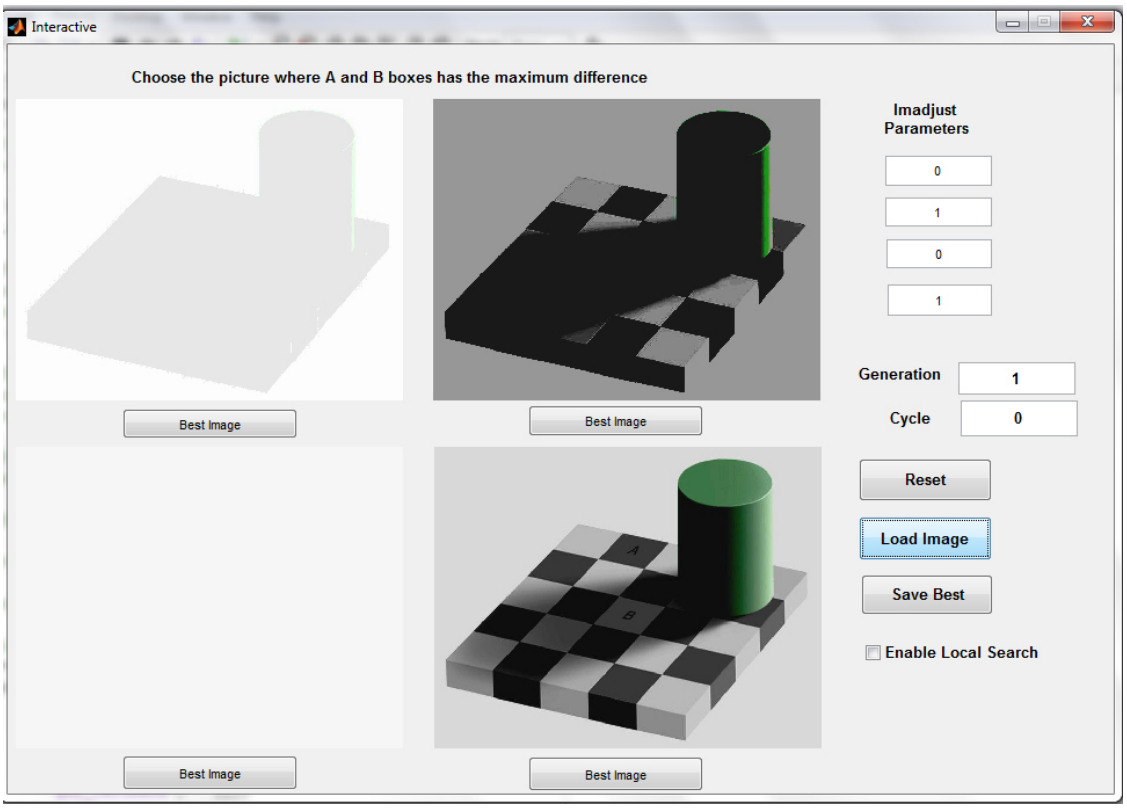

Fig. 3.2: Graphical Interface to receive user feedbacks.

result. This needs an interactive method so that the feedback of the user can be utilized in the design process. The program tries to improve the quality as well as the illusion factors. This method can be applied to different kind of pictures with variant applications.

The factors involved in the design of an illusive picture are too many and testing all the possible results is impossible, therefore, the best method is to use optimization methods to optimize the final outcome. For the reason of the subjective nature of this problem, using evolutionary algorithm seems to be meaningful. So, in this method since there is no mathematical model, users feedback is being used to select

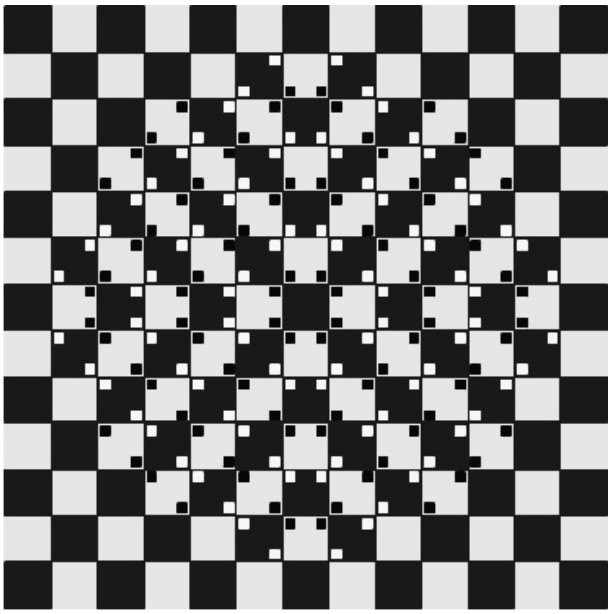

Fig. 3.3: A well-known eye illusion example known as Bulging Checkerboard, the central bulge in the image is illusionary [KITAOKA 2011].

the best candidate in the population.

The program is designed to manipulate images intensities using *imadjust* Matlab function. Imadjust function is used to map the values in the image matrix to new values in the resulted image such that the range of input values between minimum and maximum are mapped to output range with different minimum and maximum values, so four parameters are required by this function. This impose clipping all input values that falls below and above the output range and resets it to the boundaries of the output range. Since four parameters are required by imadjust the dimensionality of our problem is four as well. These four dimensions have the following constraints which should be addressed in our code:

- All parameters should be in range [0,1].

- The second parameter should be higher in value than first parameter.
- The fourth parameter should be higher in value than third parameter.
- The first and the third parameters should be kept less than one.

Differential algorithm is used to search the space of available solutions. Mutation algorithm used in DE will cause parameters to get values that violate the above mentioned restriction. A correction function is used to either properly re-initialize these parameters or to reset it to boundary limits.

Following is our proposed method:

1. Generate 40 uniformly distributed random individuals (so, the population size is 40, equals to 10 times dimensionality (D))
2. Correct populations to comply with criteria
3. Program start with Best member = original picture. It will be replaced later when new best member is found
4. While (user did not terminate)
5. While (end of population not reached)
6. View three picture of the population plus last best member
7. User choose a new best member or keep the previous one
8. End (inner while loop)
9. Generate new population using DE
10. Correct newly generated population

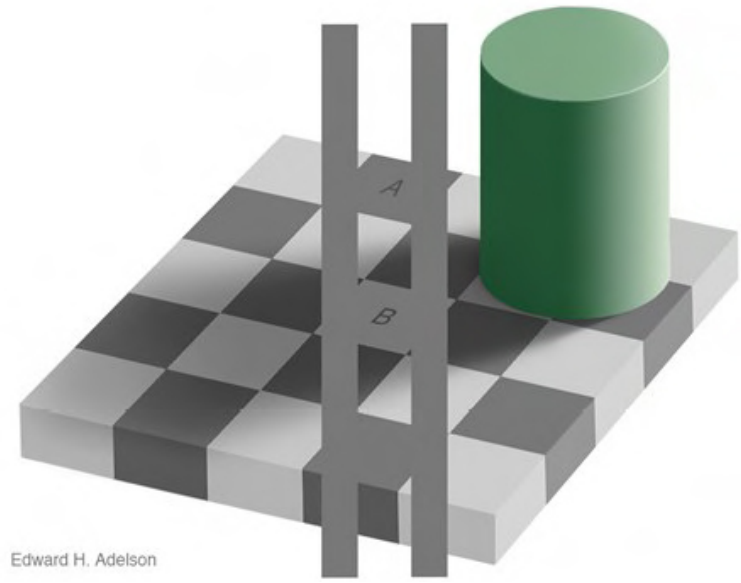

Fig. 3.4: Checker-Shadow Illusion [Adelson 2011].

11. End (outer while loop)

12. Save best member.

The program will generate 40 images in every generation to be evaluated by individuals. This is to comply with DE algorithm recommendations which states the number of populations should be between eight to ten times the number of addressed problem dimensions. The dimension for this problem is 4 so 40 images will be generated in each generation.

The first candidate for our program is the figure 3.4. As it can be seen in the image two straight lines prove that the squares A and B have the same color but due to illusion A seems to be darker than B.

Figure 3.5 shows the original image which has been enhanced after 30 generations. As it can be seen, the image gets better and better as the generations pass

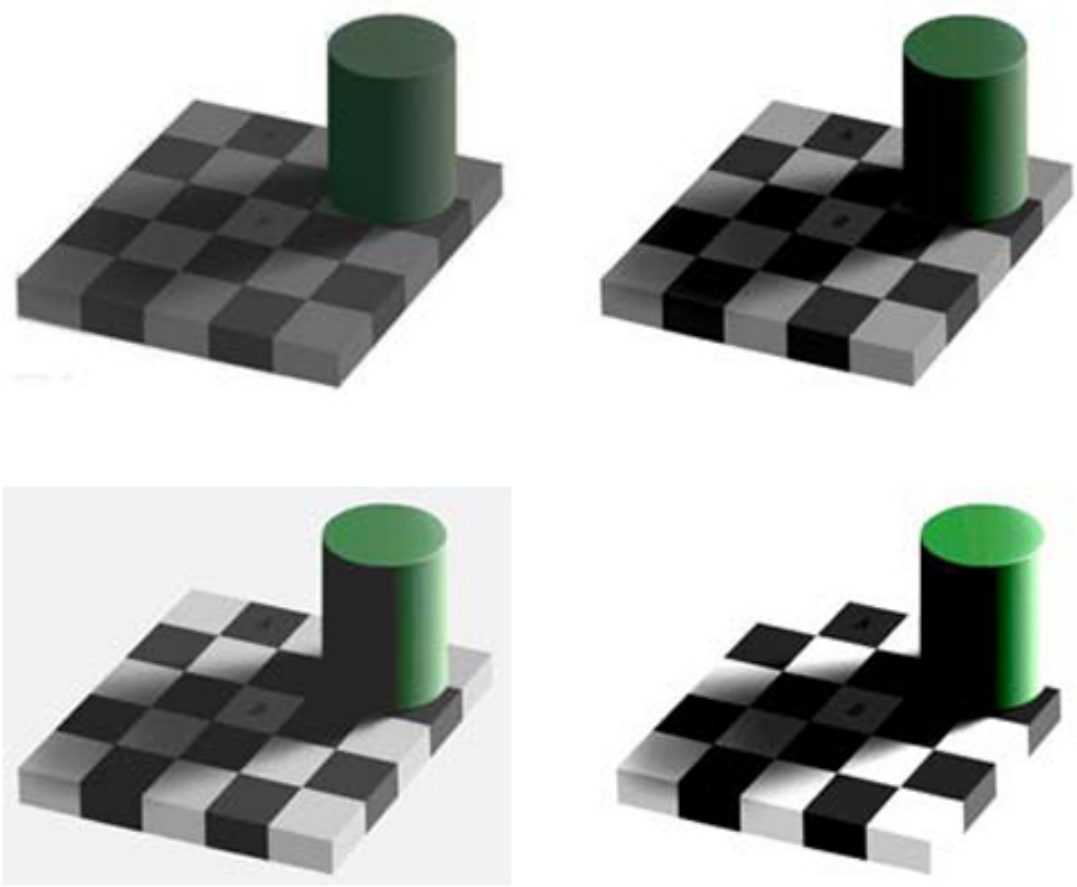

Fig. 3.5: The first experiment results with the original image as the initial image. top left: original image, top right: result after 10 generations, bottom left: result after 20 generations, bottom right: final result after 30 generations.

by. After 30 generation the result seems final and image can not be improved more. The image converged to this final result.

For the second experiment, I have started with a bad image which was dark and not clear. Figure 3.6 shows this experiment results. As it is clear in the figure the image has been enhanced after 50 generation and eye illusion is completely obvious in the final result.

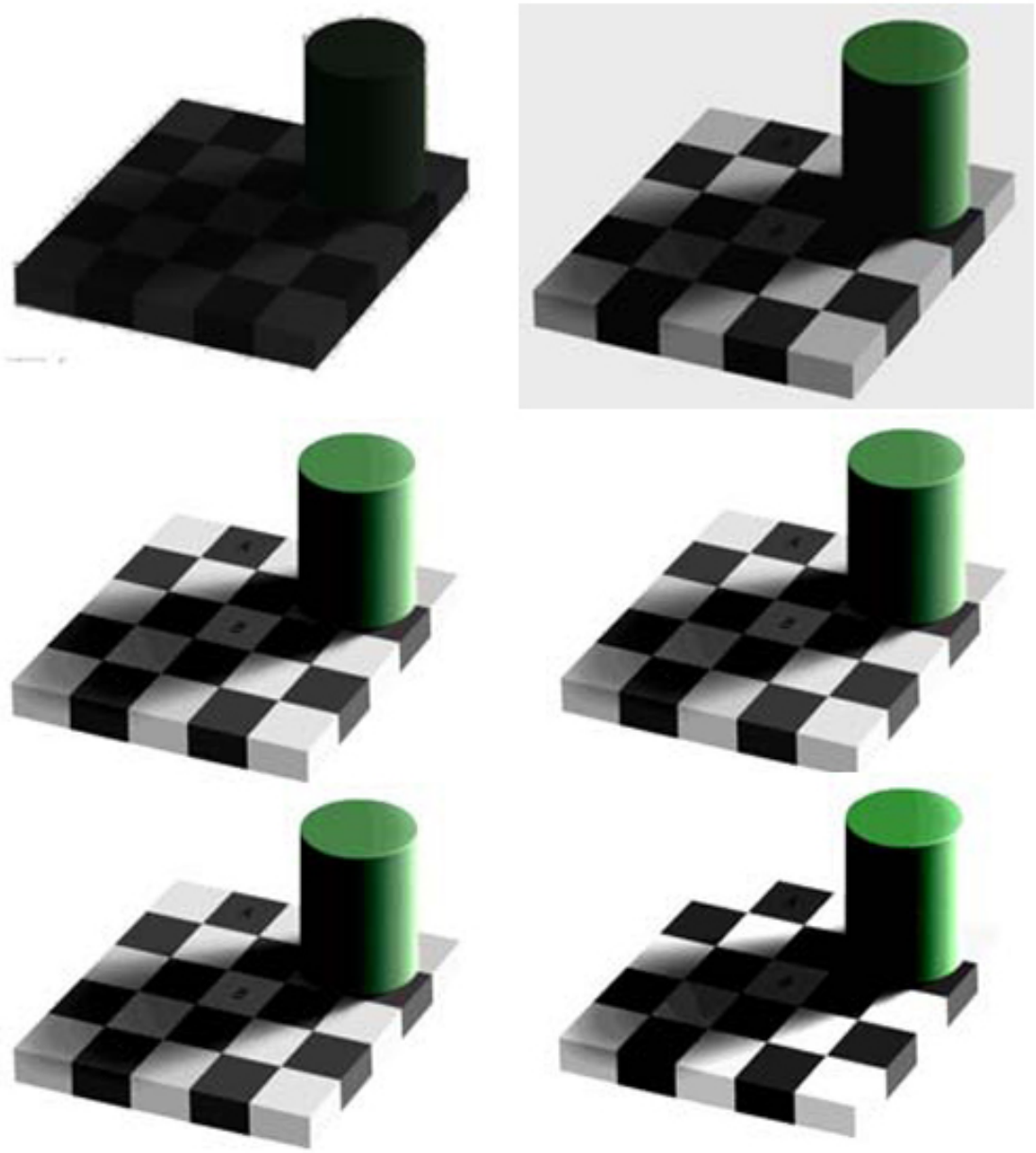

Fig. 3.6: The second experiment results. top left: initial image, top right:result after 10 generations, middle left: result after 20 generations, middle right: final result after 30 generations, bottom left: result after 40 generations, bottom right: final result after 50 generations.

As the third experiment, I start the process with a white image which the contrast in this image is really low. Figure 3.7 shows the results of this experiment. As it can be seen, again the proposed approach works well on this image.

The second candidate for our program is the famous checkboard illusion. As it is shown in figure 3.8 the straight lines of the checkboard seems to be curved due to the illusion. I tried to play around with the line thickness and arrangement of the black and white squares to improve the illusion factor in this image. For this experiments I have used five parameters as follows, separator line greylevel, separator line thickness, shift between the squares in the rows, number of pixels in each square, and number of tiles in each row. I have started with an image which does not represents the illusion factor much and tried to improve it interactively. The result is presented in figure 3.9.

At end of this section, it is necessary to mention that the proposed approach demonstrates a good result in eye-illusion experiments. Based on the results, one can say that the proposed approach can be used on eye-illusion images and it can enhance the eye-illusion as well as the image itself.

3.3.2 Interactive-based Image Enhancement

The experiments in last section showed that the proposed interactive-based approach can be applied to eye-illusion image enhancement. The promising results of last sub section give us the idea of applying this approach to other images. I have applied this method to medical images. The prostate ultrasound images are noisy and can be good candidates to test this approach. Figure 3.10 presents a prostate ultrasound image.

I have used the same program with the same user interface and parameters to enhance the prostate images (imadjust Matlab function). So the only thing which has been changed, is the input image which is a prostate ultrasound image. Figure

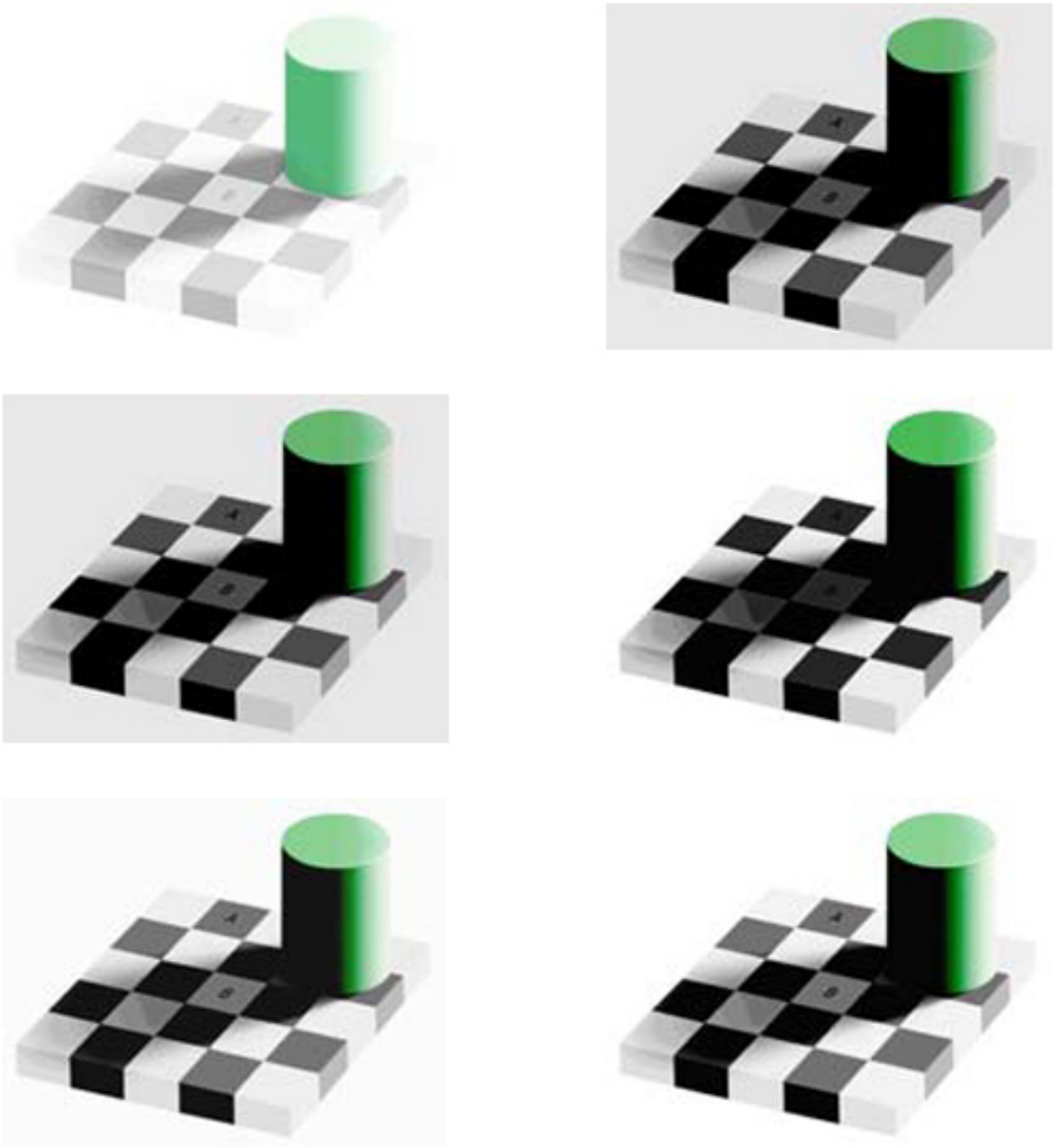

Fig. 3.7: The Third experiment results. top left: initial image, top right: result after 10 generations, middle left: result after 20 generations, middle right: final result after 30 generations, bottom left: result after 40 generations, bottom right: final result after 50 generations.

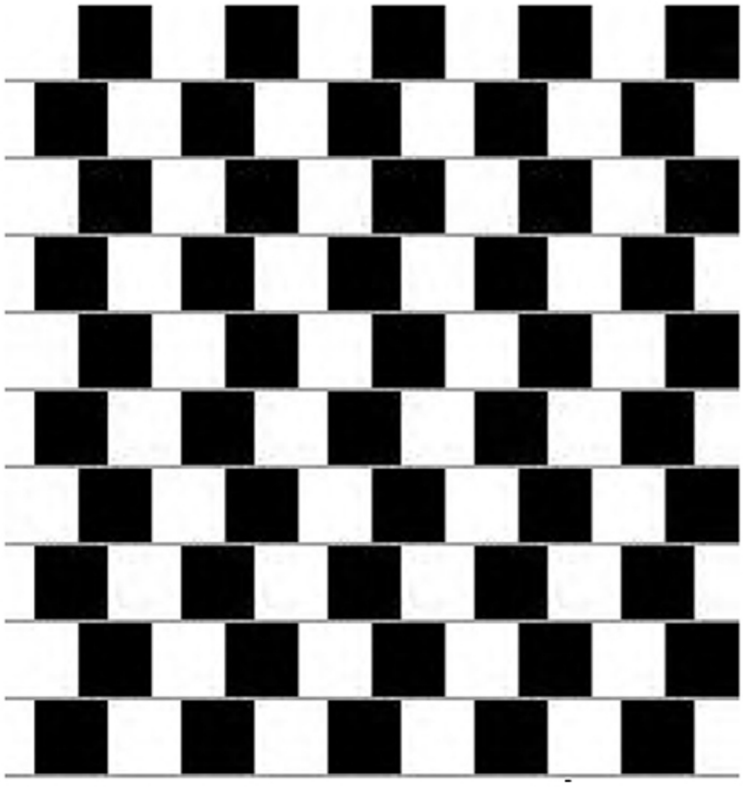

Fig. 3.8: Checkerboard illusion sample image

3.11 shows the results of this experiment. The images are all grey level images. As it can be seen the prostate can be seen better in enhanced images which is desirable. It is quite obvious that the proposed approach can enhance prostate ultrasound image as well and the contrast is enhanced to a good level that the prostate can be seen better in final results.

The desired thing about the current approach is that even amateur people can use it and they only need to choose the best image according to their opinions.

In the next subsection, an interactive-based image thresholding has been investigated.

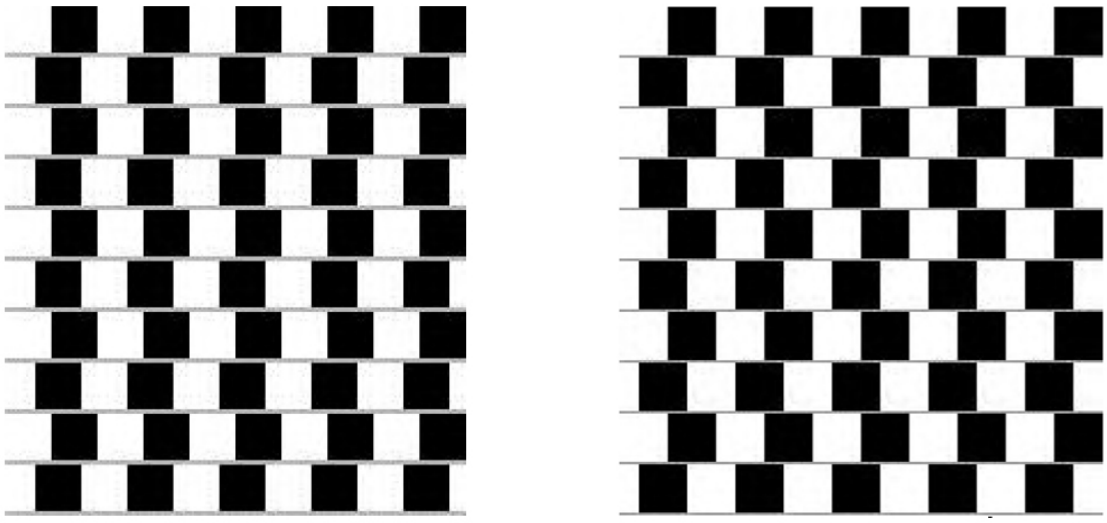

Fig. 3.9: Checkerboard illusion enhancement result. left: initial image without any significant illusion. right: optimized image after 10 generations.

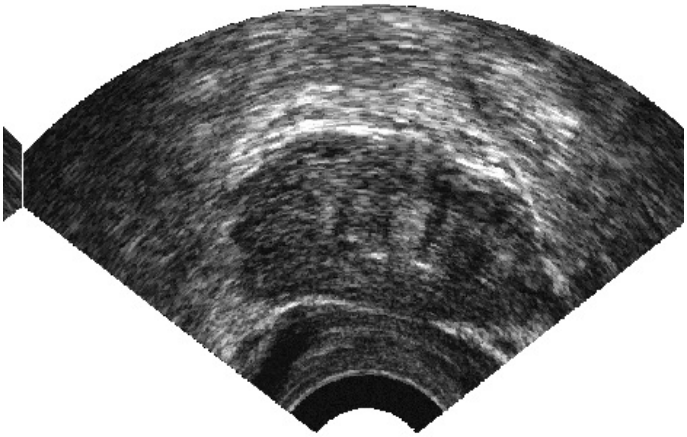

Fig. 3.10: A sample prostate ultrasound image (all prostate images are the courtesy of Robarts Research Center (London, Ontario, Canada)).

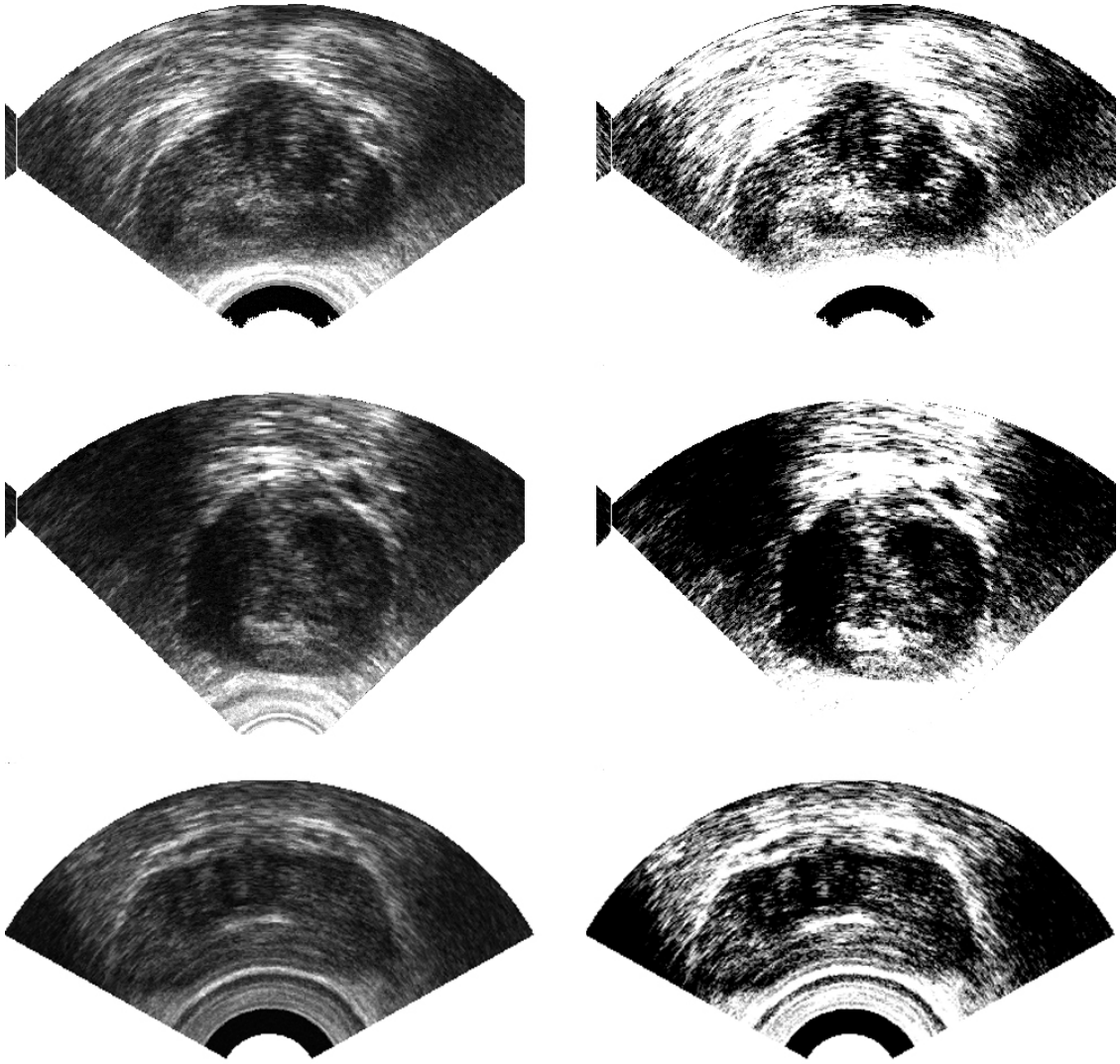

Fig. 3.11: Prostate ultrasound enhancement by Interactive optimization. left column: original input images, right column: enhanced images. (the courtesy of Robarts Research Center (London, Ontario, Canada)).

3.3.3 Interactive-based Image Thresholding

Segmentation is the process of partitioning an image into different sets. Image segmentation can be used for locating objects and boundaries in an image. The output of the segmentation process is a set of segments that cover the entire image. Each of the pixels in the region shares certain visual characteristics. This characteristic is related to the gray level of the pixels. A bi-level thresholding segments an image into two partitions of black and white pixels based on a threshold value. The pixels greater than that value will be in white partition and pixels lower than that value will be in black partition.

Thresholding plays an important role in medical image processing chain. This technique can be used to identify tumors and cancerous tissues in the body.

One of the common techniques of medical imaging is ultrasound imaging which uses high frequency broadband sound waves that are reflected by different tissue to produce an image. One of the main issues in ultrasound medical imaging is the noise. Due to the imaging nature and it dependency on sound, the quality of the image can be influenced easily and usually a lot of noise is involved in the final produced image. Due to the high amount of noise in the image, thresholding is not an easy task and usually even well-known techniques fail to properly threshold ultrasound images.

I have proposed an interactive method to set the value for thresholding in prostate ultrasound images. The proposed approach is very similar to the approach which has been explained before. The difference is that, I try to set the parameter for a thresholding value so there is only one parameter to be optimized. This means a fast convergence due to problem low dimensionality. The proposed approach is as follow.

In the current study a combination of interactive evolutionary algorithm with DE algorithm has been used to optimize the thresholding level for an image. There

is not any fitness function and the evaluation are taken place by a user. User chooses the best threshold image and based on that the value of thresholding level is calculated. The thresholding command of the Matlab has been used which accepts one variable as the thresholding level of the image ($output = im2bw(input, variable)$). The proposed approach uses the DE method to search the solution space to find the optimized solution based on the user selections. The thresholding value should be between 0 and 1 as well but as it can be seen in DE algorithm sometimes (because of the mutation operation) the values gets outside the search space so there is a code fragment to correct the value of the variable to keep them in the feasible area, so values more than 1 will be changed to 1 and values less than 0 will be changed to 0 for the next generation. Since, there is only one variable to be optimized; the population size is set to 10 (NP=10) and the mutation constant and the crossover rate are set to 0.5 (F=0.5) and 0.9 (CR=0.9), respectively. The values for the mentioned control parameters (NP, CR, and F) are set to commonly used values in literature ([Rahnamayan and Mohamad 2010], [Rahnamayan et al. 2009]). The proposed approach generates 10 images in each run to be evaluated by the user in order to find the best one. In the first run, 4 corresponding threshold images are shown on the screen and then the user selects one of them, this selected one stay in the screen and 3 more images are generated then again the best one is selected and 3 more images appear, after selecting the best one, this time the first generation run is completed and it goes to the second generation. The process continues like this until the images are so close and the value is converged to a fixed amount then optimized thresholding level can be stored for that image.

The user interface is very similar to the one which has been explained before. Figure 3.12 presents the interface of thresholding method. As it can be seen only one parameter is on the right side of the figure which is the thresholding value that needs to be set. This program runs fast because it solve a one dimensional

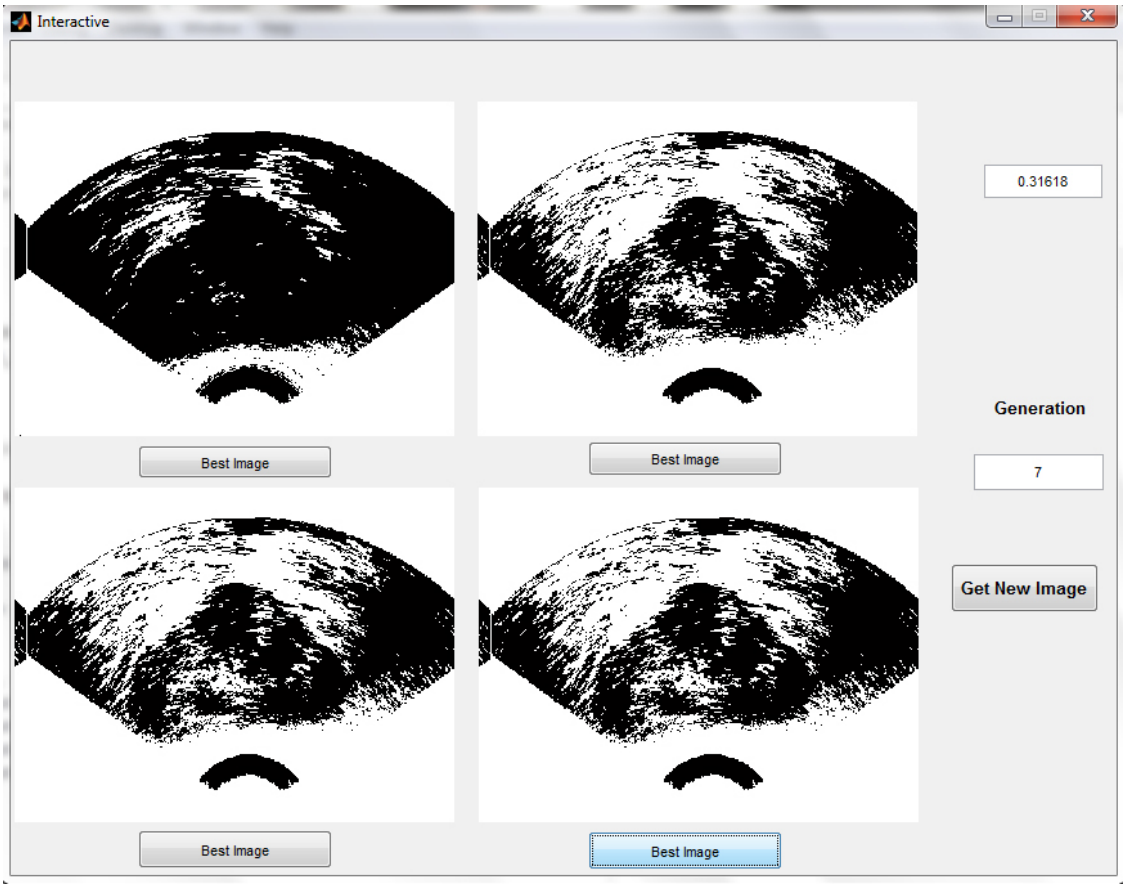

Fig. 3.12: The designed user interface for interactive image thersholding.

problem.

Before presenting the tables and the comparing results of the Otsu's, it is better to introduce some measures which have been used for comparing the methods.

Following definition and metrics are utilized to report the numerical value for comparison of two techniques.

- True Positive: Tissue pixels (foreground) correctly diagnosed as tissue pixels.
- False positive: Non-tissue pixels (Background) incorrectly identified as tissue

pixels.

- True negative: Non-tissue pixels correctly identified as non-tissue pixels.
- False negative: Tissue pixels incorrectly identified as non-tissue pixels.
- $Precision = (number\ of\ true\ negative\ pixels)/\ (number\ of\ true\ negative\ pixels + number\ of\ false\ positive\ pixels)$
- $Sensitivity = (number\ of\ true\ positive\ pixels)/\ (number\ of\ true\ positive\ pixels + number\ of\ false\ negative\ pixels)$
- $Overlap = (number\ of\ true\ positive\ pixels + number\ of\ true\ negative\ pixels)/\ number\ of\ total\ pixels$

The first set of images that has been compared is set of ultrasound prostate images. Ten images are provided in Figure 3.13. As it can be seen, the results of interactive optimization method is by far better than Otsu method's. Almost in all of the cases the tissue boundaries can easily be detected by interactive method but in Otsu method the tissue is not clear and the boundaries cannot be seen. This experiment was conducted on 33 prostate images and for all of them the interactive method offers better result than the Otsu method. Only 10 sample images are provided in this figure.

Table 3.3 and Table 3.4 summarized the numerical results of thresholding for both proposed method and Otsu method. By comparing these two tables, it can be understood that the interactive method offers a higher overlapping for all the images. The average sensitivity for Otsu method is larger value but from the definition of sensitivity, it is clear that Otsu method takes more pixels as tissue pixels which leads to a larger area of white pixels in the thresholded image without clear borders of the prostate. Meaning that although Otsu covers more pixels of

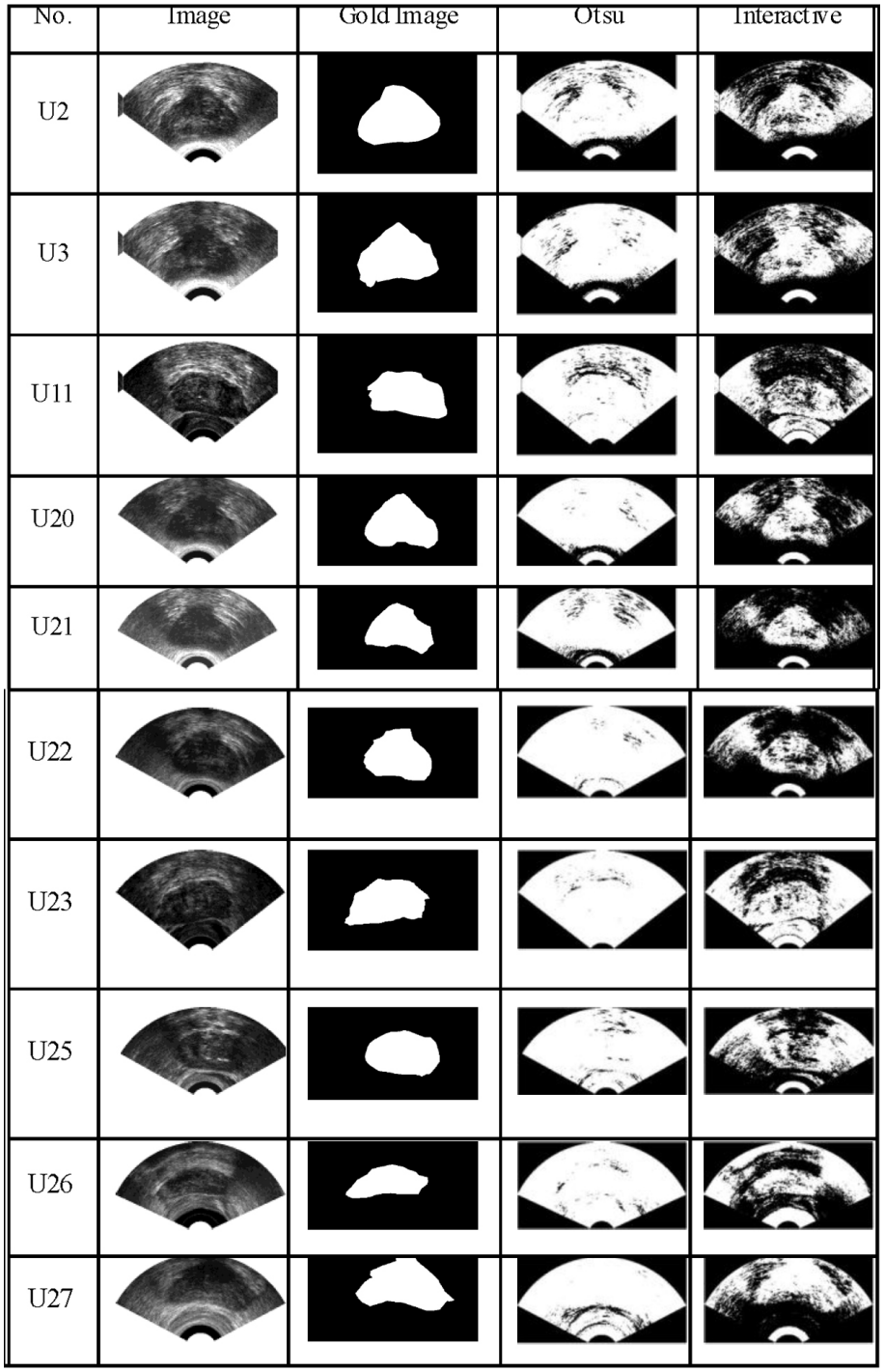

Fig. 3.13: Thresholding results for the prostate images, interactive-based method Vs. Otsu's method.

Table 3.3: Thresholding results of interactive method for prostate images.

No.	Interactive Level Value	Overlap	Precision	Sensitivity
U1	0.32	76.91	77.68	73.27
U2	0.34	78.19	79.63	71.41
U3	0.33	78.42	79.02	75.44
U4	0.30	69.54	68.81	73.75
U5	0.28	71.32	70.61	79.94
U6	0.27	76.14	76.11	76.31
U7	0.48	70.79	70.42	73.84
U8	0.46	74.13	73.95	75.49
U9	0.23	68.66	69.32	63.38
U10	0.39	69.23	67.05	82.63
U11	0.23	74.05	75.35	66.17
U12	0.54	68.65	66.15	85.77
U13	0.50	74.57	73.57	81.27
U14	0.34	64.01	62.68	75.19
U15	0.21	66.74	68.60	52.09
U16	0.60	60.55	54.29	85.90
U17	0.39	74.75	74.23	76.67
U18	0.38	66.56	58.66	95.52
U19	0.29	69.51	65.73	82.24
U20	0.24	79.89	82.83	66.70
U21	0.28	86.72	89.47	72.39
U22	0.15	76.89	81.33	54.59
U23	0.22	66.52	44.12	78.86
U24	0.17	69.17	69.35	68.39
U25	0.23	68.67	69.22	65.93
U26	0.28	67.71	67.10	72.14
U27	0.29	80.03	79.55	81.74
U28	0.35	67.98	64.60	88.01
U29	0.33	66.16	59.55	87.97
U30	0.44	53.65	48.98	80.05
U31	0.36	61.04	55.06	80.70
U32	0.39	59.17	55.62	82.00
U33	0.56	48.85	41.35	97.13
Average	**0.34**	**69.85**	**68.48**	**76.30**

Table 3.4: Thresholding results of Otsu method for prostate images.

No.	Otsu Level Value	Overlap	Precision	Sensitivity
U1	0.62	68.49	62.22	98.29
U2	0.64	68.27	61.98	97.93
U3	0.64	66.32	59.92	98.02
U4	0.59	64.99	59.28	98.14
U5	0.58	67.23	61.26	97.51
U6	0.60	65.74	59.51	99.54
U7	0.66	64.15	60.63	93.06
U8	0.64	66.56	62.72	94.93
U9	0.59	58.68	53.72	98.28
U10	0.62	62.60	56.91	97.49
U11	0.59	62.39	56.52	97.75
U12	0.66	64.21	59.91	93.64
U13	0.67	65.44	60.89	95.97
U14	0.60	58.74	53.88	99.33
U15	0.60	52.74	46.73	99.94
U16	0.63	60.22	53.08	89.13
U17	0.64	72.06	64.93	98.13
U18	0.60	59.00	47.95	99.54
U19	0.60	60.34	48.83	99.08
U20	0.63	59.51	50.51	99.84
U21	0.66	58.78	50.87	99.94
U22	0.60	53.51	44.25	99.93
U23	0.58	55.28	46.68	99.42
U24	0.58	59.43	50.57	99.80
U25	0.60	54.84	45.94	98.90
U26	0.62	48.13	41.06	99.45
U27	0.62	61.56	50.72	99.85
U28	0.63	52.81	44.96	99.35
U29	0.60	60.57	48.74	99.67
U30	0.62	52.48	44.17	99.38
U31	0.6	56.69	43.96	98.54
U32	0.62	52.73	45.48	99.27
U33	0.62	47.33	39.34	98.74
Average	**0.62**	**60.05**	**52.67**	**98.11**

the tissue but it takes a lot of background pixels as well. The average Precision value from interactive method is greater than Otsu method for all the images cause it deals with the background pixels and as it can be seen in Figure 3.13 the background pixels are better partitioned in the interactive method.

The average overlap in interactive method is 10% higher than the Otsu method's which is a significant value.

Figure 3.14 demonstrates the threshold level of all the 33 images for the interactive optimized method and Otsu method. All the values of Otsu method are larger than the interactive optimized method. Furthermore, Otsu's threshold values show low fluctuation than the proposed method, because interactive method performs dynamically, unlike the Otsu method which just follows a mathematical algorithm.

Figure 3.15 shows the overlap ratio of the both methods and it is clear that the overlap for interactive method is higher than Otsu method's.

Figure 3.16 presents the precision rate for both, and it can be seen that precision rate is higher for the interactive method.

Finally, Figure 3.17 presents the sensitivity rate and as it was mentioned before it's higher for the Otsu method because it takes more white pixels so it finds more tissue pixels but on the other hand it selects lots of background pixels by mistake which is not desirable and makes the final result confusing and useless.

In general, it is clear that the proposed technique works better with prostate ultrasound images and the threshold results are clearer. As it can be seen on the images the boundaries of the tissue are clear in the interactive optimized threshold images but on the other hand in the Otsu method images the prostate boundaries are not clear.

The second set of images is 27 real-world images. Since the amount of noise involved in these images is not high the Otsu method performs better than the prostate images. But, again the result of interactive method is better than Otsu

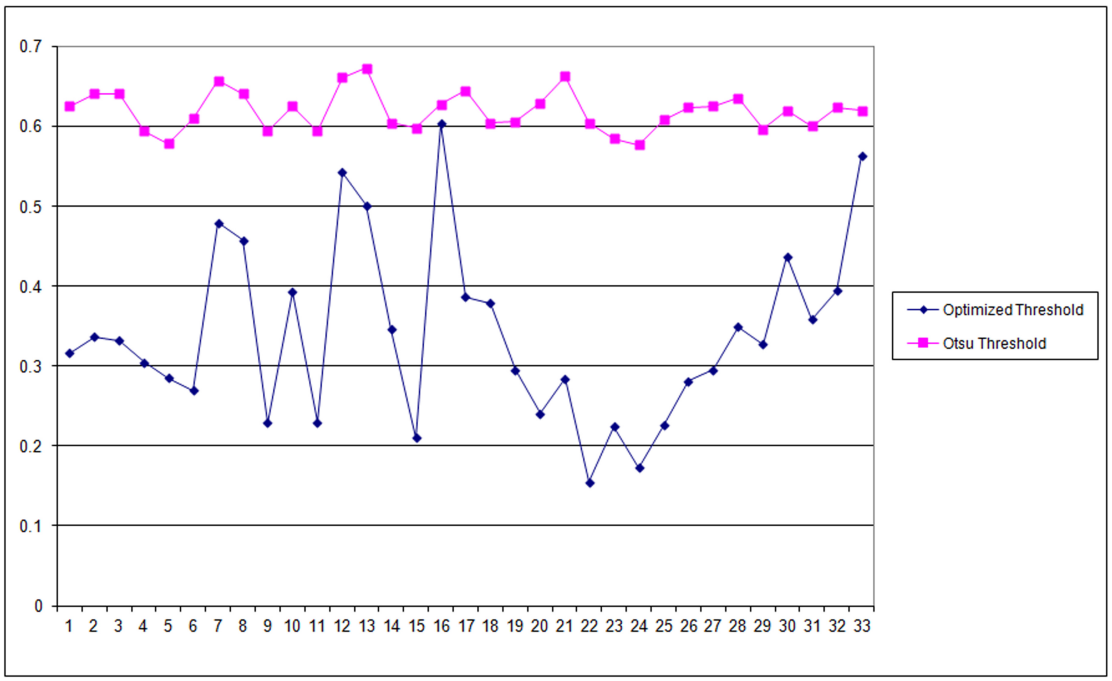

Fig. 3.14: Thresholding level chart for the proposed method and Otsu method.

method's.

Due to the fact that in this kind of images there is no just a tissue (single object) so the only attractive measure is the overlapping ratio which defines how many pixels of the results are the same as gold image.

As it can be seen in Table 3.5. the overlap ratio for all the images is either more or the same for interactive method.

In Figure 3.18 five sample images are shown which has much better results with interactive method than Otsu method. For example, for image number 16 the proposed method's overlapping ratio is almost fifty percent more than Otsu method's which is a significant difference. By looking at this five images, it is obvious that the proposed approach performs better than Otsu method even on

Table 3.5: Thresholding results for real-world images.

No.	Threshold value for Interactive method	Overlap	Threshold value for Otsu method	Overlap
1	0.35	99.31	0.34	99.31
2	0.23	99.2	0.39	98.26
3	0.30	99.32	0.49	98.46
4	0.08	98.69	0.27	97.56
5	0.23	90.73	0.49	82.05
6	0.42	93.47	0.47	90.85
7	0.65	97.84	0.52	96.10
8	0.63	91.98	0.72	78.14
9	0.70	93.28	0.68	93.00
10	0.25	94.29	0.34	74.94
11	0.56	97.42	0.50	95.99
12	0.13	95.75	0.28	93.84
13	0.69	99.69	0.68	99.68
14	0.50	100	0.49	100
15	0.83	99.74	0.70	97.04
16	0.55	99.88	0.36	49.92
17	0.47	99.78	0.32	63.74
18	0.32	98.06	0.41	95.38
19	0.73	98.70	0.65	85.07
20	0.23	98.68	0.31	93.03
21	0.58	99.91	0.60	99.87
22	0.63	99.85	0.62	99.81
23	0.30	99.02	0.31	98.03
24	0.16	99.57	0.31	94.74
25	0.58	97.00	0.50	95.93
26	0.18	98.34	0.48	91.17
27	0.68	93.34	0.68	93.34
Average	**0.45**	**97.5**	**0.48**	**90.9**

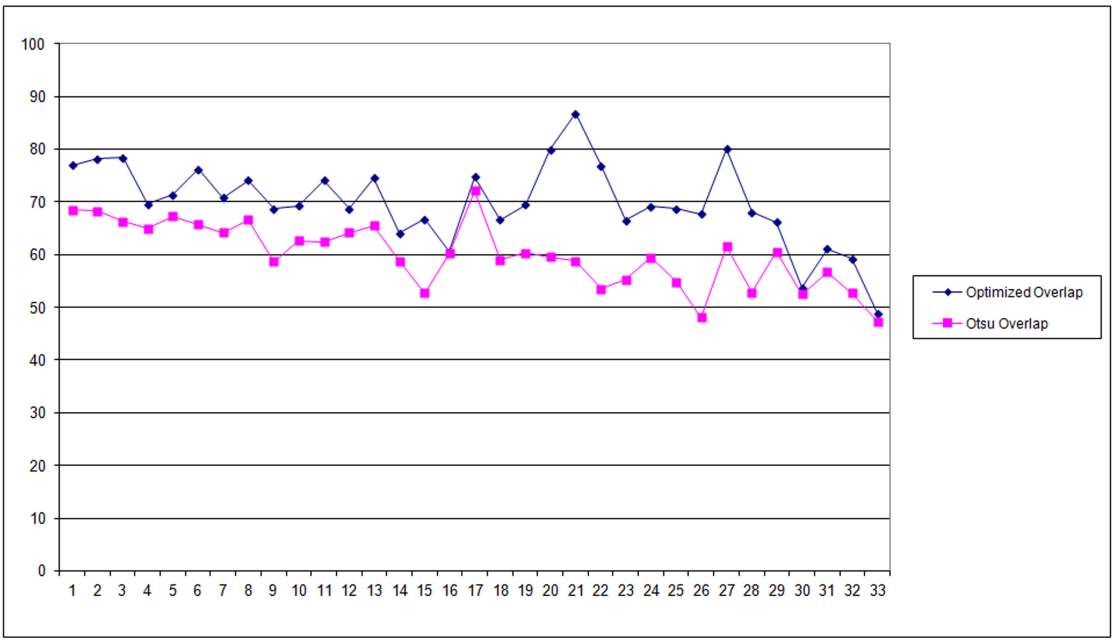

Fig. 3.15: Thresholding overlap chart for the proposed method and Otsu method.

the real-world sample images. Image number 8 is a text example, the thresholding result of Otsu method is not readable but in the result of interactive, method the whole text is readable.

Figure 3.19 demonstrates the threshold value graph of these two different approaches as it can be seen for real-world images the threshold values are near each other and there is no special trend for the differences in between the two methods.

Figure 3.20 compares the overlapping ratio of the methods and, as it can be seen in the graph, they are near each other but for some images interactive method offers better overlapping results.

In average, it is obvious that interactive method offers a more universal and robust results compared to Otsu method.

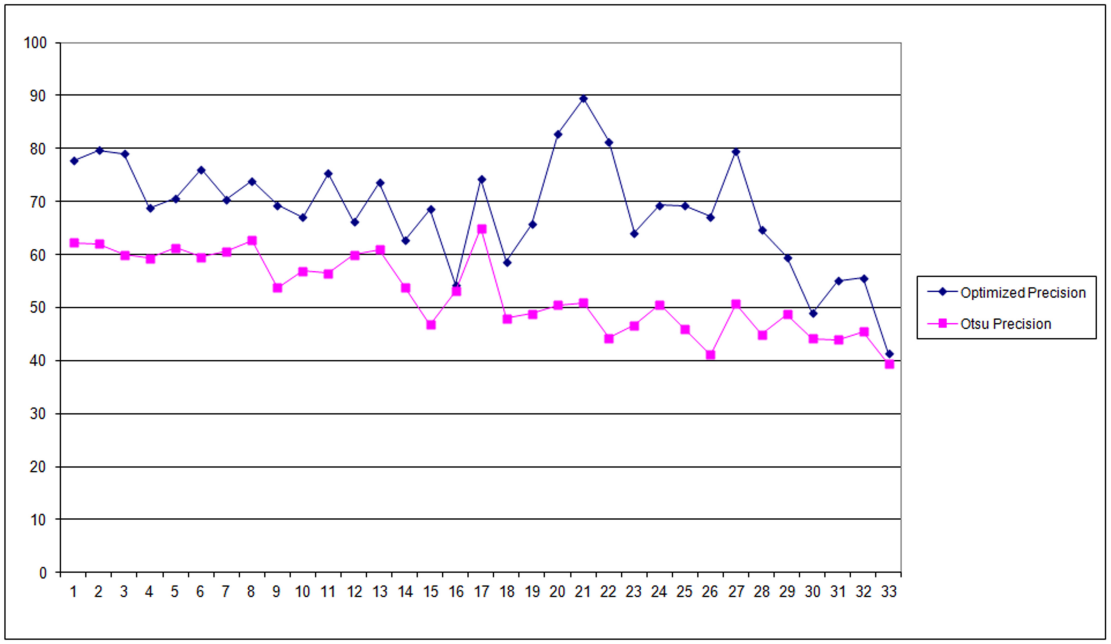

Fig. 3.16: Thresholding precision chart for the proposed method and Otsu method.

3.4 IEC Learning Ability

One interesting approach that can be incorporated in the system, is recording the history of the training. This can be saved in a Log file and for next run of the program, it can be loaded. This can improve the initialization of the system and give it a hot initialization. Since the initial population is from a better space the convergence can happen faster. The other advantage of this approach is when the user make a mistake in choosing the best member. Instead of resetting the program to the start point, the program can be reset to the last generation since it is saved in the log file.

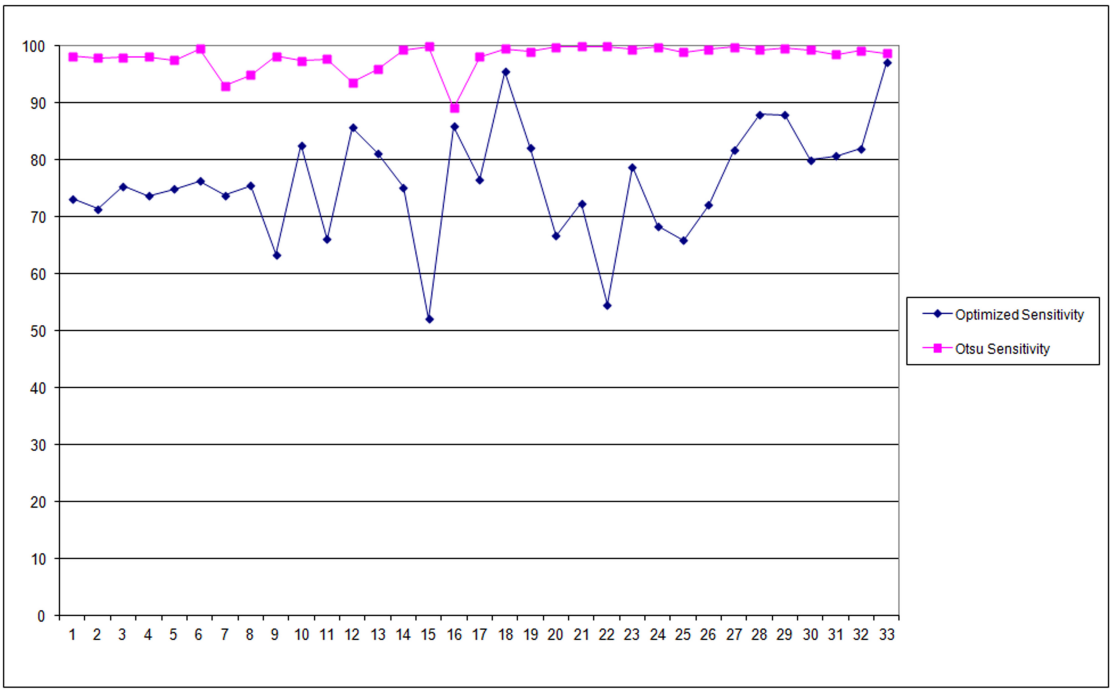

Fig. 3.17: Thresholding sensitivity chart for the proposed method and Otsu method.

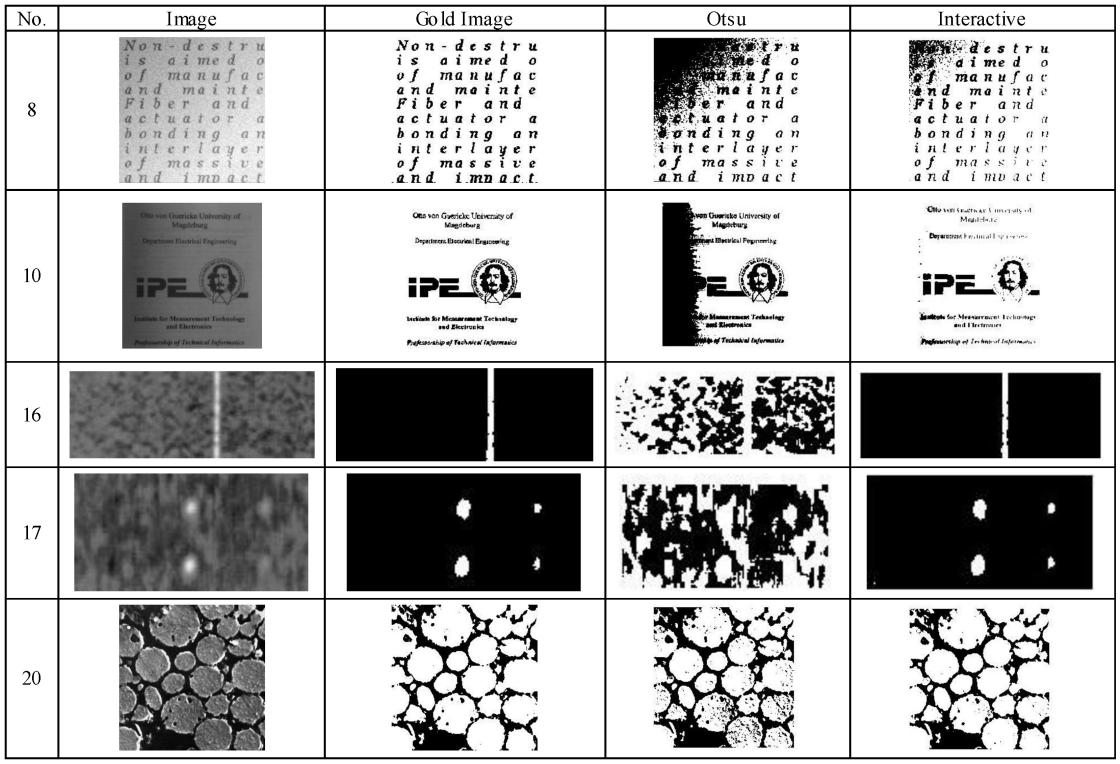

Fig. 3.18: The results of threshoding for real-world images.([Sezgin and lent Sankur 2004])

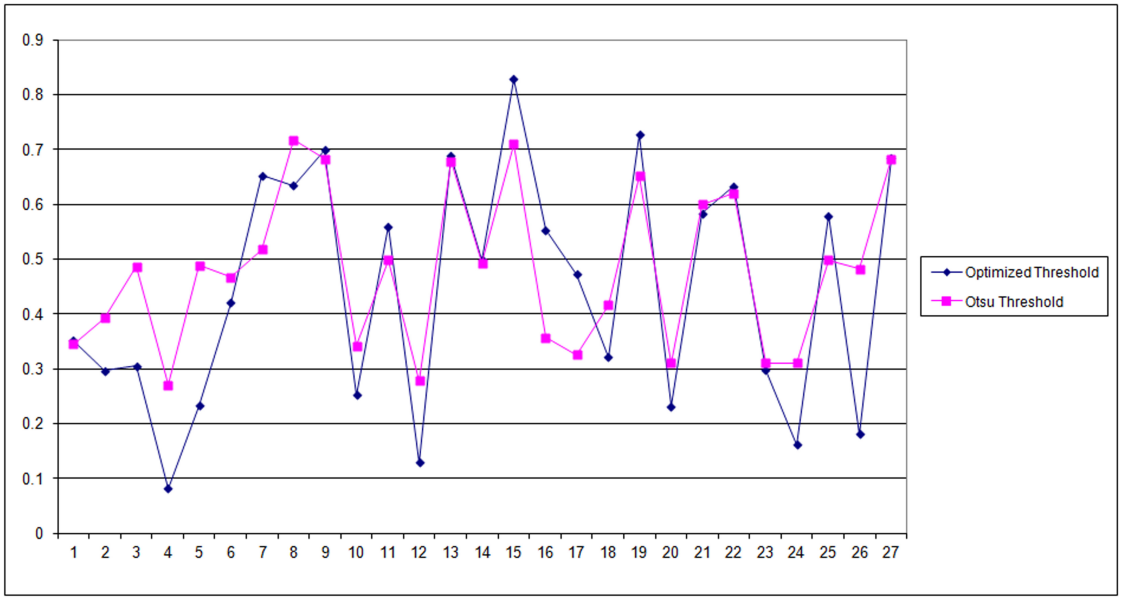

Fig. 3.19: Thresholding level chart for the proposed method and Otsu method.

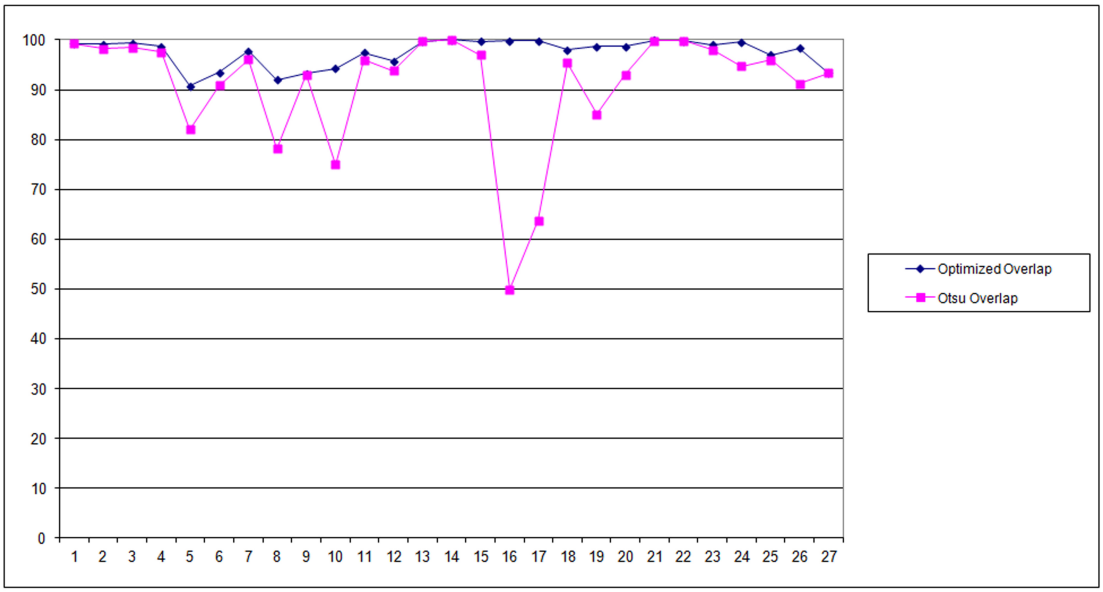

Fig. 3.20: Thresholding overlap chart for the proposed method and Otsu method.

Chapter 4

User Prepared Sample-based Evolutionary Parameter Setting

4.1 Introduction

Identifying special organs or tissues in medical images needs enough knowledge and expertise; and it usually is performed manually by expert physicians during treatment planning and diagnosis. Computer aided methods can speed up this time consuming process but due to high level of noise and low quality of these images, targeting accurate results is highly challenging.

In medical images, segmentation can be used for extracting tumours or cancerous organs for measuring their volumes, computer-guided surgery, diagnosis, treatment planning, and study of anatomical structure changes. There are many variant techniques for segmentation, such as, thresholding [Gonzalez 2002], clustering [Dunn 1974], histogram-based approaches [Qin et al. 2010], edge detection [Canny 1986], active contour [M.Kass et al. 1988], level set [Osher and Paragios 2003], and graph partitioning methods [Shi and Malik 2000], among many others.

Fig. 4.1: Example of medical images. Left: Lung X-ray, Middle: Breast ultrasound, Right: Prostate ultrasound

Obviously, none of them is a universal method applicable to all kinds of image modalities. The images I have worked on are prostate and breast ultrasound images and lung X-rays. Both of these images are hard to segment, specially the ultrasound ones. I will present a short literature review on medical image segmentation of these kind of images. Figure 4.1 presents the types of medical images which have been used in our case studies.

4.1.1 Medical Image Segmentation: Background Review

One of the most useful and crucial tasks is segmentation. Segmentation can help physician in diagnoses as well as treatment planing process. The major obstacle in medical images for segmentation is the high level of noise. One of the most challenging images to segment is ultrasound (US) images (i.e., breast and prostate ultrasound images). The high level of noise as well as shadows makes the segmentation a difficult task in US images . Active contours are used to carry out motion estimation tasks in US images [Dias and Leitao 1996],[Mikic et al. 1998]. Textural classifiers have also been used to detect pathology in US medical images [Mojsilovic et al. 1997],[Kadah et al. 1996]. [Zimmer et al. 1996] is another

research about thresholding based on intensity and texture statistics to segment ovarian cyst .

One of the most successful approach in ultrasound image segmentation is deformable models which has been utilized to segment echocardiograms [Coppini et al. 1995], [Sonka et al. 1995], [Jones and Metaxas 1997], [Kucera and Martin 1997]. There is another research on active contour segmentation on broadband ultrasonic attenuation parameter images which has lower noise level compared to standard ultrasonic images [Lefebvre et al. 1998].

One of the recent works on breast ultrasound images tries to segment the breast cancer ultrasound through a chain of image processing tasks. It starts with removing noise and then tries to enhance the contrast of the image and at last tries textural classifiers to segment the image [Madabhushi and Metaxas 2003].

Another test suite which I have used is lung X-ray images. The problem with chest X-ray segmentation is the projection nature of these images which makes quantification and localization difficult tasks to carry out. Some research works have been done on chest X-ray segmentation through classifier methods [McNitt-Gray et al. 1995], [Vittitoe et al. 1998]. Using the Markov random fields to segment chest X-ray is another research approach [Vittitoe et al. 1998]. Lung 3-D X-ray images have also been studied on; in [Hu et al. 2003] these kind of images are segmented in three steps: at first, thresholding is used to find the bounderis of lungs and then dynamic programming tries to separate left and right lung and at last morphological operations are used to segment the lungs. There is a survey paper about medical image segmentation which covers many research works in this field ([Pham et al. 2000]).

4.1.2 Active Contour Model: A Background Review

Active contour method (snake) tries to find boundary of an object by minimizing an energy associated to the current contour as a sum of an internal and external energy. The drawback of this method is its high sensitivity to the control parameters. These parameters are correlated and problem-oriented. In practice, adjusting the parameters is carried out by a trial-and-error approach which makes it very time consuming and most of the times obtaining the optimal (or at least sub-optimal) values is not guaranteed. The proposed approach in this section is not limited to active contours and can be applied to other kinds of segmentation approaches (e.g., Level Sets). The DE algorithm is utilized to optimize the snake's parameters which can be replaced with other global optimization techniques. In other words, the proposed scheme is general enough to be used for optimal parameter setting of other image processing tasks, such as, image filtering and enhancement. The proposed scheme is a sample-based optimization method which has been inspired from image processing chain optimization proposed by Rahnamayan et al. [Rahnamayan and Mohamad 2010]-[Rahnamayan et al. 2009].

There are many works related to medical image segmentation using active contour algorithms. Because of higher noise level and lower quality of images, this algorithm should be enhanced or customized to tackle with the challenging images. An enhanced active contour algorithm was introduced by Liu et al. [Liu and J. Ma 2007]. They have used geodesic active contour and tested with CT images. The edge detector in their model ensures that the data on both sides of the contour is as dissimilar as possible, and it also makes interior of a interest region as homogeneous as possible. Another work was conducted by Wang et al. [Wang et al. 2009] which tries to intensify the energy in active contour for brain MR image segmentation. They have defined an energy function with a local intensity fitting term, which induces a local force to attract the contour and stops it at object boundaries, and

an auxiliary global intensity fitting term, which drives the motion of the contour far away from object boundaries. Another paper by McInerney and Terzopoulos [McInerney and Terzopoulos 1997] introduced a technique for the segmentation of anatomic structures in medical images using a topologically adaptable snake's model. The model is set in the framework of domain subdivision using simplified decomposition. Boscolo et al. [Boscolo et al. 2002] proposed a segmentation technique that combines a knowledge-based segmentation system with a sophisticated active contour model. This approach utilizes the help of a higher-level process to perform the segmentation of different anatomic structures. Knowledge about the anatomic organs to be segmented is defined mathematically in terms of probability density functions of different parameters such as location, size, and image intensity level.

Many other attempts have been carried out to enhance active contours but mostly the works have been performed on the enhancing algorithm itself not its parameters, such as the work which has been conducted by Williams and Shah [Williams and Shah 1992]. They proposed a greedy algorithm for the active contour model which makes the whole algorithm faster. Another paper is about the optimization of the shape which should be segmented [van Ginneken et al. 2002]. For each of the landmarks which describe the shape, a distinct set of optimal features is determined. The selection of features is automatic, using the training images and sequential feature forward and backward selections. A paper used genetic algorithm to do parameter setting for the Active Contour [Rousselle et al. 2003]. It minimizes the energy related to the image so in this approach they try to use the snake algorithm as the fitness function and try to find the parameters based on minimizing this function. For straightforward images, this approach performs better but for noisy images it is prone to fail because object boundaries are not necessarily in the minimized position of the total fitness function. Our approach

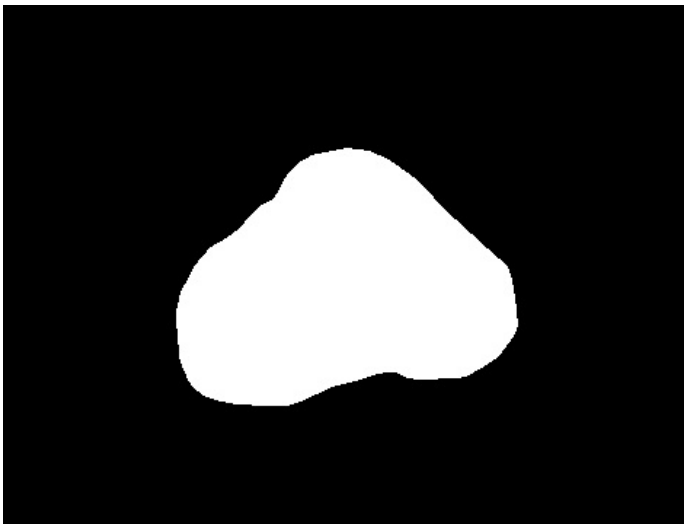

Fig. 4.2: A sample of a gold image for prostate ultrasound image.

uses a gold image which is segmented by an expert to be used during the parameter optimization process. This approach enables us to set the parameters for any image based on the desired needs of a professional, which are imbedded in the segmented image (called gold image).Figure 4.2 shows an example of a gold image.

4.2 Active Contour Algorithm (Snake)

The idea of active contour (snake) segmentation originated from Kass et al. work in 1988 [M.Kass et al. 1988]. This method is one of the well-known segmentation methods. It extracts objects in 2D images using the concept of internal and external energies. This algorithm gets a set of points near the object's boundary and builds an initial snake to start with. The performance of algorithm is highly sensitive to its control parameters, which controls the behaviour of the snake movements toward the object's boundary. Optimal setting of these parameters is crucial task

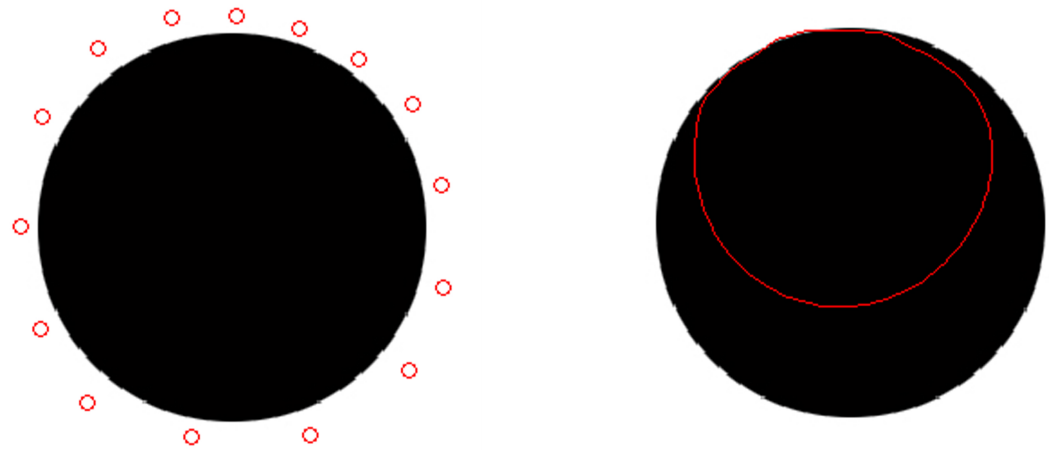

Fig. 4.3: A sample experiment which demonstrates that how snake segmentation fails to segment an object when its parameters are set to none optimal values (left image: input image and outer initial seed points, right image: failed snake to segment the object).

to end up with an accurate segmentation result. Figure 4.3 illustrates the output of snake segmentation algorithm on an easy to segment image. The algorithm fails to extract object because of the non-optimal parameters setting. Generally speaking, the optimal parameter setting is really important for any segmentation algorithms (including the snake algorithm) and it can affect the outcome drastically.

A snake works based on minimizing of energy of the snake which is the sum of internal and external energies.

$E_{snake} = \int E_{snake}[(V(s))]ds = \int E_{int}(V(s)) + E_{images}(V(s)) + E_{con}(V(s))ds$ (1)

where E_{int} represents the internal energy, E_{images} gives rise to the image forces, and E_{con} gives rise to the external constraint forces.

Internal energy deals with the coherence of the curve and is consist of two terms as follow:

$$E_{int} = (\alpha(s)|V_s(s)|^2 + \beta(s)|V_{ss}(s)|^2)/2 \qquad (2)$$

As seen, the first order term is controlled by $\alpha(s)$ and the second order term by $\beta(s)$. Large values for $\alpha(s)$ increases the internal energy of the snake and it can stretch more and more, whereas, small values for $\alpha(s)$ makes the snake insensitive to the amount of stretch. Large values for $\beta(s)$ will increase the internal energy as it develops more curves, meaning that snake can find more curves in the segmented shape, oppositely, small values for $\beta(s)$ makes snake insensitive to the curves and this is not good for shapes with lots of curves in them. As it can be seen $\alpha(s)$ and $\beta(s)$ are two variables that can be optimized in order for snake to work better till now.

In order to minimize the snake energy, we have to solve the following Euler equations:

$$\alpha x_{ss} + \beta x_{ssss} + (dE_{ext}/dE_x) = 0 \qquad (3)$$

$$\alpha y_{ss} + \beta y_{ssss} + (dE_{ext}/dE_y) = 0 \qquad (4)$$

These equations show how $\alpha(s)$ and $\beta(s)$ are correlated when it comes to solving the snake equations. As it can be seen, $\alpha(s)$ is related to first order term and $\beta(s)$ is related to the second order term of the equations.

The Gradient-decent minimization method is one of the approaches to solve these equations. So, if we simplify the equations based on the step-size and matrix formulation, we will have the following equations:

$$AX_t + f_X(X_{t-1}, Y_{t-1}) = -\gamma(X_t - X_{t-1}) \qquad (5)$$

$$AY_t + f_X(X_{t-1}, Y_{t-1}) = -\gamma(Y_t - Y_{t-1}) \qquad (6)$$

The above equations show the gradient-decent method to solve the Euler equations which were introduced above. γ is the step-size for each iteration. This method is implicit with respect to internal forces, so it can solve very rigid snakes with large step-sizes, meaning that if the internal energy is large then we need to have larger step-size in order to solve the snake equations. However, if the external

forces become large, the explicit Euler steps of the external forces require much smaller step-sizes. The external energy deals with the boundary of the object and it should be minimal when the contour is at the object boundaries. The external constraint energy, E_{con}, in first Equation adds a constraint to the external energy. The term for E_{con} is as follow:

$$-\kappa(x_1 - x_2)^2 \qquad (7)$$

This term basically creates a spring between two points of x_1 and x_2 which can be a point on snake and a fixed point or two different points on snake and connect them with a spring with coefficient equals to κ. This basically is connected to the arrangement of the points near each other. When κ has a large value the points can not expand much and the spring force tries to bring them back near each other and the other way around. So, this is a parameter which can be optimized to enhance the performance of a snake algorithm and the points which should be arranged around the segmented shape.

E_{image} is consisting of three terms as follow:

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term} \qquad (8)$$

These three terms can attract snake to salient features in images which are lines, edges, and terminations. By adjusting these weights a wide range of snake behavior can be achieved. So, they can be optimized and are among the snake important control parameters.

Snake's seven control parameters $(\alpha, \beta, \gamma, \kappa, w_{line}, w_{edge}, w_{term} allin[0, 1])$ have been introduced which need to be set optimally. In order to make snake sensitive to image scale as well, the Gaussian smoothing filter has been incorporated. The Gaussian filter applies a weighted average of each pixel's neighborhood, with the increasing weights toward the value of the central pixel, This filter blurs out the image but reduces the noise level in the image as well. It adds another parameter which is the coefficient for the Gaussian filter (σ). By this way, we need to solve

an eight dimensional optimization problem. But, as mentioned previously, finding optimal values for eight correlated variables introduces infinite combinations and is hard to be solved by any brute force method. In order to tackle this problem, I have utilized DE optimization algorithm because it is a well-known commonly used effective global optimization approach.

4.3 Proposed Approach: Sample-Based Optimization Algorithm

There are different kinds of medical images, such as, X-ray, CT, MRI, and Ultra Sound (US) images. Each image is different from others in terms of resolution, contrast level, noise type, and noise ratio. Even, the same imaging modality from human's different tissues (such as, ultrasound from breast and prostate) are significantly variant from image processing point of view. All these characteristics make a customized segmentation more complicated task. Extracting an organ or a tissue from these images, by experts, is a time consuming process, especially when they need to segment 50-100 images during a treatment planning. The proposed approach utilizes a gold sample image (segmented by an expert) for optimal setting of segmentation algorithm's control parameters. So, that is a sample-based optimization approach. A general schematic illustration of the proposed approach is presented in figure 4.4.

As shown, the optimizer passes the candidate parameters to the segmentation algorithm and the results of the segmentation (based on the suggested candidate control parameters) is compared with the gold image; and the mismatching ratio (see Equation. 9) is returned as objective value to the optimizer. Then, the optimizer works on that as a minimization problem and tries to minimize that ratio.

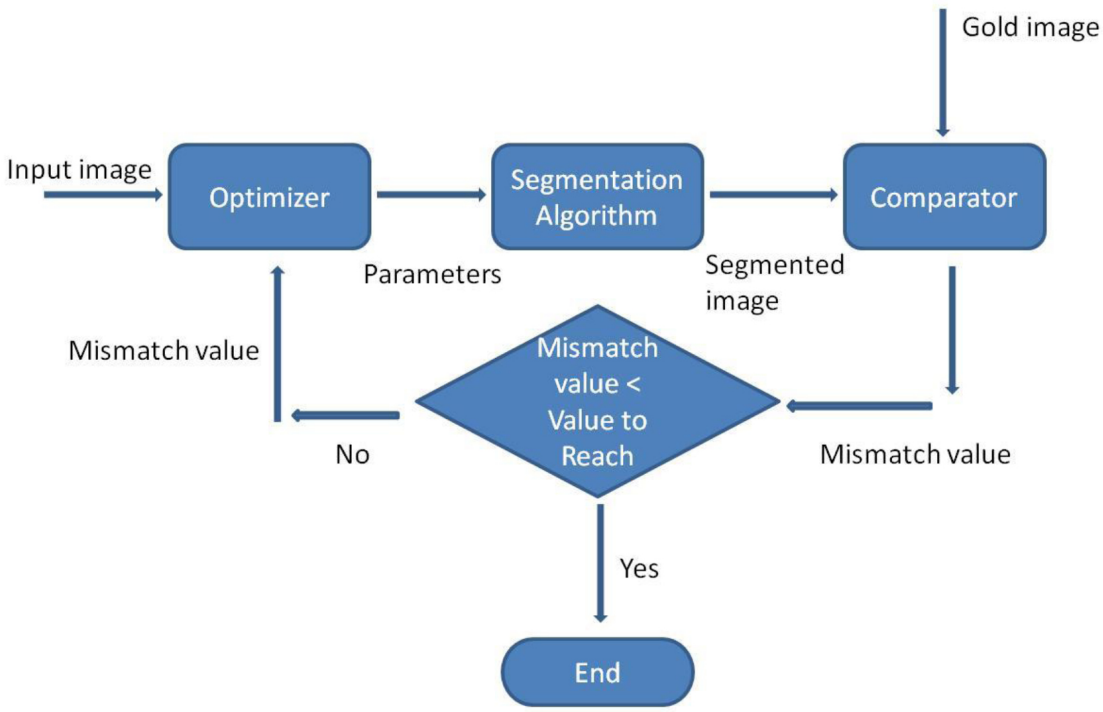

Fig. 4.4: General schematic illustration of the proposed approach.

The process stops when the accuracy level is less than a threshold value determined by the user. As indicated, this scheme is general, but for our case study, I chose differential evolution algorithm and active couture approach as my optimization and segmentation algorithms, respectively. The comparator compares the gold image pixel-by-pixel with the segmented image by active couture and reports the result as mismatch ratio. The objective function for the optimizer is defined as follow:

$$f = \frac{|G| - |S \cap G|}{|G|} \times 100 \qquad (9)$$

where, G and S indicate the gold and segmented images, respectively. $|A|$ represents the cardinality of set $|A|$ (i.e., number of pixels).

4.4 Experimental Results and Analysis

There are eight variables which need to be optimized. The first variable which is the coefficient for the Gaussian filter can be assigned any continues value in $[0, 5]$ and all others which are the snake control parameters can be any real number in $[0, 1]$. For all experiments, the number of snake iterations is set to 200 and it is coming from the default value which has been set on the snake code by its developers. The Np for DE algorithm is set to 64 (Np = 8D); the mutation amplification factor (F) is set to 0.85 and crossover probability constant (Cr) is set to 1. Maximum number of function calls (MAX_NFC) is set to 50,000 for all the experiments and termination criteria (VTR) is changed based on the noise level. For more noisy images like prostate and breast ultrasound images it is set to 1% and for less noisy images like X-ray lung it is set to 0.5% . These settings remain the same during all experiments.

The next step would be using the snake algorithm with the obtained optimal parameters by DE to segment the rest of images in the same test suite. The following subsections present the experimental results for three sets of medical images, namely, Breast ultrasound, Lung X-ray, and Prostate ultrasound images.

4.4.1 Visual and numerical results for Breast ultrasound images

Breast Ultrasound images are heavily noisy, so hard to segment. The optimization process has been conducted for inner and outer initial snakes, the stopping criteria is set to 1%, which means the DE terminates the optimization of the snake's parameters when the mismatch ratio is less than 1%. The segmentation results for some sample images are shown in figure 4.5; the green contour indicates the gold segmentation boundary and the red contour presents the result of the proposed

Table 4.1: Numerical results for Breast ultrasound segmentation test suits.

Image No.	Starting with an outer initial Snake	Starting with an inner initial Snake	Image No.	Starting with an outer initial Snake	Starting with an inner initial Snake
1	1.50	3.29	16	3.08	0.75
2	1.73	0.61	17	4.37	11.09
3	1.76	1.11	18	1.08	1.48
4	0.40	0.19	19	0.95	1.19
5	1.21	0.62	20	1.81	2.39
6	2.86	2.97	21	1.35	1.47
7	2.55	2.25	22	2.44	1.06
8	7.39	2.76	23	2.72	2.13
9	0.83	0.44	24	0.71	0.42
10	0.93	0.81	25	1.71	0.50
11	0.21	0.11	26	1.55	0.48
12	2.40	2.34	27	1.07	1.06
13	1.63	1.25	28	2.04	1.28
14	2.51	1.83	29	1.36	0.63
15	3.09	2.46	30	2.66	2.69

approach (snake with optimal parameters). The numerical results (mismatch ratios) for all 30 images in the test suite are presented in table 4.1. The results for both segmentations, starting with inner and outer initial snakes, are given. Going through the Table shows that the worst segmentation result belongs to image 17 (4.3% and 11%). This image is shown in figure 4.6, the boundary of the cancer tissue is not clear even based on an eye judgment.

Figure 4.7 presents a bar-chart for the breast segmentation results. By looking at the chart, it can be seen that the results are comparable for segmentation starting with inner and outer initial snakes, except for few images. The average mismatch ratio and corresponding standard deviation (SD) is less than 2% for this test set (see table 4.4), starting with inner initial snake performs better than outer ones

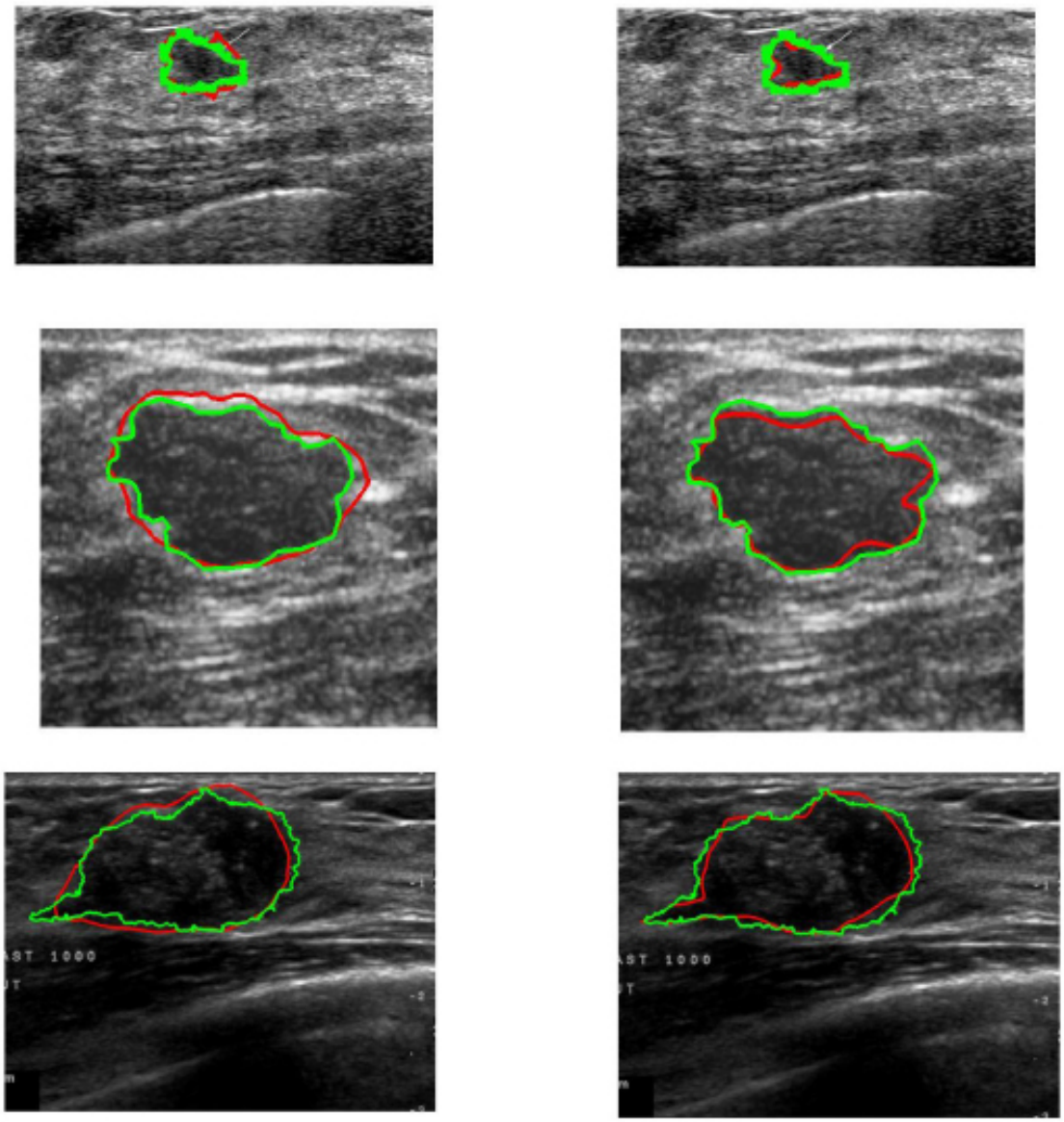

Fig. 4.5: Sample results for Breast ultrasound images, Left column: Starting with an outer initial snake; Right column: Starting with an inner initial snake (the green contour indicates the gold segmentation boundary and the red contour presents the result of snake with optimal parameters) .

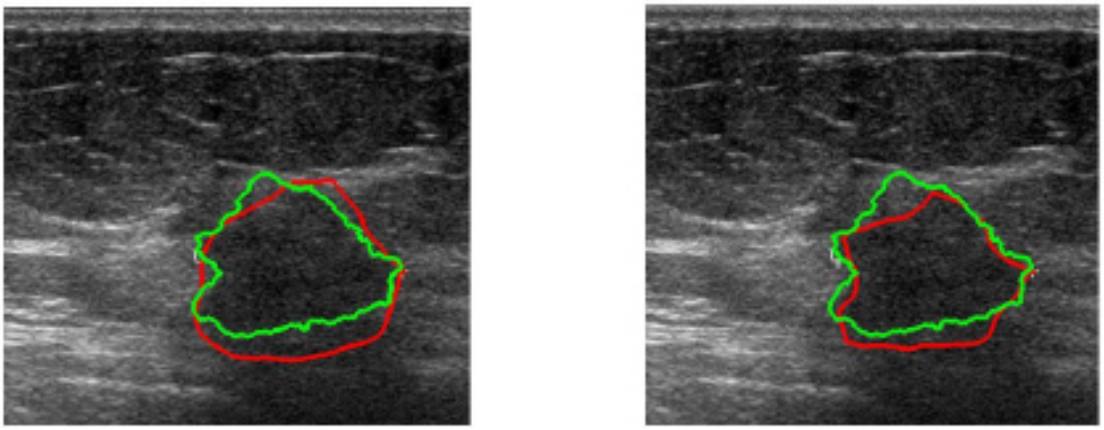

Fig. 4.6: The worst result of the Breast Ultrasound test suite (image 17); Left column: Starting with an outer initial snake; Right column: Starting with an inner initial snake. As seen, the gold boundary is not clear even based on an eye judgment

but the average standard deviation for outer initial snake is better. In general, for all 30 images, the overall accuracy ($> 98\%$) is acceptable in medical environments.

4.4.2 Visual and numerical results for X-ray Lung images

Lung X-ray images are high-contrast low noise images; the segmentation should be easier than Breast ultrasound images. That is why, the stopping criteria is set to 0.5%. I have applied the segmentation to left lungs since their extraction is more challenging because of the existence of sharp corners (due to appearance of the heart in the left side). The segmentation results for some sample images are given in figure 4.8. The mismatch ratios are reported for all 48 images in table 4.2. The corresponding bar-chart is presented in figure 4.9.

Table 4.2: Numerical results for Lung X-ray segmentation test suits.

Image No.	Starting with an outer initial Snake	Starting with an inner initial Snake	Image No.	Starting with an outer initial Snake	Starting with an inner initial Snake
1	0.94	0.80	25	1.38	1.55
2	1.11	1.07	26	1.80	1.85
3	0.68	0.57	27	1.33	1.10
4	0.76	0.81	28	1.75	1.57
5	0.53	0.57	29	0.80	1.05
6	0.65	0.93	30	1.21	1.21
7	1.19	1.05	31	1.33	1.09
8	0.69	0.76	32	1.34	1.57
9	0.61	1.07	33	1.20	1.42
10	0.97	1.15	34	1.45	1.19
11	1.63	1.13	35	1.23	0.88
12	0.73	0.78	36	0.98	1.02
13	1.07	1.01	37	1.33	1.14
14	1.09	1.04	38	1.62	1.36
15	0.90	0.76	39	0.87	0.72
16	1.16	0.94	40	0.78	0.97
17	1.04	0.88	41	1.26	0.86
18	1.23	1.02	42	0.93	1.10
19	1.31	1.08	43	1.00	1.58
20	0.92	0.91	44	1.34	1.39
21	1.48	0.95	45	1.90	1.87
22	1.08	0.96	46	1.33	1.80
23	0.85	0.89	47	1.20	1.46
24	1.00	0.94	48	0.87	0.80

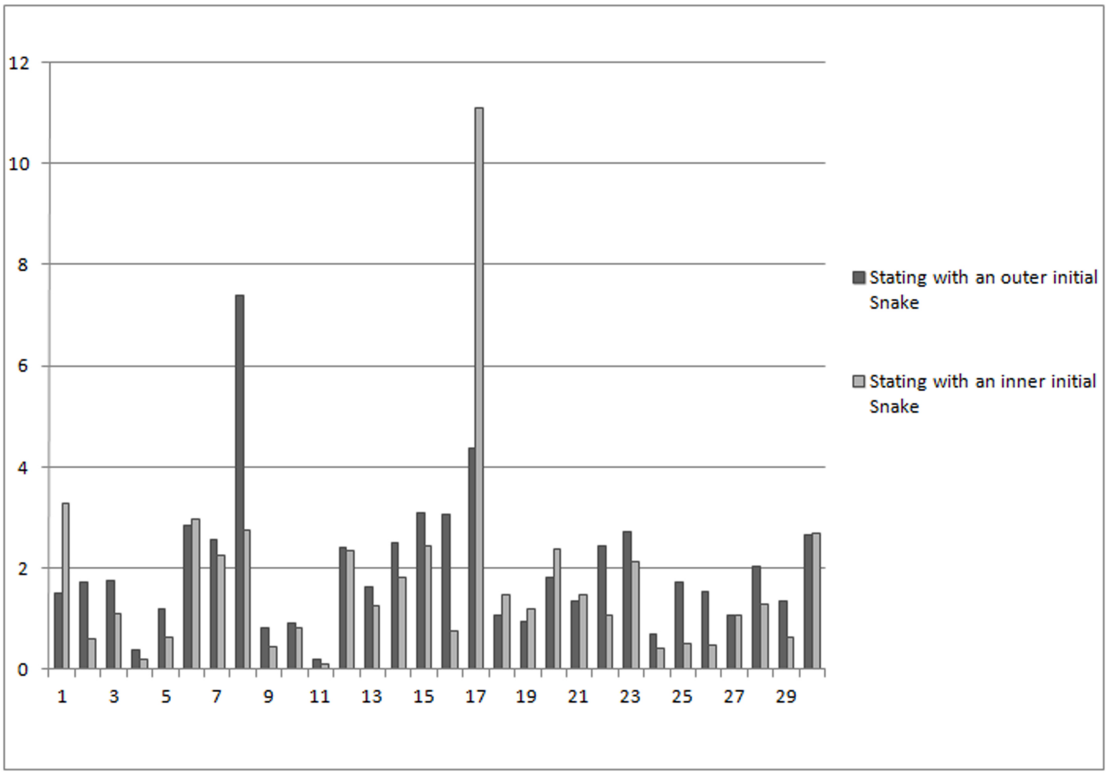

Fig. 4.7: Results for the Breast test suite (mismatch ratio of each input image).

4.4.3 Visual and numerical results for Prostate ultrasound images

In general, ultrasound medical images are low contrast noisy images, the prostate ultrasound images are not exception in this regard. The stopping criteria is set to 1%. Some sample results are presented in Figure 4.10. The numerical results are summarized in Table 4.3. The results, for a sample challenging prostate ultrasound image with sharp edges near the image border and connected shadow region is given in Figure 4.11. As reported in Table 4.4, the proposed method works slightly better with outer initial snakes. This is because of prostate images border problem. The

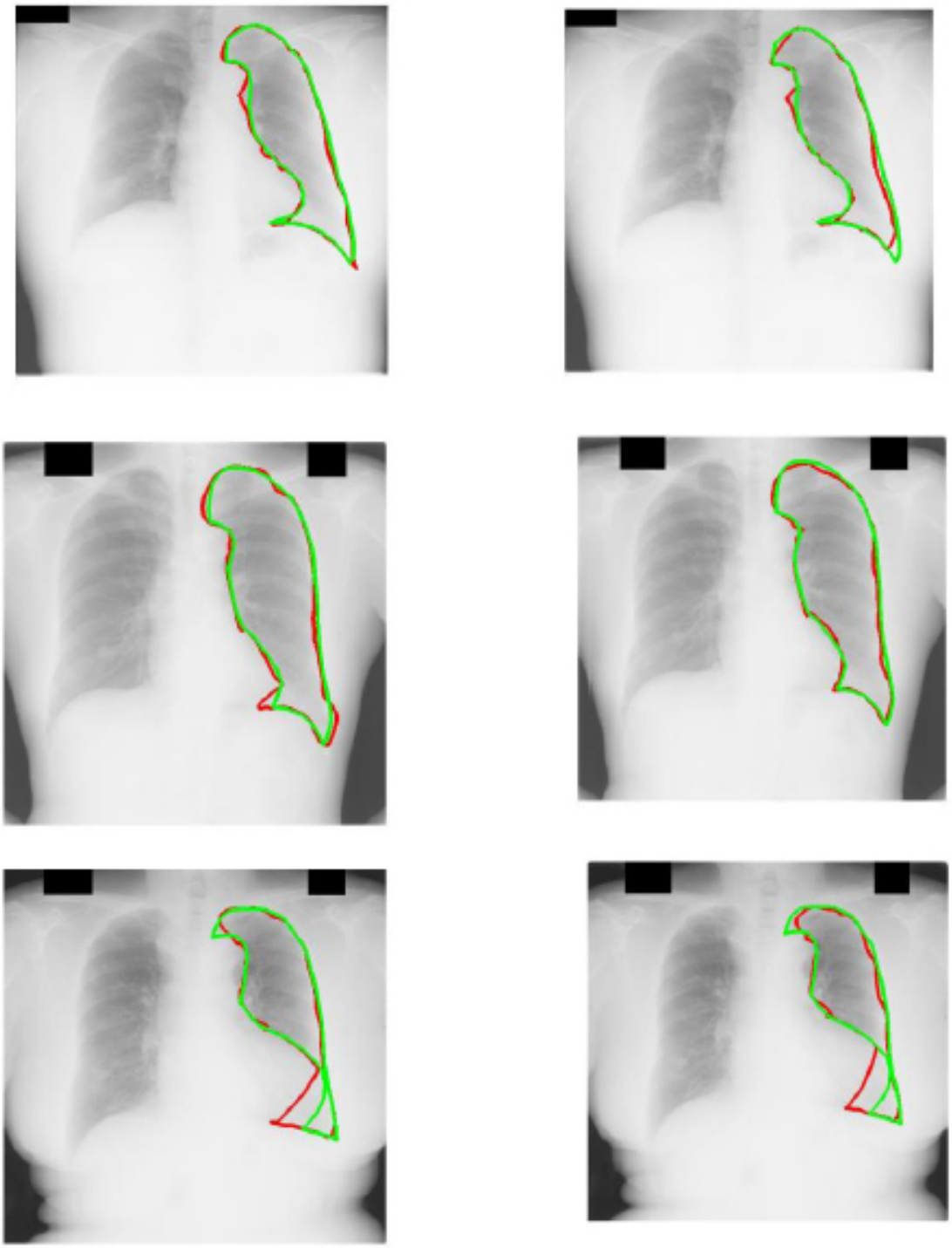

Fig. 4.8: Sample results for X-ray Lung images, Left column: Starting with an outer initial snake; Right column: Starting with an inner initial snake (the green contour indicates the gold segmentation boundary and the red contour presents the result of snake with optimal parameters) .

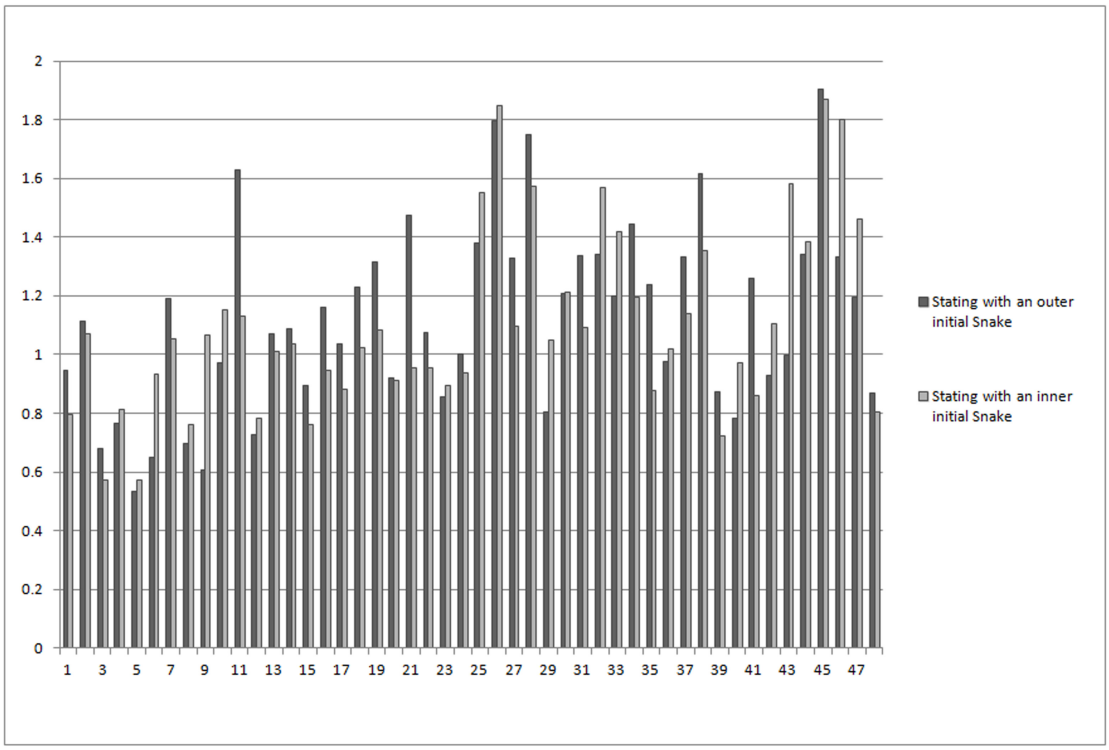

Fig. 4.9: Results for the Lung test suite (mismatch ratio of each input image).

border is faded with the background and the contrast levels are close, so when the initial snake starts from inside (which has almost a uniform pattern) it fails to reach the boundaries and it is trapped inside the prostate. So, as it can be seen in all the prostate images almost all the ones which have inner initial points are terminated before reaching the borders because the pattern inside, is mostly uniform and in some places the borders are the same as the background contrast level and in some places before the border edges inside the prostate there are some brighter points that can mislead the snake algorithm. The average mismatch ratio is less than 2%. Considering the noise level in prostate ultrasound images, still the proposed approach achieves excellent results. Figure 4.12 presents a bar-chart for

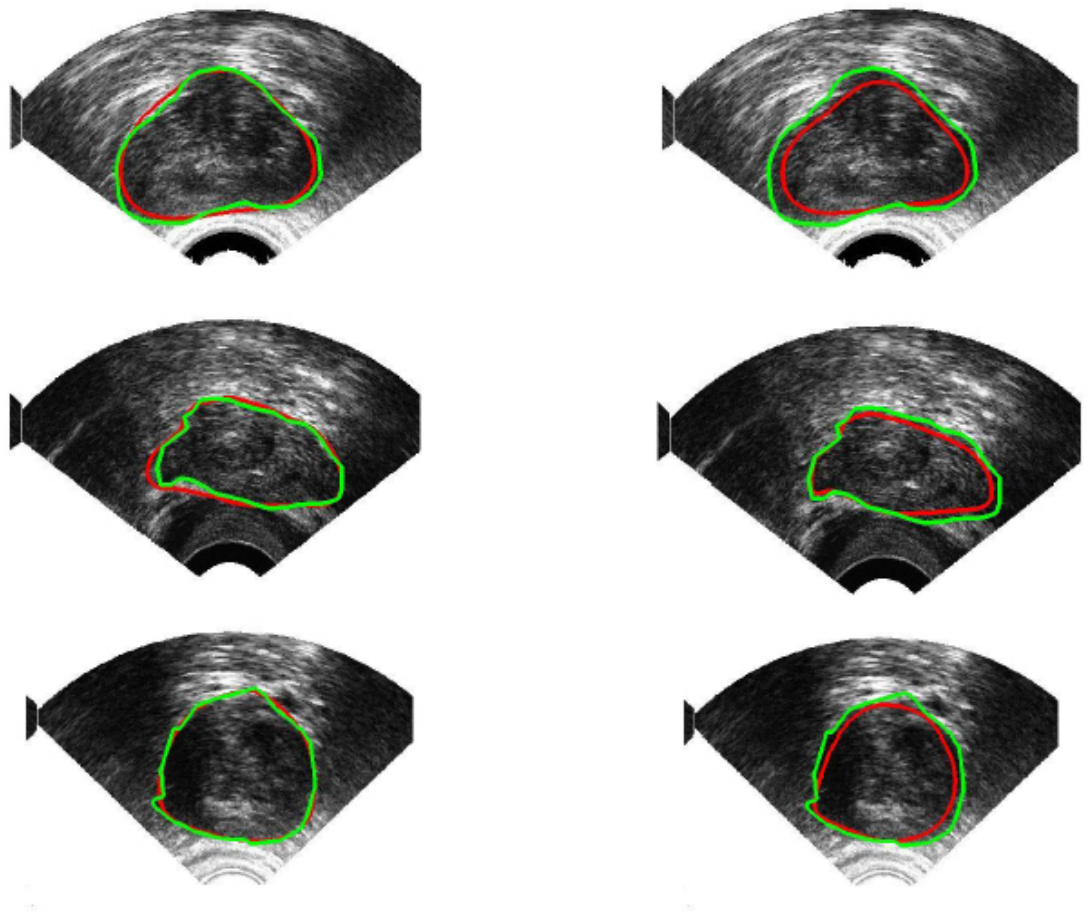

Fig. 4.10: Some sample results of Prostate ultrasound segmentation (Left column: Starting with an outer initial snake, Right column: Starting with an inner initial snake).

prostate images.

Table4.5 presents the obtained optimal values for the snake control parameters for each test suite. As seen, the optimal values are different for each test set even for both situations which algorithm starts with an outer or inner initial snakes for the same test suite.

Table 4.3: Numerical results for Prostate Ultrasound segmentation test suits.

Image No.	Starting with an outer initial Snake	Starting with an inner initial Snake	Image No.	Starting with an outer initial Snake	Starting with an inner initial Snake
1	1.58	4.14	18	2.80	2.45
2	2.12	4.32	19	3.39	4.25
3	1.65	3.17	20	1.87	3.68
4	0.76	3.88	21	3.06	3.02
5	0.64	2.83	22	1.36	2.80
6	1.22	2.83	23	1.53	1.92
7	1.08	2.62	24	1.54	2.14
8	1.97	1.55	25	1.55	2.12
9	1.22	1.87	26	1.99	2.50
10	1.19	1.38	27	2.94	3.40
11	1.12	1.66	28	2.64	1.70
12	1.6296	1.17	29	3.54	4.60
13	1.77	1.43	30	1.95	1.66
14	1.22	1.25	31	3.27	2.64
15	1.05	1.24	32	2.31	1.42
16	2.52	2.72	33	1.78	1.51
17	1.93	3.38			

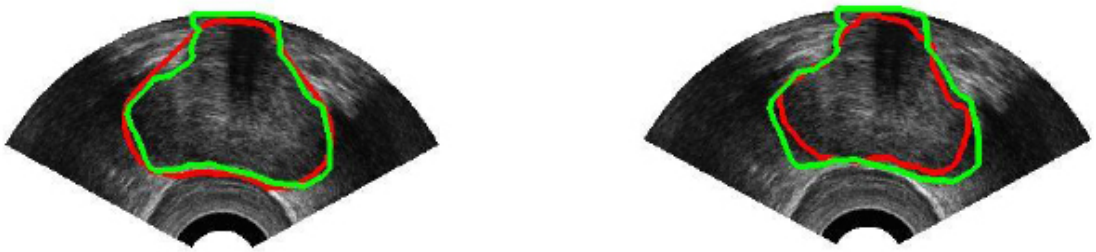

Fig. 4.11: A sample challenging prostate ultrasound image with sharp edges near the border of the image and connected shadow regain, which makes segmentation challenging (Left column: Starting with an outer initial snake; Right column: Starting with an inner initial snake).

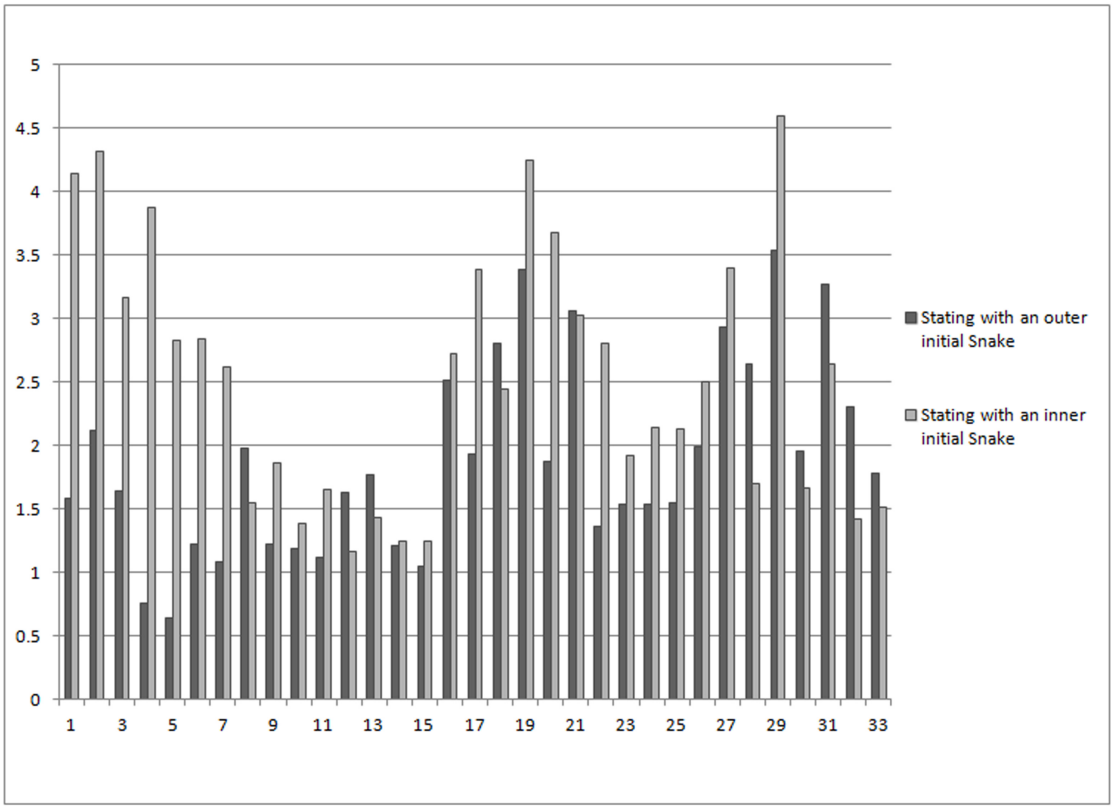

Fig. 4.12: Results for the Prostate test suite (mismatch ratio of each input image).

Table 4.4: Summarized average and SD values for the three test suites

Test suites	Measures (%)	Starting with an outer initial Snake	Starting with an inner initial Snake
Breast Ultrasound	Average mismatch with Gold image	1.99	1.72
	Standard Deviation(SD)	1.37	1.98
Lung X-Ray	Average mismatch with Gold image	1.12	1.09
	Standard Deviation(SD)	0.32	0.31
Prostate Ultrasound	Average mismatch with Gold image	1.88	2.52
	Standard Deviation(SD)	0.76	1.01

Table 4.5: Obtained optimal values for the snake control parameters by the proposed sample-based optimization approach

Test suites	Initial Snake(inner/outer)	Obtained optimal control parameters							
		σ	α	β	γ	κ	W_{line}	W_{edge}	W_{term}
Breast Ultrasound	Outer Initial Snake	0.66	0.29	0.96	0.17	0.34	0.01	0.51	0.33
	Inner Initial Snake	0.47	0.0	0.64	0.45	0.28	0.0	0.34	0.97
Lung X-Ray	Outer Initial Snake	0.23	0.58	0.60	0.60	0.45	0.03	0.51	0.41
	Inner Initial Snake	0.35	0.0	0.99	0.04	0.10	0.0	0.89	0.87
Prostate Ultrasound	Outer Initial Snake	0.58	0.23	0.39	0.82	0.01	0.10	0.67	0.68
	Inner Initial Snake	0.63	0.0	0.98	0.12	0.1	0.0	0.16	0.99

4.5 Conclusion

By checking all the results, it is obvious that the proposed approach can be used for optimal parameter settings which can be applied to the same category of images. Thus, for each group of the images, one time optimization process should be conducted. This approach helps users set the parameters for any kind of images with variant applications, without any required magical guesses or brute force trail-and-error approaches. The only thing which should be set by the user is the initial snake which can be done by even a non-expert user. This step cannot be avoided because the nature of snake is interactive and the starting seed points should be fed to the algorithm. This approach can be extended to any other segmentation methods which involve several control parameters. Furthermore, it opens a door to all algorithms to introduce more control parameters without worrying about their optimal settings. Other related works, so far, tried to enhance the snake algorithm itself but the current approach aimed to optimize control parameters based on the input which is provided by an expert user as a sample gold image. This approach experimentally shows that if the snake algorithm is equipped with its optimal con-

trol parameters, it can be utilized even for noisy images such as ultrasound medical images, which are hard to tackle.

Chapter 5

Conclusions and Future Work

5.1 Contributions

The author's contributions are spread over two almost different research areas, namely, image processing and evolutionary optimization algorithms.

Before all, I had a background in cameras and image processing back to my work experiences. I started to work on image enhancement methods. My first task was trying to increase eye-illusion factors in an image [Mohamad et al. 2011]. It was an interesting research. After being successful in that, I started to work on medical images and trying to enhance snake model using sample-based optimizing method.

After working in medical image processing filed for a while, I became familiar with the problems surrounding this field. One of the main issues in medical image processing is the tissue extraction (segmentation). The easiest way of segmentation is thresholding. So, setting threshold value in an optimized way became my next task. I developed a program to set the threshold value in an interactive way. So, any user in any field can threshold their images through the mentioned interactive approach.

As I was working on segmentation, I realized that active contour methods are among the best methods. But setting the parameters in this method is a challenging and time consuming process and sometimes for images with low quality it is almost impossible. Medical images, specially ultrasound images have high level of noise, so setting snake parameters for this images is very complicated. Because of my previous works, I had enough knowledge about evolutionary optimization methods. This time an interactive method was not an option, because of the number of the variables. I tried sample-based method to set the parameters. So, I developed an approach to receive the user prepared gold image and using it in the parameter setting process through an evolutionary optimization

methods[Darvish and Rahnamayan 2011].

5.2 Conclusions

Trying to make a around between optimization and digital image processing was the main objective of this work; which gets human feedbacks to optimize some control parameters of image processing tasks. This work tries to get amateur users involved in the whole process of digital image processing and enables them to enhance images based on their applications without having any prior knowledge about the digital image processing methods.

There are two main directions in this thesis. The first one tackles the image processing parameter setting problem in a fully interactive way. This approach can be applied to methods just with a few parameters. The problems with more than four parameters are not usually good candidates for these kinds of approaches due to the fact that their convergence takes a long time and causes user fatigue. The second approach takes the gold image from the expert user and tries to set the parameters based on that, trying to make the result as much close as possible to the gold image. Both of these two approaches employ DE algorithm as an optimizer.

Results of the current work are promising and they experimentally prove that the proposed approach can be really beneficial in variant image processing applications. The turning point of this work was parameter setting of the active contour model (snake). The eight parameters should be set to make it work properly. All these values are correlated and optimal setting of these values is a challenging task.

The proposed approach is general and the involved components such as optimizer or image processing methods can be replaced based on the applications' requirements.

5.3 Future Work

Trying to optimize the control parameters of other segmentation methods, such as level set, is in my future plans. So, the results of different approaches can be compared to come up with a desirable method to segment medical images.

Using more than one sample images during the optimization process makes my another direction for the future study. This approach may lead to a more accurate results.

To reach more precise results, same modality of medical images can also be classified to different class of images (for example cancerous and cyst breast ultrasound images), and the optimization process can be applied to different classes separately.

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