A Novel Context Sensitive Image Thresholding Technique

Thesis

submitted in partial fulfillment of the requirements

for the award of degree of

Master of Technology
In
Computer Science and Applications

Submitted By

Rahul Gautam
601103019

Under the supervision of

Dr. Swarnajyoti Patra
Assistant Professor

SCHOOL OF MATHEMATICS AND COMPUTER APPLICATIONS
THAPAR UNIVERSITY
PATIALA – 147004

July 2013

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "*A Novel Context Sensitive Image Thresholding Technique*", in partial fulfillment of the requirements for the award of degree of "Master of technology in Computer Science and Applications" submitted in "School of Mathematics and Computer Applications", Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Swarnajyoti Patra** *(Assistant Professor)* and refers other researcher's works which are duly listed in the reference section. The matter embodied in this report has not been submitted anywhere for the award of any degree.

Rahul Gautam

Date: 15/07/13

Rahul Gautam

Roll No.-601103019

It is certified that the above statement made by the student is correct to the best of our knowledge and belief.

Dr. Swarnajyoti Patra

Assistant Professor,
SMCA Department
Thapar University, Patiala

Countersigned by:

(Dr. Rajesh Kumar)

Head
SMCA
Thapar University
Patiala

(Dr. S.K. Mohapatra)

Dean (Academic Affairs)
Thapar University
Patiala

ACKNOWLEDGEMENT

First and foremost I thank Almighty for giving me this meaningful life to serve human beings with great intensity and quest to learn more and more. Acknowledging individuals who have helped me directly, indirectly, tangibly and/or intangibly to this research effort reflects honestly my deep regards to their contributions. This note of acknowledgement is my sincere appreciation to those people who stand out most notably in my mind as contributing to the effort.

I must acknowledge my revered supervisor, due to his importance and inspiration to my work. He urged me on and on by way of his untiring support and seemingly unlimited belief in me. My profound regards to Dr. Swarnajyoti Patra. I would like to thank Dr. Rajesh Kumar, Professor and Head, School of Mathematics and Computer Applications for his moral support and the research environment he had facilitated.

My gratitude to my department, particularly my teachers and to all of my wonderful colleagues, for their stimulating discussion and invaluable support, I have received during the period of this research. There are many that from behind the scenes have encouraged and supported my work, and I wish to thank them. My deep regards to my family for their immense love and support, and my friends for all their enthusiastic encouragement throughout my life without which i could not complete this work.

At last but not the least, support provided by all the concerned people is highly appreciated and deeply acknowledged.

Rahul Gautam

(601103019)

ABSTRACT

Image segmentation is a fundamental task in image processing, video processing and computer vision applications. This is a wide area of research. A lot of research work has been done in this field, still there is not a unique technique to segment each type of image i.e., for each type of images there exist a different technique to segment the image.

Histogram based traditional thresholding techniques do not considered spatial contextual information for selecting the optimum threshold and are effective only to identify single threshold. In this thesis we proposed a novel thresholding technique that mitigated both these limitations. First, we proposed an energy function that computes the energy of the image at each gray value by taking into an account the spatial contextual information of the image. The energy value is computed in such a way that the characteristic of the energy curve is similar to histogram of the image. Thus, by using the energy curve instead of using histogram, we incorporated spatial contextual information in threshold selection process. Second to mitigate multiple thresholds selection problem, here we exploited genetic algorithm. The fitness function of the genetic algorithm is modeled by extending the criterion proposed in [17].

We improved Kapur's method [17] results by using the energy curve generated by our spatial contextual information method and compared the results on the basis of DB index with Kapur's original method. To find the thresholds values is an optimization problem. So we used genetic algorithms to find the multiple thresholds values. Thresholds result shows that genetic algorithm is very promising in this field. Results show that this spatial contextual information which represented as the energy curve for the image is very effective for the better segmentation of the image.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Image

An image is a rectangular grid of pixels. It has a definite height and a definite width as the dimension, counted in pixels. Every pixel of an image has a definite shape and has a fixed size on a given display, whether different computer monitors may use different sized pixels.

An image is an artifact that shows or records visual perception, for example a two-dimensional picture, which has a same appearance to some subject–usually a physical object or a person, thus providing a depiction of it. Images may be captured by natural objects and phenomena, such as the human eye or water surfaces and by optical devices–such as cameras, mirrors, lenses, telescopes, microscopes, etc. A photograph, screen display etc are two dimensional images. There may be a three dimensional images such as a statue or hologram.

1.2 Image Segmentation

In computer vision, image segmentation is the process of partitioning a digital image into sets or group of pixels or multiple segments. The goal of image segmentation is to simplify and/or change the representation of an image into more meaningful image, which is easier to analyze [1].

Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The process of image segmentation can be viewed as the process of assigning a label or tag to every pixel in an image such that pixels with the same label or tag share certain depictive characteristics.

Image segmentation has wide research area in fingerprint recognition and face recognition which mainly uses for security purposes. Image segmentation is one of the largest research areas in medical image processing. New algorithms, algorithmic techniques, methodologies and improvements to existing methods are continuously being proposed to segment medical images into their constituent organs and tissues. It is difficult to choose one segmentation technique over another and to understand the benefits and disadvantages of each method. The selection of the segmentation technique depends upon the nature of the medical images to be segmented (MR, CT, X ray, ultrasound, etc.). Other factors for choosing an algorithmic approach are: 1) available technology, 2) degree of segmentation automatization,3) prior information available on the images, and 4) number of organs and tissues to be segmented. Whatever the method, one of the main objectives of every method is to achieve high segmentation accuracy [1].

Image segmentation can be performed using statistics, fuzzy logic, neural networks, active contours, mathematical morphology, mathematical models, texture and any combination of the previous methods or any other technique.

Medical imaging, face recognition, object detection, machine vision, fingerprint recognition are main applications of image segmentation.

1.3 Applications of Image Segmentation

Image segmentation applications have a wide range of fields. Image segmentation applications are mainly uses for better information collection for analysis and measurement, perspective of the field. Some of the image segmentation applications are given as follow as:

1. **Recognition Tasks**

Image segmentation has a wide research area in recognition tasks. The recognition tasks are mainly uses for the identification of person, things or objects. At this time of technology, password security is not enough; we have to enhance the security level. Some of the security perspective recognition tasks are given as follow:

- Face recognition
- Fingerprint recognition
- Iris recognition

2. **Medical Imaging**

Image segmentation is widely used in medical imaging. Some of the applications of image segmentation in medical field are given:

- Locate tumors and other pathologies
- Measure tissue volumes
- Diagnosis
- Study of anatomical structure

As health care systems and hospitals become more digitalized, medical image processing has become an essential part of it. Medical image segmentation offers help in diagnosis, analysis of disease and treatment in many situations. Also, doctors can estimate dimension (volume, area, length) of the object of interest such as a tumor such that radiation therapy can be automated. With the trend of the digitization of medical data, segmentation also helps to form a digital atlas of the patient's anatomy, thus eliminating the need for patient specific tools.

3. **Locate objects in satellite images**

Image segmentation is also beneficial in satellite images i.e., recognition of objects, place and forests etc. Image segmentation is also used in creation of maps.

4. **Automatic Traffic Controlling System**

Highway toll systems use cameras to extract car license plates, and in manufacturing, images help discover possible defects in products such as cracks or breakages.

5. **Machine Vision**

In machine vision, robots can rely on cameras to give information about the surroundings, such as identifying proper route or possible obstacles.

1.4 Image segmentation techniques

Image segmentation is a fundamental task in computer vision. So many methods have been proposed, but it is still difficult to accurately segment an arbitrary image by a particular method alone. From few years, more attention has been paid to combining segmentation algorithms and information from multiple feature spaces like texture, colour and pattern, in order to improve image segmentation results. There are so many methods of segmenting the image, few methods we are discussing here:

1.4.1 Edge Detection Methods

Edge detection is a well-developed field on its own within image processing. Edge detection techniques are used where to define the objects in terms of edges and region boundaries are main objective. There is a sharp adjustment in intensity at the region boundaries, so region boundaries and edges are closely related. Edge detection techniques have therefore been used as the base of another segmentation technique.

The edges identified by edge detection are often disconnected. Closed region boundaries are needed to segment an object from an image. Discontinuities are bridged if the distance between the two edges is within some predetermined threshold [2].

1.4.2 Region Growing Methods

The first region growing method was the seeded region growing method. This method takes a set of pixels as seeds as input along with the image. The pixels or seeds mark each of the objects to be segmented. The regions are continuously grown by comparing all unallocated neighbouring pixels to the regions. The difference between an intensity of pixel value and the region's mean is used as a similarity measure. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to the respective region. Seeded region growing requires pixels as seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed, so the region or cluster will not be much efficient [3].

1.4.3 Graph Partitioning Methods

Graphs can be used efficiently and effectively for image segmentation. Usually a pixel or a group of pixels are vertices and edges define the dissimilarity among the neighbourhood pixels [4]. Some popular algorithms of this category are random walker, minimum mean cut, minimum spanning tree-based algorithm, normalized cut etc.

In ‘normalized cut’ method, the image being segmented is modelled as a weighted, undirected graph. Each pixel is a node in the graph, and an edge is formed between every pair of pixels. The weight of an edge is a measure of the similarity between the pixels. The image is partitioned into disjoint sets by removing the edges connecting the segments. The optimal partitioning of the graph is the one that minimizes the weights of the edges that were removed.

1.4.4 Mathematical Morphology

Mathematical morphology examines the geometrical structure of an image by probing it with small patterns, called ‘structuring elements’ of varying size and shape. This procedure results in nonlinear image operators which are well-suited to exploring geometrical and topological structures.

Mathematical Morphology is a tool for extracting image components that are useful for representation and description. Morphology can provide boundaries of objects, their skeletons, and their convex hulls. It is also useful for many pre and post processing techniques, especially in edge thinning and pruning. Most morphological operations are based on simple expanding and shrinking operations. The primary application of morphology occurs in binary images, though it is also used on grey level images [5].

Morphology has been used in a wide range of applications. A few of the possible applications are image enhancement, image restoration, Edge detection, texture analysis, noise reduction.

1.4.5 Split-and-merge methods

Split-and-merge segmentation is based on a quad tree partition of an image. It is sometimes called quad tree segmentation.

This method starts at the root of the tree that represents the whole image. If it is found non-uniform (not homogeneous), then it is split into four son-squares, and so on so forth. Conversely, if four son-squares are homogeneous, they can be merged as several connected components. The node in the tree is a segmented node. This process continues recursively until no further splits or merges are possible [6, 7].

When a special data structure is involved in the implementation of the algorithm of the method, its time complexity can reach $O(n \log n)$, an optimal algorithm of the method [8].

1.4.6 Histogram based methods

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the Histogram is used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. This may affect the quality and usefulness of the final solution.

1.4.7 Clustering methods

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1. Choose K cluster centers, either randomly or based on some heuristic.
2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster center.
3. Re-compute the cluster centers by averaging all of the pixels in the cluster.
4. Repeat steps 2 and 3 until convergence is attained.

The variance is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

1.4.8 Thresholding methods

In digital image processing, thresholding is a well-known technique for segmenting gray level images. Because of its wide applicability to other areas of digital image processing, a variety of techniques have been proposed over the years for determining thresholds at which to segment an image in order to divide the image in object and background. Using threshold we divide the image into two regions, one including those pixels with their gray values above a certain threshold, and other including those pixels with their gray values below a certain threshold.

For multi thresholding we divide the image in many regions. Suppose we have to divide the image in n regions or classes then we have to choose $n-1$ threshold values. In our thesis work we are using multi thresholding. To find an optimal solution from a search space is an optimization problem, so we are solving it using genetic algorithms.

1.5 Thesis Objective

The objectives of thesis are:

- To understand the image segmentation and to study the different image segmentation techniques.
- To study the basic concepts and working knowledge of Genetic Algorithms and how it can be implemented in image segmentation.
- Segmentation is to be done through spatial contextual information of the image rather than histogram information of the image.
- To compare the results with our proposed method to Kapur's method.

1.6 Thesis Framework

The thesis has been organized in following chapters:

Chapter 2: This chapter is the literature review. The researchers work contribution in image thresholding is discussed in this chapter in brief.

Chapter 3: This chapter is dedicated to genetic algorithms. The terms used in genetic algorithms is explained. This chapter describes the basic concepts and working knowledge of genetic algorithms.

Chapter 4: This chapter explains the proposed methodology. The designed method is explained clearly in this chapter.

Chapter 5: This chapter is experimental results and discussion. In this chapter results are showing by proposed method and Kapur's method and discussion is done over results by comparing the DB index.

Chapter 6: Conclusion and future scope is discussed in this chapter.

CHAPTER 2

LITERATURE SURVEY

In this Literature Survey, we mainly studied about thresholding methods. Our main focus is on thresholding techniques and uses of genetic algorithms in image segmentation. As we know that, thresholding is widely used and most common method used in image segmentation. There are so many method come to existence in implementing the thresholding. Thresholding techniques are divided mainly into two types, global and local techniques. A global thresholding technique is one that thresholds the entire image with a single threshold value, whereas a local thresholding technique is one that partitions a given image into sub images and determines a threshold for each of these sub images.

Those images which have more than one object and have to identify boundaries, which correspond to object-object discontinuities, or to internal structure of the object, may not exhibit a clear foreground background distinction. One cannot expect a single threshold to detect all or even most of the object boundaries in the scene. In order to detect most of the interesting boundaries within an image, some alternative or additional processing must be done to obtain a clearer result. One alternative is to use multiple thresholds or threshold that varies across an image. These multiple thresholds will be defined in terms of a set of n thresholds rather than a single threshold. These n thresholds will partition the feature space into $n+1$ possible class. So, the whole images pixels will be divided into $n+1$ cluster [9]. Some contribution of research work that has been done in this field is described in brief here:

T.W. Ridler, S. Calvard, "Picture thresholding using an iterative selection method":

This method [10] was one of the first iterative schemes based on two-class Gaussian mixture models. At iteration n, a new threshold T_n is established using the average of the foreground and background class means:

$$T_{opt} = \lim_{n \to \infty} T_n \tag{1}$$

Where,

$$T_{n+1} = \frac{m_f(T_n) + m_b(T_n)}{2} \tag{2}$$

In practice, however, iterations terminate when the change $|T_n - T_{n+1}|$ becomes sufficiently small.

Nobuyuki Otsu, "A Threshold Selection Method from Gray-Level Histograms":

There are so many methods to thresholding the image, the most common clustering method is *Otsu method* [11], it's one of the oldest method to threshold the image. We use discriminate criterion for the measure of class seperability. To get the threshold value for segmenting the image we get the histogram information of the image.

Suppose the pixels of a given picture be represented in l gray level $[0,1,2...l-1]$. The number of pixels at level i is denoted by n_i and the total number of pixels by $N = n_0 + n_1 + n_2 ... n_{l-1}$. In order to simplify the discussion, the gray level histogram is normalized representing the image probability distribution:

$$p_i = \frac{n_i}{N}, \qquad p_i \geq 0, \qquad \sum p_i = 1 \tag{1}$$

Now threshold operation is partitioning of image pixels into two classes C_0 and C_1 (background and object, or vice versa) at gray level t, C_0 denotes pixels with level $[0,1,2...t]$ and C_1 denotes pixels with level $[t+1, t+2...l-1]$.

$$w_0 = \Pr(c_0) = \sum_{i=0}^{t} p_i = w(t) \tag{2}$$

$$w_1 = \Pr(c_1) = \sum_{i=t+1}^{l-1} p_i = 1 - w(t) \tag{3}$$

$$\mu_0 = \sum_{i=0}^{t} i \Pr(i \mid C_0) = \frac{\mu_t}{w(t)} \tag{4}$$

$$\mu_1 = \sum_{i=t+1}^{l-1} i \Pr(i \mid C_1) = \frac{\mu_T - \mu_t}{1 - w(t)} \tag{5}$$

Where, $\mu_t = \sum_{i=0}^{t} i \, p_i$ (6)

$$\mu_T = \sum_{i=0}^{l-1} i\, p_i \tag{7}$$

μ_T , is the total mean level of the original picture.

$$\sigma_0^2 = \sum_{i=0}^{t} \left(i-\mu_0\right)^2 * \left(\frac{p_i}{w0}\right) \tag{8}$$

$$\sigma_1^2 = \sum_{i=t+1}^{l-1} \left(i-\mu_1\right)^2 * \left(\frac{p_i}{w1}\right) \tag{9}$$

In order to evaluate the "goodness" (fitness function) of the threshold at level t, the measure of class separability used in the discriminate analysis is defined as:

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2}, \qquad \kappa = \frac{\sigma_T^2}{\sigma_W^2}, \qquad \eta = \frac{\sigma_B^2}{\sigma_T^2} \tag{10}$$

Where,

$$\sigma_W^2 = w_0\sigma_0^2 + w_1\sigma_1^2 \tag{11}$$

$$\sigma_B^2 = w_0 w_1 \left(\mu_1 - \mu_0\right)^2 \tag{12}$$

$$\sigma_T^2 = \sum_{i=0}^{l-1} \left(i-\mu_T\right)^2 p_i \tag{13}$$

σ_W^2, σ_B^2 and σ_T^2 are within class variance, between-class variance and total class variance of levels, respectively. Then the problem is reduced to an optimization problem to search for a threshold t that maximizes the object function of equation (9). This standpoint is motivated by a conjecture that good threshold classes would be separated in gray levels, and conversely, a threshold giving the best separation of classes in gray levels would be the best threshold.

T. Pun, "A New Method for Gray-Level Picture Threshold Using the Entropy of the histogram":

Suppose, for threshold value t two a posteriori entropies are defined as:

$$H'_1 = -\sum_{i=0}^{t} p_i \log_e p_i \tag{1}$$

$$H'_2 = -\sum_{i=t+1}^{l-1} p_i \log_e p_i \tag{2}$$

Where, H'_1 and H'_2 respectively, as measures of the a posteriori information associated with the black and white pixels after the thresholding. Knowing the a priori entropy of the gray level histogram, Pun [12] proposes an algorithm to determine the optimal threshold by maximizing the upper bound of the a posteriori entropy

$$H' = H'_1 + H'_2 \tag{3}$$

Pun [12, 13] has shown the maximizing *H'* is equivalent to maximizing the evaluation function with respect to *t* as:

$$f(t) = \frac{H_t}{H_T} * \frac{\log_e p_t}{\log_e \max\{p_0, p_1 .. p_t\}} + \left[1 - \frac{H_t}{H_T}\right] * \frac{\log_e (1 - p_t)}{\log_e \max\{p_{t+1}, p_{t+2} .. p_{l-1}\}} \tag{4}$$

Where,

$$H_t = -\sum_{i=0}^{t} p_i \log_e p_i \tag{5}$$

$$H_T = -\sum_{i=0}^{l-1} p_i \log_e p_i \tag{6}$$

$$p_t = -\sum_{i=0}^{t} p_i \tag{7}$$

T. Pun, “Entropic Thresholding: A New Approach”:

In this method, Pun [14] proposes the use of an anisotropy coefficient, α in thresholding, where

$$\alpha = \frac{\sum_{i=0}^{t} p_i \log_e p_i}{\sum_{i=0}^{l-1} p_i \log_e p_i} \tag{1}$$

And, t is the smallest integer such that,

$$\sum_{i=0}^{t} p_i \geq 0.5 \tag{2}$$

The optimal threshold t_1 is chosen such that,

$$\sum_{i=0}^{t_1} p_i = \begin{cases} 1-\alpha & \text{if } \alpha \le 0.5 \\ \alpha & \text{if } \alpha > 0.5 \end{cases} \qquad (3)$$

G. Johannsen and J. Bille, "A threshold selection method using information measures": This method [13,15] uses the entropy of the gray level histogram of the digital image. Essentially, it divides the set of gray levels into two parts so as to minimize the interdependence (in information theoretic sense) between them. The Johannsen and Bille method chooses the threshold value t_1 from the relation:

$$t_1 = Arg \underset{t \in G}{Min} \left\{ S(t) + \bar{S}(t) \right\} \qquad (1)$$

Where,

$$S(t) = \log_e \left(\sum_{i=0}^{t} p_i \right) - \frac{1}{\sum_{i=0}^{t} p_i} \left[p_t \log_e p_t + \left(\sum_{i=0}^{t-1} p_i \right) \log_e \left(\sum_{i=0}^{t-1} p_i \right) \right] \qquad (2)$$

And

$$\bar{S}(t) = \log_e \left(\sum_{i=t}^{l-1} p_i \right) - \frac{1}{\sum_{i=t}^{l-1} p_i} \left[p_t \log_e p_t + \left(\sum_{i=t+1}^{l-1} p_i \right) \log_e \left(\sum_{i=t+1}^{l-1} p_i \right) \right] \qquad (3)$$

D.E. Lloyd, "Automatic Target Classification Using Moment Invariant of Image Shapes": It is assumed [16] that the image can be characterized by a mixture distribution of foreground and background pixels $p(g) = p(T)p_f(g) + (1 - p(T))p_b(g)$. Under the assumption of equal variance Gaussian density functions, the threshold that minimizes the total misclassification error becomes:

$$T_{opt} = \arg\min \left[\left(\frac{m_f(T) + m_b(T)}{2} \right) + \left(\frac{\sigma^2}{m_f(T) - m_b(T)} \right) \log \frac{1 - P(T)}{P(T)} \right] \qquad (1)$$

Where, σ^2 is the variance of the whole image. The minimum of the above expression that yields the optimum threshold can be found via an iterative search.

J. N. Kapur and P. K. Sahoo, "A New Method for Gray-Level Picture Thresholding using Entropy of the Histogram":

In this method [17], the optimal threshold is determined based on the concept of entropy. Let $p_1, p_2, ... p_n$ be the probability distribution of gray-levels. Now we derive two probability distributions from the original gray level distribution for the threshold value t .

The two distributions are:

$$X : \frac{p_1}{p_T}, \frac{p_2}{p_T}, ... \frac{p_t}{p_T} \tag{1}$$

$$Y : \frac{p_{t+1}}{1-p_T}, \frac{p_{t+2}}{1-p_T}, ... \frac{p_n}{1-p_T} \tag{2}$$

Where, $p_T = p_1 + p_2 ...... p_t$ (3)

The entropies associated with each distribution are as follow:

$$H(X) = -\sum_{i=1}^{t} \left(\frac{p_i}{p_T}\right) * \log_2 \left(\frac{p_i}{p_T}\right) \tag{4}$$

$$H(Y) = -\sum_{i=t+1}^{n} \left(\frac{p_i}{1-p_T}\right) * \log_2 \left(\frac{p_i}{1-p_T}\right) \tag{5}$$

The optimal threshold t is selected by maximizing the overall entropy $H(X)+H(Y)$.

$$\Psi(t) = H(X)+H(Y) \tag{6}$$

We maximize $\Psi(t)$ to obtain the maximum information of object and background in image for the threshold value t .

Kittler, J. and Illingworth, J., "Minimum error thresholding":

In this method [18], the distribution of the grey levels in the image is represented in the form of a histogram $h(g)$, which gives the frequency of occurrence of each grey level in the image. The histogram can also be represent as an estimate of the probability density function $p(g)$ of overall population comprising grey levels of object and background pixels. We assume that two components $p(g \mid i)$ for object and background of the population are normally distributed with mean μ_i , standard deviation σ_i and a priori probability P_i, i.e.

$$p(g) = \sum_{i=1}^{2} P_i \, p(g \mid i) \tag{1}$$

Where, $$p(g \mid i) = \frac{1}{\sqrt{2\pi}\,\sigma_i} \exp\left(- \frac{(g - \mu_i)^2}{2\sigma_i^2} \right) \tag{2}$$

According to Bayes rule the minimum error threshold t is obtained by solving the following quadratic equation.

$$\frac{(g - \mu_1)^2}{\sigma_1^2} + \log \sigma_1^2 - 2 \log P_1 = \frac{(g - \mu_2)^2}{\sigma_2^2} + \log \sigma_2^2 - 2 \log P_2 \tag{3}$$

Instead of solving this quadratic equation (3), *Kittler and Illingworth* defined a criterion function $J(t)$ for threshold t as follows:

$$J(t) = 1 + 2(P_1 \log \sigma_1 + P_2 \log \sigma_2) - 2(P_1 \log P_1 + P_2 \log P_2) \tag{4}$$

Where $$\sigma_1^2 = \frac{\left[\sum_{i=0}^{t} (g - \mu_1)^2 \; p_i \right]}{P_1}, \quad \sigma_2^2 = \frac{\left[\sum_{i=t+1}^{l-1} (g - \mu_2)^2 \; p_i \right]}{P_2} \tag{5}$$

The optimal threshold t is obtained by minimizing $J(t)$.

M.K. Yanni, E. Horne, “A New Approach to Dynamic Thresholding”:

This method [19] assumes that two distinct peaks at gray levels l_{peak1}, l_{peak2} are identifiable in the probability mass function. A midpoint is first established as $l_{mid} = (l_{\max} + l_{\min})/2$ where $l_{\max}$ is the highest nonzero gray level and $l_{\min}$ is the lowest one. This midpoint is updated using the mean of the two peaks on the right and left of, that is as $l_{mid}^{*} = (l_{peak1} + l_{peak2})/2$. The threshold is then

$$T_{opt} = (l_{\max} - l_{\min}) \sum_{i = l_{\min}}^{l_{mid}^{*}} p(g) \tag{1}$$

Where, $(l_{\max} - l_{\min})$ is the span of non-zero gray values in the histogram.

Ping-Sung Liao, Tse-Sheng Chen and Pau-Choo Chung, "A Fast Algorithm for Multilevel Thresholding":

In this paper [20], a faster version of Otsu's method is proposed for improving the efficiency of computation for the optimal thresholds of an image. First, a criterion for maximizing a modified between-class variance that is equivalent to the criterion of maximizing the usual between-class variance is proposed for image segmentation. Next, in accordance with the new criterion, a recursive algorithm is designed to efficiently find the optimal threshold. This procedure yields the same set of thresholds as the original method. In addition, the modified between-class variance can be pre-computed and stored in a look-up table. Our analysis of the new criterion clearly shows that it takes less computation to compute both the cumulative probability (zero order moment) and the mean (first order moment) of a class, and that determining the modified between-class variance by accessing a look-up table is quicker than that by performing mathematical arithmetic operations.

P. Kanungo, P. K. Nanda and U. C. Samal, "Image Segmentation Using Thresholding and Genetic Algorithm":

In this paper [21] a method based on Genetic Algorithms is proposed for selection of threshold from the histogram of images. Specifically Genetic Algorithms based crowding algorithm is proposed for determination of the peaks and valleys of the histogram. This method is applicable only for bimodal images. For the multi-modal images it fails; so, experimental results is shown only for bimodal images.

Prof. Hisham Al-Rawi, Dr. Jane J. Stephan, "Histogram Based Optimal Multiple Thresholding Using Genetic Algorithm":

This paper [9] presents an approach for truly segmenting gray scaled images through thresholding. Thresholding is considered as an optimization problem. Genetic algorithm is used to search for the optimal thresholds. An Otsu [11] fitness criterion is used as a fitness function for the genetic algorithms. Single and multiple optimal thresholds are considered. Results showed that genetic algorithm is very promising in the area of image segmentation.

Ruohui Xiao, "An Image Segmentation Algorithm using Genetic Strategy":

This paper [22] describes about theoretical knowledge of genetic algorithms and proposes an image segmentation algorithm based on genetic algorithms. This paper tells how a population is chosen, how to select a fitness function and how combine the population to get a better population over an iteration or generation. This shows the wide applicability of genetic algorithm in image segmentation.

CHAPTER 3
GENETIC ALGORITHMS

In our thesis work we used genetic algorithms to find the threshold values, as we know that to find a threshold values is an optimization problem and genetic algorithm works well to solve the optimization problem. So, the basic concepts and working of genetic algorithm is explained here.

Genetic Algorithms are mainly the search based algorithms, they are not calculations based algorithm, means that we have to search an optimal threshold value from a given range of solutions and we don't have to calculate gradient etc, just we have to find the solution from a given range by applying some rules and assumptions. Genetic algorithms don't follow the deterministic rules, its follows the stochastic rules.

Genetic Algorithms (GAs) are a class of iterative procedures that simulate the evolution process of a population of structures subject to the competitive forces prescribed in '*survival of the fittest*' principle. The process of evolution is random yet guided by a selection mechanism based on the fitness of individual structures or population. GAs exhibit a behavior similar to evolution theory- relatively high fitness structures have a larger chance to survive and to produce even higher fitness offspring. The result will be an increase in the overall fitness of a population in each generation [23].

GAs starts by randomly generating a population of individuals (chromosomes). Each represents a point in the search space (the range of the population). The chromosomes are then evaluated to obtain a quantitative measure of how well they perform as possible problem solutions. Reproductive opportunities are allocated such that the best individuals receive more opportunities to reproduce than those which have poor performance, this bias need not be great to produce the required selective pressure to allow "artificial selection" to occur. This search uses probabilistic calculations, not deterministic, to find parameter sets and tends to be slower but has greater success at finding the global optima [24].

3.1 Genetic algorithms terminology

The explanations of Genetic Algorithms terms are given as follow:

Table- 3.1 Genetic algorithm terms

Genetic Algorithms Term	**Explanations**
Chromosome(string, individual)	Solution (coding)
Locus	Position of gene
Genes (bits)	Part of solution
Alleles	Values of gene
Phenotype	Decoded solution
Genotype	Encoded solution

3.2 Basic Principle of Genetic Algorithms

Genetic Algorithms don't deal with the solutions of the problem directly. It deals with the coding of the solutions. Coding of solution variables is an important characteristic because it describes the problem. The most used coding technique is to transform the variables to a binary string or vector. GAs performs best when solution variables are binary. When the problem has more than one variable, a multi-variable coding is used by concatenating as many single variables coding as the number of variables in the problem.

The major steps involved in the genetic algorithms are shown by the flow chart represented in figure 3.1. Genetic Algorithm processes a number of solutions simultaneously. In the first step a population having P individuals is generated by pseudo random generators (stochastically method) whose individuals represent a feasible solution in the given range of solutions. So it's the initial solution representation of solution vector in a solution space. This initial search method of solutions ensures the search to be robust and unbiased, as it starts from wide range of solutions in the solution space [24]. Now we calculate the objective function value for each individual or solution, individuals are chooses on the basis of their fitness value for the next generation to produce offspring. In next step we perform reproduction and crossover operator than we perform mutation operator to get the variations in solutions for the high fitness value. This process repeats until we don't get the stopping criteria (maximum generation etc.)

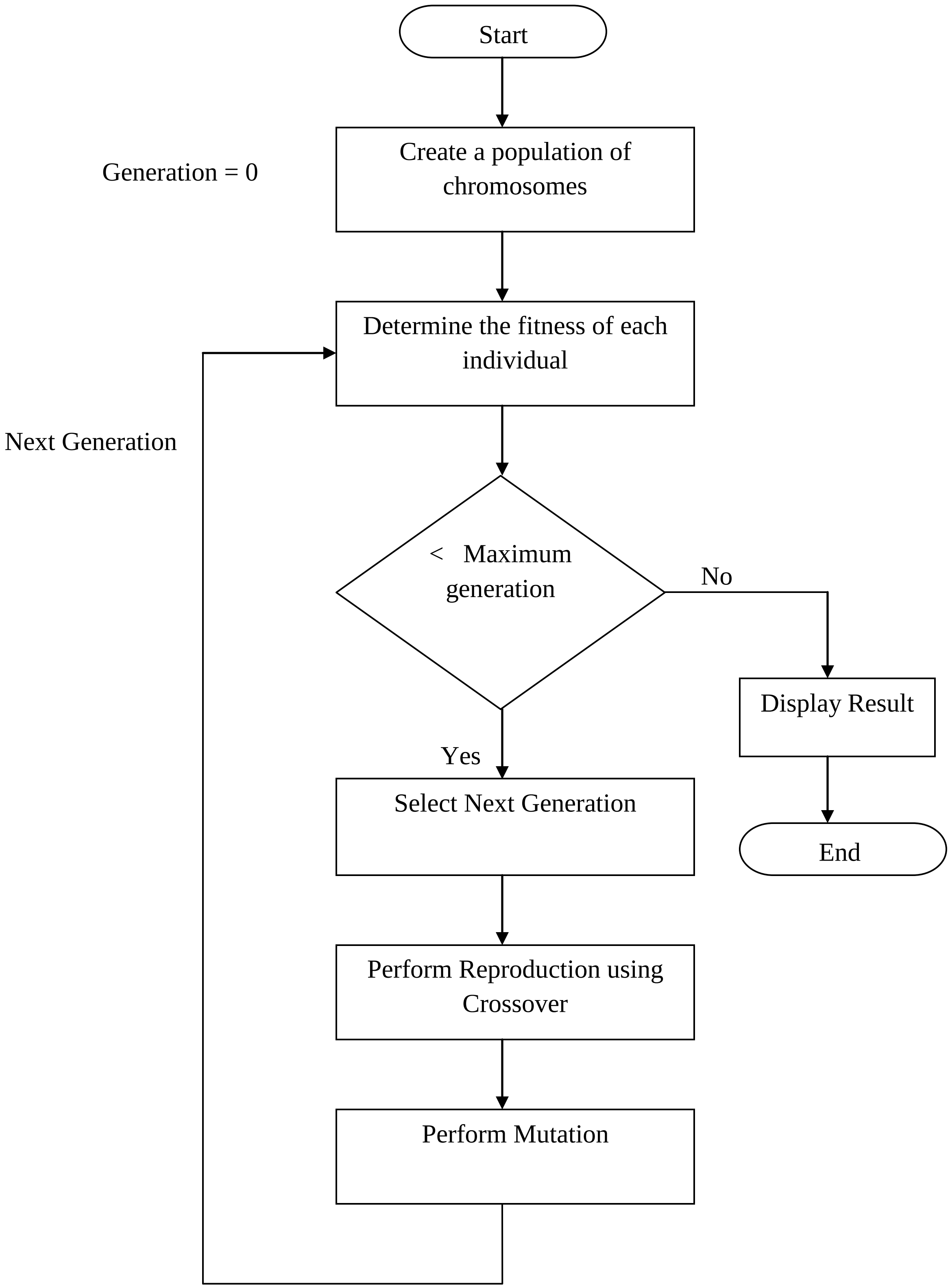

Figure 3.1 Steps of Genetic Algorithms

3.3 Working Principle of Genetic Algorithms

As we know that Genetic Algorithm works on the Darwinian Theory "the survival of the fittest" i.e. the fittest will survive. So we are considering about which have maximum fitness value, will survive. So Genetic Algorithm mainly works for maximization problem. If we have to deal with minimization problem then firstly we convert it into maximization problem [25].

Consider following maximization problem:

$$Maximize\ F(x), \qquad x_i^l \leq x \leq x_i^u$$

Where, $i = 1,2,.....N$

If we want to $Minimize\ f(x)$, for $f(x) > 0$ then we can write the objective function as

$$F(x) = \frac{1}{1 + f(x)} \tag{1}$$

If $f(x) < 0$, instead of $Minimize\ f(x)$, $Maximize\ f(x)$ [25].

3.4 Fitness function

Fitness is the measure of the goodness. Fitness function tells the goodness of the individual for a problem. GAs mimics the *"Survival of the fittest"* principle of nature to make a search process. Therefore, GAs is naturally suitable for solving maximization problems. Maximization problems are usually converted into minimization problem by suitable transformations, as shown above in the working principle of genetic algorithm. In general, a fitness function $F(x)$ is first derived from the objective function and used in successive genetic operations.

Fitness in biological sense is a quality value which is a measure of the reproductive efficiency of chromosomes. In genetic algorithm, fitness is used to allocate reproduction to the individuals in the population and thus act as some measure of goodness to be maximized. This means that individuals with higher fitness value will have higher probability of being selected as candidates for further iteration or generation [24].

3.5 Genetic Algorithms operators

The operation of GAs begins with a population of random chromosomes, representing design or decision variables. The population is operated by three main operators- reproduction or selection, crossover and mutation to create a new population of solutions. GAs can be viewed as trying to maximize the fitness function using these operators. The purpose of these operators is to create new solution vectors by selection, combination and alteration in the current solution vectors that have shown to be good temporary solutions for that iteration. The new population is further evaluated for next iteration and tested till last iteration or termination criterion of the genetic algorithm matched. Each iteration or evaluation procedure is called a generation. This procedure is continued until the process reach until maximum generation or If the cumulative change in the fitness function value over stall generations is less than Function tolerance or if the best fitness value is less than or equal to the value of fitness limit. The operators are described as given as follow:

3.5.1 Reproduction

Reproduction is usually the first operator applied on a population. Reproduction (or selection) is an operator that makes more copies of better strings in a new population. Reproduction selects good strings in a population and forms a mating pool. That's why reproduction operation to be sometimes known as the selection operator. Thus, the process of reproduction operation of natural selection causes those individuals that encode successful structures to produce copies more frequently [24]. To get the new population in next generation, the reproduction of the individuals in the current population is necessary. Better individuals; get by mixing and matching from the fittest individuals of the current population.

There exist many reproduction operators in GAs literature, but the basic idea in all of them is that the above average strings are picked from the current population and their multiple copies are inserted in the mating pool in a probabilistic manner for recombination of solutions.

3.5.1.1 Roulette-Wheel Selection

The commonly-used reproduction operator is roulette-wheel selection operator. In this operator a string is selected for the mating pool with a probability proportional to its fitness that's why it's called proportionate reproduction operator. The i^{th} string in the population is selected with a proportional probability F_i. The population size is usually kept fixed over iterations in a simple

GAs; the sum of the probability of all string being selected for the mating pools must be one. So, the probability for selecting the i^{th} string from population is:

$$P_i = \frac{F_i}{\sum_{i=1}^{n} F_i} \qquad (2)$$

Where, n is the population size. This selection scheme can be implemented by imagine a roulette-wheel with its circumference marked for each string proportionate to the fitness of the string. The roulette-wheel is spun n times, each time selecting an instance of the string chosen by the roulette-wheel pointer. Since the circumference of the wheel is marked according to a string's fitness, this roulette-wheel mechanism is expected to make $F_i / F_i^{'}$ copies of the i^{th} string in the mating pool [24]. The average fitness of the population is calculated as:

$$F^{'} = \sum_{i=1}^{n} F_i \qquad (3)$$

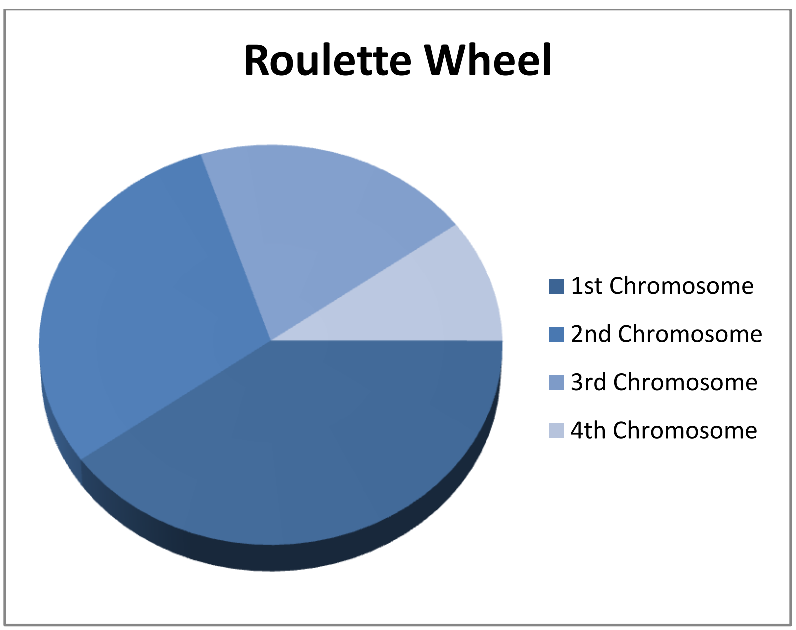

Figure 3.2 Roulette Wheel selection

The figure 3.2 shows a roulette-wheel for each individual having different fitness values. Since the first individual has higher fitness value than any other, it is expected that the roulette-wheel selection will choose more copies of the first individual than any other individual.

3.5.1.2 Stochastic Uniform Selection

Stochastic Uniform lays out a line, *figure 3.3*, in which each chromosome corresponds to a section of the line of length proportional to its scaled value. The process moves in steps of equal size along the line. At each step, the process allocates a parent from the section it lands on. For example, assume a population of 4 individuals with scaled values 5, 4, 2 and 1. The individual with the scaled value of 5 is the best and should contribute its genes more than the rest. We create a line of length 1+2+4+5=12. Now, let's say that we need to select 6 individuals for parents. We step over this line in steps of 12/6 and select the individual we land in, *figure 3.3*.

Selection Line (part lengths are proportional the scaled values)

1	2	3	4	5	6	7	8	9	10	11	12

4 individuals

Scaled fitness

5
4
2
1

Sum = 12

we want to select 6 parents

1	=1*12/6	2.0
2	=2*12/6	4.0
3	=3*12/6	6.0
4	=4*12/6	8.0
5	=5*12/6	10.0
6	=6*12/6	12.0

Figure 3.3 Stochastic uniform selection methods

3.5.1.3 Stochastic Remainder Selection

The basic idea of Stochastic Remainder selection is to remove or copy the string of the population depending on the values of reproduction counts. So we compute the reproduction count associated with each string.

Reproduction count for a string is computed on the basis of fitness value of that string. In the Stochastic remainder selection, first the probability of selection p_i is calculated as $p_i = F(i)/\sum F(i)$. Then, the expected number of individuals of each string is calculated as $e_n = n * p_i$, where *n* is the population size. The fractional parts of e_n are treated as probabilities with which individuals are selected for reproduction. One by one Bernoulli trials (i.e. weighted coin tosses) are performed using the fractional part of e_n. For example, a string with e_n = 1.3 will get a single count surely and another with a probability of 0.3. This is done until all the candidates in the population are examined. Reproduction is done on the basis of computed reproduction counts. Individuals with 0 counts are removed from the population. Other individuals with non-zero reproduction counts get multiple copies in population equal to the values of their reproduction counts [24]. The size of the population is kept constant over all iterations and this completes the reproduction operation. Different selection schemes vary in principle by assigning different number of copies to get better strings in the population but in all selection schemes the essential idea is same that more copies are allocated to the strings which have higher fitness value.

3.5.2 Crossover

A crossover operator is used to recombine two strings to get a better string. In crossover operation, recombination process creates different individuals in the successive generations by combining genes from two individuals of the previous generation or iteration. In reproduction, good strings in a population are probabilistically assigned a larger number of copies and a mating pool is formed. As we know that there is no new strings are formed in the reproduction phase. In the crossover operator, new strings are created by exchanging information among strings of the mating pool [24].

Many crossover operators exist in the GA literature, like one site crossover, two site crossovers, uniform crossover and scattered crossover. In most crossover operators, two strings are picked from the mating pool at random and some portion of the strings is exchanged between the strings. Crossover operation is done at string level by randomly selecting two strings for crossover operations.

3.5.2.1 Single site crossover

A one site crossover operator is performed by randomly choosing a crossing site along the string and by exchanging all bits on the right side of the crossing site as shown below. In one site crossover, a crossover site is selected randomly (shown as vertical lines). The right portion of the selected site of these two strings is exchanged to form a new pair of strings. The new strings are thus a combination of the old strings.

String 1	1 1 1|0 1 1 0 0	New String 1	1 1 1|1 1 0 0 1
String 2	1 1 0|1 1 0 0 1	New String 2	1 1 0|0 1 1 0 0
	before Crossover		after Crossover

Figure 3.4 Single site crossovers

3.5.2.2 Two site crossover

Two site crossovers is a variation of the one site crossover, except that two crossover sites are chosen and the bits between the sites are exchanged as shown in figure 3.5. One site crossover is more suitable when string length is small while two site crossovers are suitable for large strings. The underlying objective of crossover is to exchange information between strings to get a string that is possibly better than the parents. Two site crossovers are showing in figure 3.5.

String 1	1 1 1|0 1 1|0 0	New String 1	1 1 1|1 1 0|0 0
String 2	1 1 0|1 1 0|0 1	New String 2	1 1 0|0 1 1|0 1
	before Crossover		after Crossover

Figure 3.5 Two site crossovers

3.5.2.3 Scattered crossover

This type of crossover creates a random binary vector. So, the genes are selected from the first parent where the vector is a 1, and from the second one where the vector is a 0, and combines the genes to form the first child, and verse versa to form the second one. Scattered crossover is showing in figure 3.6.

Parent 1	A B C D E X Y Z	Parent 2	a b c d e x y z
Random Vector		1 1 1 1 0 1 0 1	
Child 1	A B C D e X y Z	Child 2	a b c d E x Y z

Figure 3.6 Scattered crossovers

3.5.3 Mutation

Mutation adds new information in a random or stochastic way to the genetic search process to find the global optima and ultimately helps to avoid getting trapped at local optima. It maintains the diversity in the population whenever the population tends to become homogeneous due to repeated use of reproduction and crossover operators. Mutation may cause the chromosomes of one generation to be different from next generation [24].

Mutation in a way is the process of randomly disturbing genetic information. They operate at the bit level; when the bits are being copied from the current string to the new string, there is probability that each bit may become mutated. This probability is called mutation probability p_m which is mutation probability. A stochastic mechanism is employed, if random number between zero and one is less than the mutation probability, then the bit is inverted, so that zero becomes one and one becomes zero. This helps in introducing a bit of diversity to the population by scattering the occasional points. This random scattering would result in better optima, or even modify a part of genetic code that will be beneficial in later operations or it might produce a weak individual that will never be selected for further operations in a iteration.

CHAPTER 4

PROPOSED METHODOLOGY

Image segmentation is a fundamental and a necessary process in image, video, and computer vision applications. In this thesis we propose a context sensitive thresholding technique for image segmentation by defining an energy curve associated with each gray value of the image. In order to take contextual information for selecting appropriate thresholds, first the proposed technique computes the energy of the image corresponding to each gray value. The energy is computed by taking into account the spatial contextual information of the image. Then a thresholding technique is used to find out multiple thresholds from the generated energy curve instead of Histogram of the image. To compute optimal thresholds here a GA based approach is used. The objective function of GA is modeled by using Kapur entropy formula as discussed in [17]. The detail of the proposed technique is given below.

4.1 Proposed Method

In the literature most of the existing thresholding techniques do not take into account the contextual information to find out appropriate thresholds. In this work we proposed a novel context sensitive thresholding technique for image segmentation. In order to take the spatial contextual information for thresholds selection process, we compute the energy value of the image associated with each gray value *t*. Then energy curve is used to select the thresholds instead of using Histogram of the image.

Let $I = \{l_{ij}, 1 \leq i \leq m, 1 \leq j \leq n\}$ be an image of size $m \times n$ where l_{ij} represents the gray value of image I at pixel position(i, j). The spatial correlation between neighboring pixels of image I is modeled by defining the neighborhood systems N of order d, for given spatial position (i, j) as $N_{ij}^{d} = \{(i + u, j + v), (u, v) \epsilon N^{d}\}$. According to the value of d, the neighbourhood system assumes different configurations. In this work, only the second-order neighbourhood systems is considered, i.e., $(u, v) \epsilon \{(\pm 1,0), (0, \pm 1), (1, \pm 1), (-1, \pm 1)\}$. Figure 4.1 depicts second-order (N^{2}) neighbour pixels of the pixel at spatial position(i, j).

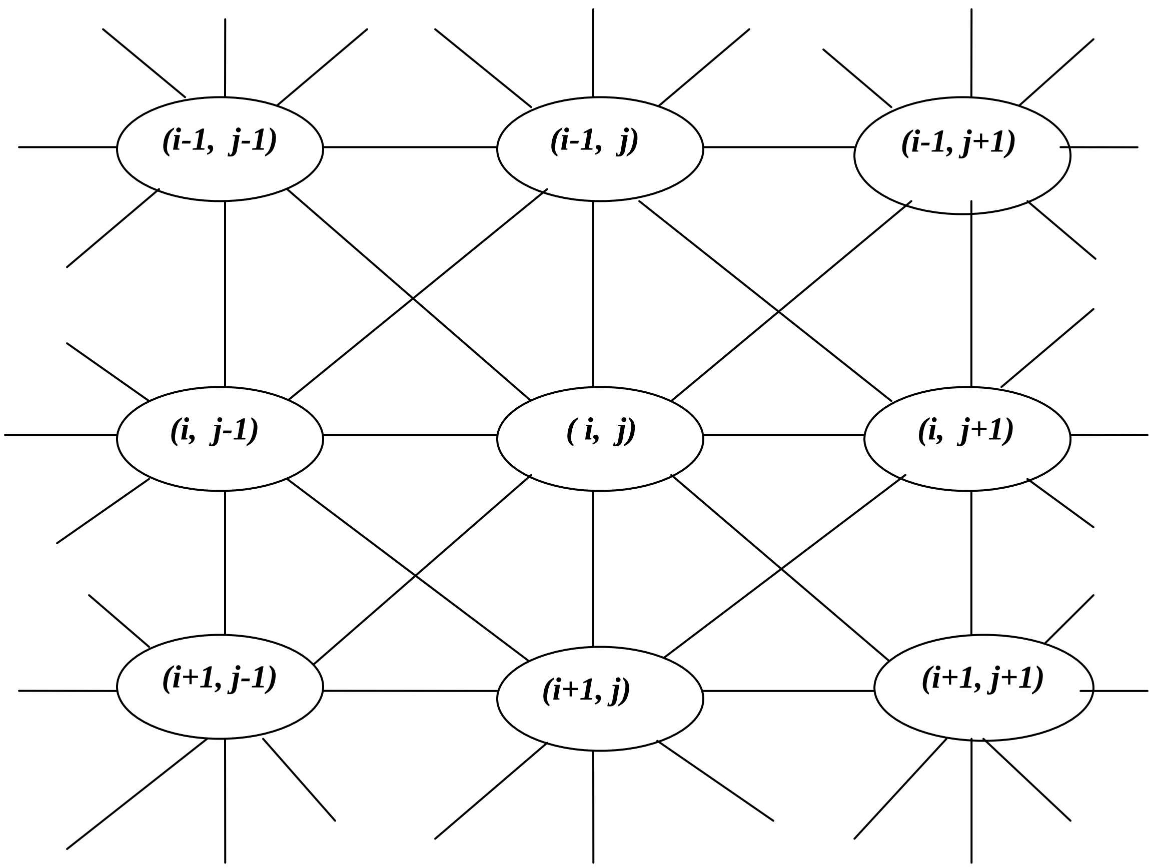

Figure 4.1 Second-order neighbors of the pixel at position (i, j)

In this work we proposed an energy function that computes the energy of an image corresponding to each gray value by taking into account the spatial contextual information of the considered image. To compute the energy of the image I at gray value t, first we generate a two-dimensional binary matrix $B_t = \{b_{ij}, 1 \le i \le m, 1 \le j \le n\}$ such that $b_{ij} = 1\ if\ l_{ij} > t; else\ b_{ij} = -1$. Thus, the value of each element b_{ij} in B_t is assigned either 1 or -1 depending on the corresponding pixel gray value l_{ij} and the value of t. let $C = \{c_{ij}, 1 \le i \le m, 1 \le j \le n\}$ be represents another binary matrix in which all the value of c_{ij} is either +1 or -1. Then energy value E_t of an image at gray value t is computed as:

$$E_t = -\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{(p,q)\epsilon N_{ij}^2} b_{ij} . b_{pq} + \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{(p,q)\epsilon N_{ij}^2} c_{ij} . c_{pq} \qquad (1)$$

From (1) we can say that for an image I, the energy value associated with a gray value t will be zero when all the elements of the generated matrix B_t are either +1 or -1 i.e., all the pixels of image I has gray values either greater than or less than t. Otherwise, the energy values will be positive as shown in Figure 4.2. In the proposed approach, we first compute the energy associated with each gray value of an image. Then instead of analyzing Histogram we used this energy curve for detecting the appropriate threshold.

4.1.1 Characteristics of energy curve

Like the Histogram, the energy curve of an image has a value corresponding to each gray label of the image. Figure 4.2 shows the energy curve of a real image. By analyzing the behavior of this curve, one can see that initially at $t = 0$, the energy value is minimum and does not change significantly by increasing the value of t since most of the pixels of the image have gray value greater than t. After certain gray value, the energy values starts to change by increasing the value of t for a specific range. In this range, the changes of energy value is very much similar to the bell shape curve i.e., initially it increases to reach peak then decreases. This is because of the pixels represent an object in the image has gray values in the same range. After that if we increase the gray value, energy will not be change significantly until it reaches near to the gray values that represent another object in the image. Thus, our proposed energy curve behaved like a Histogram of an image where we need to find out thresholds passes through the valley regions of the energy curve to segment the image. Since the energy curve is generated by considering spatial contextual information of the image, it is more clearly discriminate different objects in the image compared to the Histogram. Thus, become more effective to detect appropriate thresholds.

4.1.2 Multiple thresholds selection using Genetic Algorithm

After obtaining the energy curve corresponding to an image we may apply any of the Histogram based thresholding techniques exist in the literature to detect suitable thresholds form it. Most of the existing Histogram thresholding techniques are suitable for finding out single threshold. To find out multiple thresholds, they needs exhaustive search that may become computation demanding and also difficult to implement. To overcome this problem, in this work we used genetic algorithm to find out multiple thresholds from the energy curve of an image. The basic steps of GA, which also followed in the thresholds selection, are now described in detail.

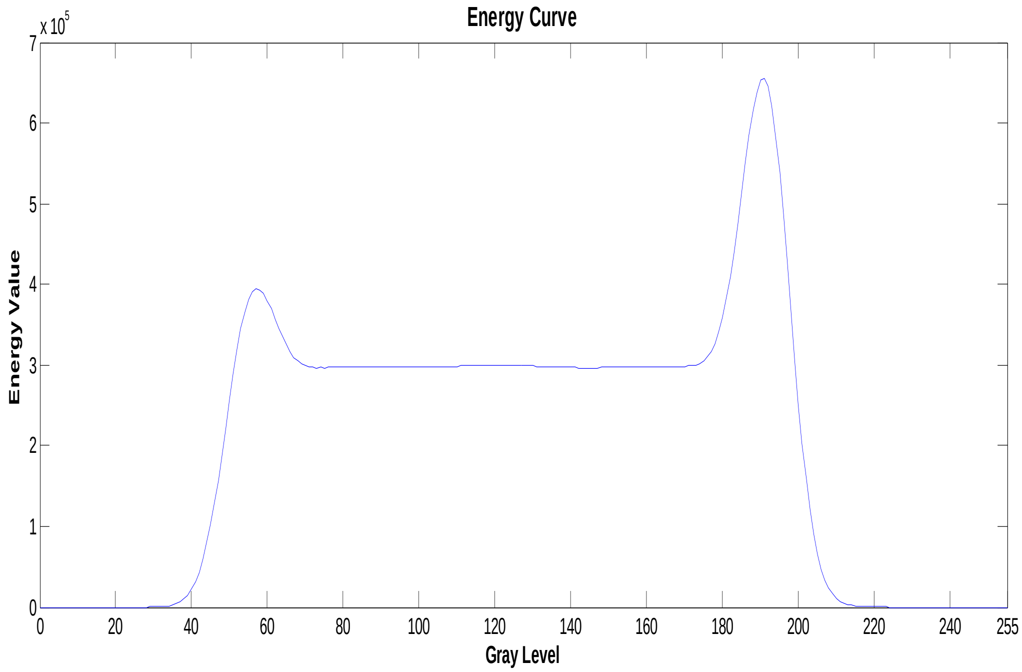

Figure 4.2 energy based curve

Chromosome representation: our problem is an integer constraint problem. So, here we used a double vector for represent the chromosome. So, for k thresholds we used k double values in a chromosome.

Population initialization: The total number of chromosomes belongs in a population is called the size of the population. The k thresholds in each chromosome are initialized randomly. In this thesis work we considered the population size 20.

Fitness computation: Fitness function is the most important component of GA. To compute fitness value of each chromosome in the population, here we exploit Kapur's entropy-based histogram-thresholding technique [17], where we used energy curve based on spatial contextual information based on our technique in place of histogram of the image. This is described briefly here:

Let ω_1 and ω_2 be two classes represent background and object of an image and EC be the Energy curve for the image that represents the energies for each gray level calculated by equation (1). After normalizing the energy curve, let the occurrence of energy for gray level i as p_i. For a threshold, assuming t, the entropies of classes ω_1 and ω_2(donated as $EN_{\omega_1}(t)$ and $EN_{\omega_2}(t)$, respectively) are computed as follows:

$$EN_{\omega_1}(t) = -\sum_{i=1}^{t} \frac{p_i}{P_{\omega_1}(t)} log_2\left(\frac{p_i}{P_{\omega_1}(t)}\right)$$

$$EN_{\omega_2}(t) = -\sum_{i=t+1}^{L-1} \frac{p_i}{P_{\omega_2}(t)} log_2\left(\frac{p_i}{P_{\omega_2}(t)}\right) \qquad (2)$$

Where $P_{\omega_1}(t) = \sum_{i=0}^{t} p_i$ and $P_{\omega_2}(t) = 1 - P_{\omega_1}(t)$. To select a threshold on the Histogram that properly discriminate the back ground and object pixels in image (i.e., that passes through the valley region of the Histogram), the entropies of classes ω_1 and $\omega_2$are computed by assuming all possible values of the threshold t. Then, the optimal threshold is selected by maximizing the total entropy $EN_{\omega_1}(t) + EN_{\omega_2}(t)$.

Now if the image contains multiple objects with different gray values then we need to find out multiple thresholds to separate one object from other. Let $\omega_1, \omega_2, \ldots, \omega_k$ are the k objects of an image separated from each other by defining thresholds $t_1, t_2, \ldots, t_k$, where $t_1 < t_2 < t_3, \ldots, < t_k$. Then entropy of j^{th} object is computed as: $EN_{\omega_j}(t_j) = -\sum_{i=t_{j-1}+1}^{t_j} \frac{p_i}{P_{\omega_j}(t_j)} log_2\left(\frac{p_i}{P_{\omega_j}(t_j)}\right)$ where, $t_0 = 0$ and the total entropy will be:

$$EN = \sum_{j=1}^{k} EN_{\omega_j}(t_j) \qquad (3)$$

Then the thresholds represent by a chromosome are used to compute its fitness value by computing total entropy using (3).

Selection: The selection process selects chromosomes from the mating pool directed by the survival of the fittest concept of natural genetic systems. The stochastic uniform selection strategy adopted in this article, a chromosome is assigned a number of counts, based on the fitness value in the population, that go into the mating pool according to their counts for further genetic operations.

Crossover: Crossover exchanges information between two parent chromosomes for generating two child chromosomes. In this article scattered crossover is used. Scattered crossover is done using a random vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.

Mutation: For our integer constraint problem, there is no mutation done.

Termination criterion: The processes of computation of fitness function, reproduction (selection), crossover operations are executed for a maximum number of iterations or generations. In these work maximum iterations is set as 50.

After termination criterion satisfied the chromosome in the population that has maximum fitness value is considered for selecting the optimal thresholds. Then depending on these thresholds values the image is segmented to discriminate different objects.

4.2 Experimental setup

The experimental setup used for implementing the proposed method is given as follow:

Table 4.1 Experimental Setup

Physical Machine	Intel core i3 CPU @ 2.53 GHz with 4.00 GB RAM
Operating System	Windows 7, 64 bit operating system
Software/Tool	MATLAB 7.14 (Release 2012a)

CHAPTER 5

RESULTS AND DISCUSSION

As we have discussed the proposed method in the last chapter i.e., chapter 4, now we carried out some results by applying this method. Segmentation problem is treated as a clustering problem, results obtained are evaluated using a cluster validity measure called Davies Bouldin (DB) index, which was proposed by Davies and Bouldin. It is a function of the ratio of the sum of within-cluster scatter to between-cluster separation. Let $C_1, C_2, \ldots\ldots C_k$ be the k clusters then, the DB measure is defined as:

$$DBindex = \frac{1}{k}\sum_{i=1}^{k} R_i \tag{1}$$

Where, $R_i = \max_{j=1\ldots k,\, i\neq j} \{R_{ij}\}$ and $R_{ij} = \frac{\left(\sigma_i^2 + \sigma_j^2\right)}{d_{ij}^2}$ (2)

Where σ_i^2 and σ_j^2 are the variances of cluster C_i and C_j , respectively and d_{ij}^2 is the distance between cluster centers C_i and C_j. The value of Rij will be small when there is a low variance and a high distance between clusters. Clusters that are compact and have centers far away from each other have small *DBindex* value. So the clustering is better when *DBindex* value is smaller.

In order to assess the effectiveness of the proposed technique a comparison between proposed technique and Kapur's method [17] is carried out. We took the results on the four images by both methods and the clustering accuracy is estimated in terms of DB index. For each image we carried out five results i.e., for 1,2,3,4 and 5 thresholds, respectively for each method and estimated the DB index value corresponding their thresholds value. We showed the segmented image result only for 1 and 3 threshold value for each method. The results for the images are given as follow:

5.1 Image 1

Figure 5.1(a) Original Image 1

Our first image, a *bitmap* image which has dimensions of *512*512* and a size of *257 KB,* is shown in figure 5.1(a). Figure 5.1(b) is the Histogram of the image i.e., number of the pixels corresponding to their gray values. Figure 5.1(c) shows the energy curve proposed by our method for this image. Figure 5.1(d) and 5.1(e) are the segmented images carried out by Kapur's method and proposed method with 1 threshold. Where, figure 5.1(f) and 5.1(g) are the segmented images with 3 thresholds by Kapur's method and proposed method, respectively. Table 5.1(a) and Table 5.1(b) shows the results for 1, 2, 3, 4 and 5 thresholds values and their corresponding DB index values for this image by Kapur's method and proposed method, respectively.

By comparing the DB index value we can compare their accuracy of clustering on the basis of thresholding value, where low DB index shows the better thresholding of the images. Threshold values are calculated in the valley of the energy curve and histogram. Energy curve shows the peaks clearly, so, to detect the object in energy curve is easier than histogram of the image.

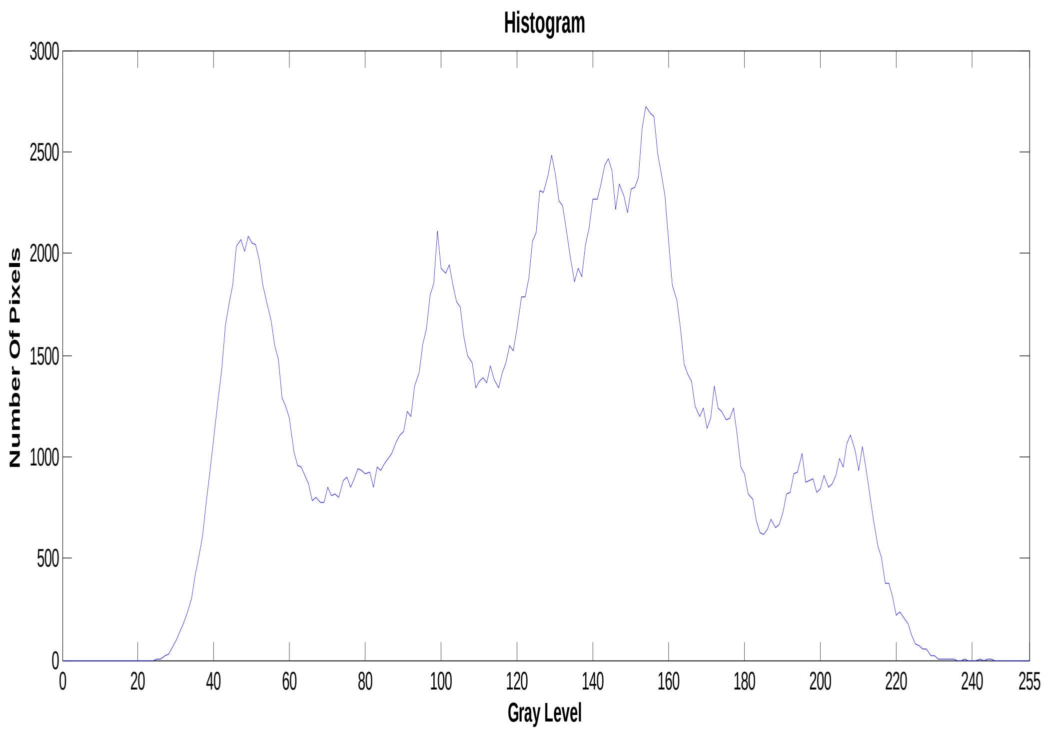

Figure 5.1(b) Histogram of the Image 1

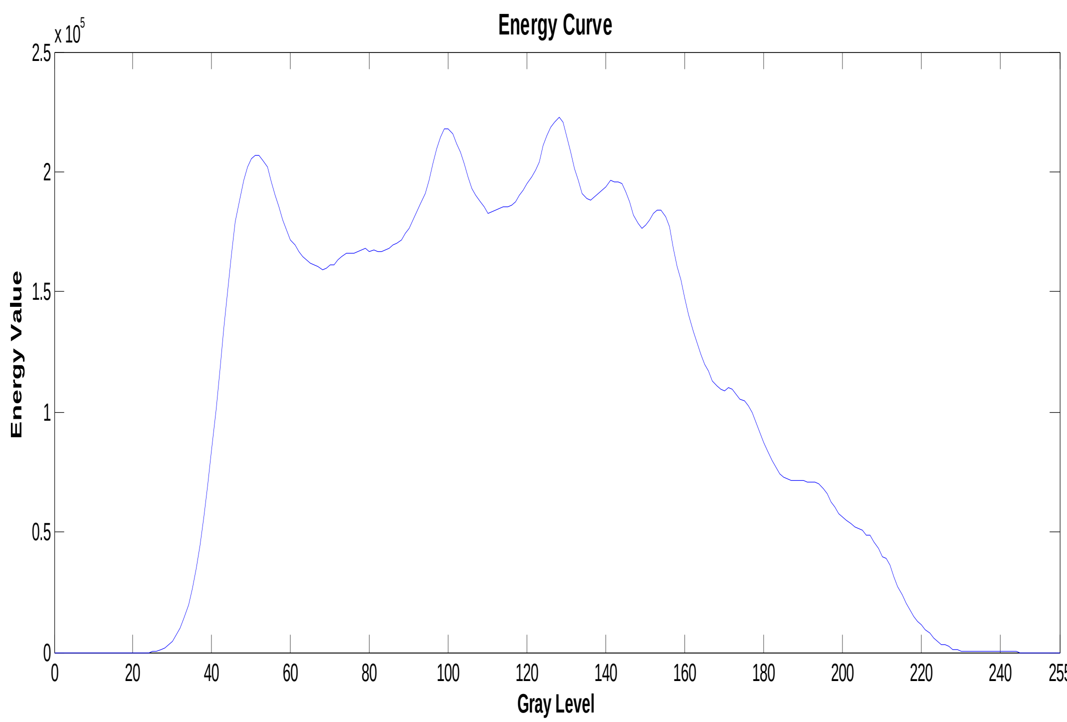

Figure 5.1(c) energy curve for the Image 1

Figure 5.1(d) Segmented image for Image 1 by Kapur's method with 1 threshold

Figure 5.1(e) Segmented image for Image 1 by proposed method with 1 threshold

Figure 5.1(f) Segmented image for Image 1 by Kapur's method with 3 thresholds

Figure 5.1(g) Segmented image for Image 1 by proposed method with 3 thresholds

Table 5.1(a) Kapur's method results for Image 1

	1 Threshold	**2 Thresholds**	**3 Thresholds**	**4 Thresholds**	**5 Thresholds**
Thresholds values	123	97 164	91 129 178	77 118 159 189	60 99 132 165 197
DB index	0.2167	0.1827	0.1629	0.1651	0.1833

Table 5.1(b) proposed method results for image 1

	1 Threshold	**2 Thresholds**	**3 Thresholds**	**4 Thresholds**	**5 Thresholds**
Thresholds values	131	99 164	83 131 178	72 109 146 184	71 102 133 166 197
DB index	0.2372	0.1838	0.1598	0.1621	0.1708

By proposed method the clustering is better than Kapur's method for 3, 4 and 5 thresholds values, but for 2 thresholds Kapur's method clustering is little more accurate and for 1 threshold value Kapur's method gives better results. Because *Image 1* is a multimodal image, it's not a bimodal image. So, to segment the image with 1 threshold is not a better idea. As the clustering done for 3, 4 and 5 thresholds are better by our proposed method.

5.2 Image 2

Figure 5.2(a) Original image 2

Our Second image, a *JPEG* image which has dimensions of *256*256* and a size of *12.2 KB*, is shown in figure 5.2(a). Figure 5.2(b) is the Histogram of the image i.e., number of the pixels corresponding to their gray values. Figure 5.2(c) shows the energy curve proposed by our method for this image. Figure 5.2(d) and 5.2(e) are the segmented images carried out by Kapur's method and proposed method with 1 threshold. Where, figure 5.2(f) and 5.2(g) are the segmented images with 3 thresholds by Kapur's method and proposed method, respectively. Table 5.2(a) and Table 5.2(b) shows the results for 1, 2, 3, 4 and 5 thresholds values and their corresponding DB index values for this image by Kapur's method and proposed method, respectively.

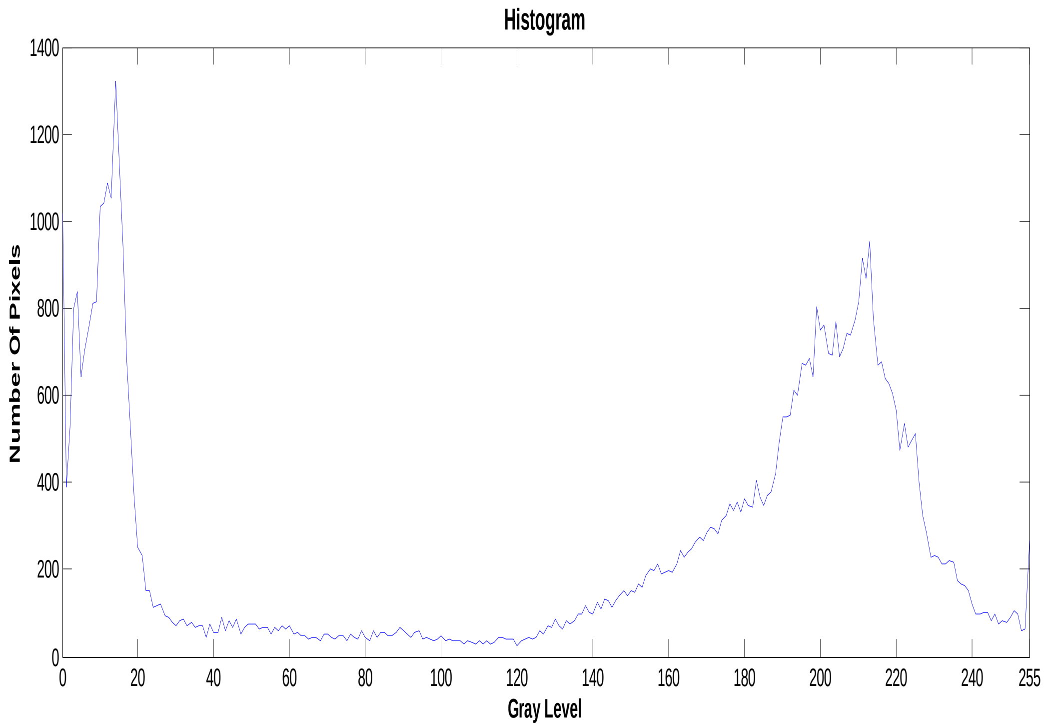

Figure 5.2(b) Histogram of the Image 2

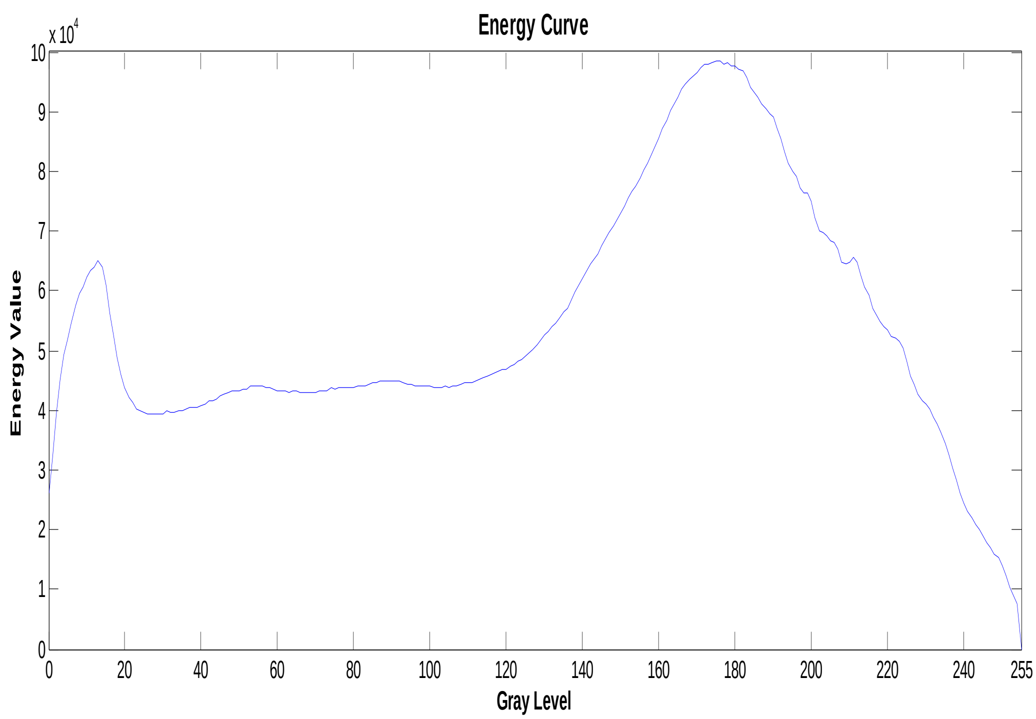

Figure 5.2(c) Energy curve for Image 2

Figure 5.2(d) segmented image for Image 2 by Kapur's method with 1 threshold

Figure 5.2(e) segmented image for Image 2 by proposed method with 1 threshold

Figure 5.2(f) segmented Image for Image 2 by Kapur's method with 3 thresholds

Figure 5.2(g) segmented Image for Image 2 by proposed method with 3 thresholds

Table 5.2(a) Kapur's method results for image 2

	1 Threshold	2 Thresholds	3 Thresholds	4 Thresholds	5 Thresholds
Thresholds values	167	47 141	37 126 180	25 101 134 173	27 63 121 168 212
DB index	0.1493	0.1415	0.1833	0.1952	0.2024

Table 5.2(b) proposed method results for Image 2

	1 Threshold	2 Thresholds	3 Thresholds	4 Thresholds	5 Thresholds
Thresholds values	125	80 160	62 128 190	58 108 159 214	56 100 143 181 218
DB index	0.0489	0.1474	0.1673	0.1856	0.1795

Here, for 1, 3, 4 and 5 thresholds proposed method gives better clustering, but for 2 thresholds Kapur's method gives better clustering. The graph for this image is a bimodal graph, showing in figure 5.2(b) & 5.2(c). So, the segmentation should be done for the single threshold and for single threshold proposed method shows more accurate clustering than Kapur's method.

5.3 Image 3

Figure 5.3(a) Original Image 3

Next image is a *JPEG* image has dimensions of *400*480* and a size of *147 KB*, shown in figure 5.3(a). Figure 5.3(b) is the Histogram of the image i.e., number of the pixels corresponding to their gray values. Figure 5.3(c) shows the energy curve proposed by our method for this image. Figure 5.3(d) and 5.3(e) are the segmented images carried out by Kapur's method and proposed method with 1 threshold. Where, figure 5.3(f) and 5.3(g) are the segmented images with 3 thresholds by Kapur's method and proposed method, respectively. Table 5.3(a) and Table 5.3(b) shows the results for 1, 2, 3, 4 and 5 thresholds values and their corresponding DB index values for this image by Kapur's method and proposed method, respectively.

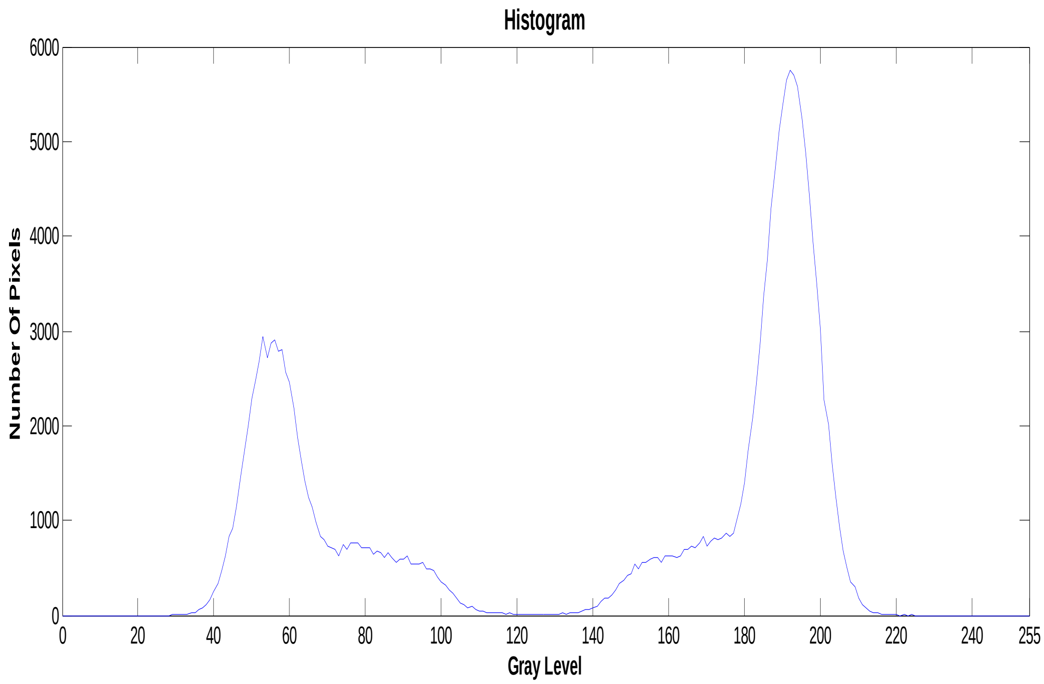

Figure 5.3(b) histogram for Image 3

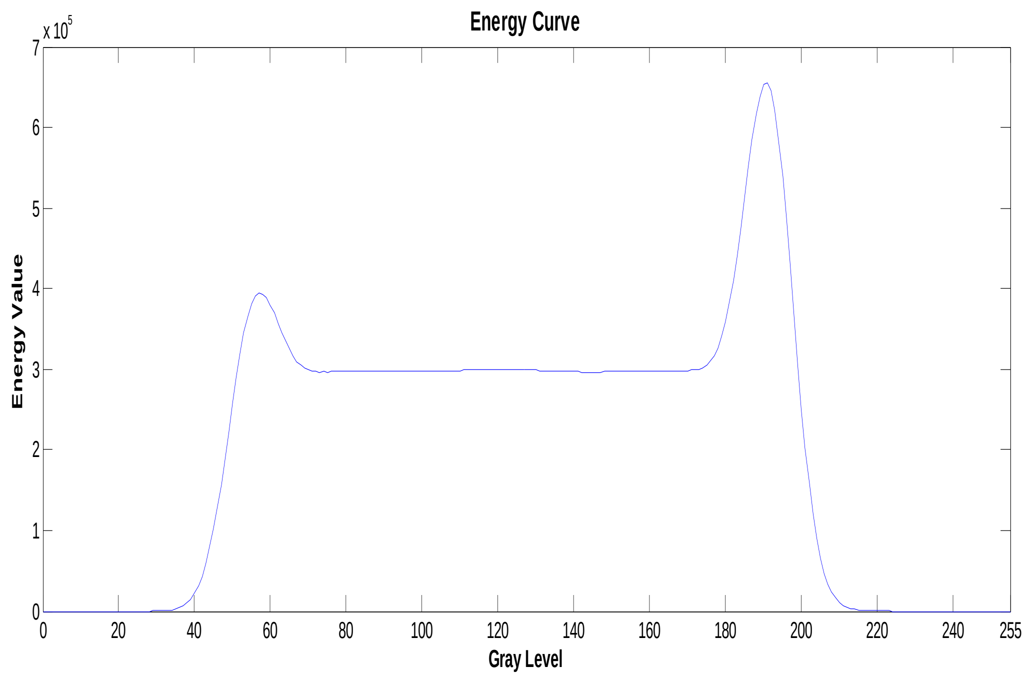

Figure 5.3(c) energy curve for Image 3

Figure 5.3(d) segmented image for Image 3 by Kapur's method with 1 threshold

Figure 5.3(e) segmented image for Image 3 by proposed method with 1 threshold

Figure 5.3(f) segmented image for Image 3 by Kapur's method with 3 thresholds

Figure 5.3(g) segmented image for Image 3 by proposed method with 3 thresholds

Table 5.3(a) Kapur's method results for Image 3

	1 Threshold	2 Thresholds	3 Thresholds	4 Thresholds	5 Thresholds
Thresholds values	154	86 165	107 141 178	68 109 140 178	70 109 138 162 183
DB index	0.0533	0.2430	0.1443	0.1626	0.1702

Table 5.3(b) proposed method results for Image 3

	1 Threshold	2 Thresholds	3 Thresholds	4 Thresholds	5 Thresholds
Thresholds values	124	97 151	83 122 162	84 122 151 181	66 92 119 138 172
DB index	0.0290	0.1722	0.1104	0.1677	0.1540

For 1, 2, 3 and 5 thresholds proposed method done better clustering, whether for 4 thresholds Kapur's method looks more accurate. This image shows a bimodal graph, showing in figure 5.3(b) & 5.3(c). So, the clustering should be done for the single threshold. As in the results our proposed method shows better clustering than Kapur's method for single threshold. So, there is a nice clustering done through our proposed method for *Image 3*.

5.4 Image 4

Figure 5.4(a) Original Image 4

Last image is a *bitmap* image which has dimensions of *286*430* and a size of *121 KB*, is shown in figure 5.4(a). Figure 5.4(b) is the Histogram of the image i.e., number of the pixels corresponding to their gray values. Figure 5.4(c) shows the energy curve proposed by our method for this image. Figure 5.4(d) and 5.4(e) are the segmented images carried out by Kapur's method and proposed method with 1 threshold. Where, figure 5.4(f) and 5.4(g) are the segmented images with 3 thresholds by Kapur's method and proposed method, respectively. Table 5.4(a) and Table 5.4(b) shows the results for 1, 2, 3, 4 and 5 thresholds values and their corresponding DB index values for this image by Kapur's method and proposed method, respectively.

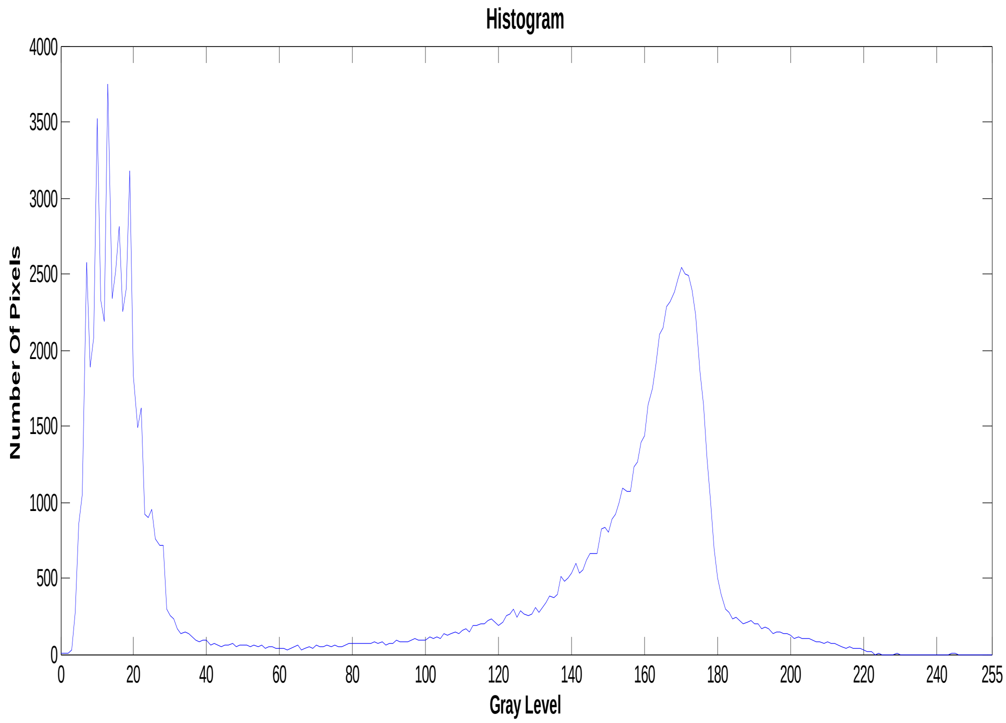

Figure 5.4(b) histogram for Image 4

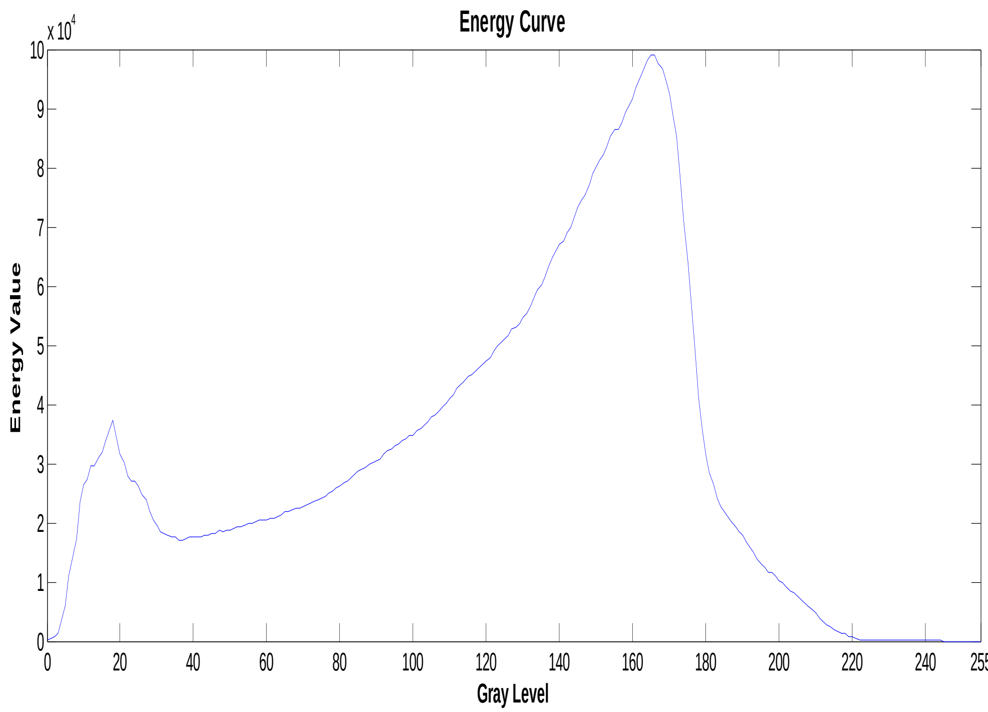

Figure 5.4(c) energy curve for Image 4

Figure 5.4(d) segmented image for Image 4 by Kapur's method with 1 threshold

Figure 5.4(e) segmented image for Image 4 by proposed method with 1 threshold

Figure 5.4(f) segmented image for Image 4 by Kapur's method with 3 thresholds

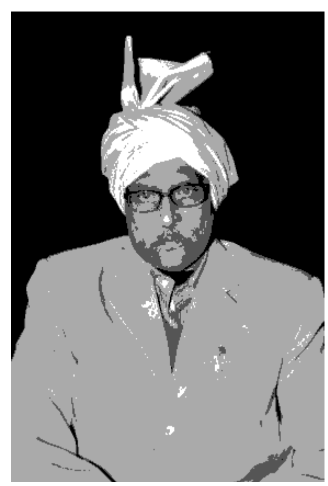

Figure 5.4(g) segmented image for Image 4 by proposed method with 3 thresholds

Table 5.4(a) Kapur's method result for Image 4

	1 threshold	2 threshold	3 threshold	4 threshold	5 threshold
Thresholding	138	33 113	38 121 183	35 93 135 183	32 61 99 137 182
DB index	0.0999	0.1721	0.1872	0.1812	0.1658

Table 5.4(b) proposed method results for Image 4

	1 Threshold	2 Thresholds	3 Thresholds	4 Thresholds	5 Thresholds
Thresholds values	101	71 132	67 124 181	48 96 139 181	53 99 142 183 223
DB index	0.0326	0.1194	0.1689	0.1648	0.1458

The clustering done for this image by our proposed method is looks better than Kapur's method for all the examined thresholds clustering. As the given image is a bimodal image, so, the clustering done with single threshold would be better idea. As we can see that, proposed method shows better clustering for single threshold.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

Energy curve shows the spatial contextual information of the image, which is a very efficient way of representation of the information of the image as compared to histogram information. In energy curve to recognize the peaks is much easier job as compared to histogram, so, to detect the objects and to separate them is easier task as compared to histogram. Histogram does not take spatial contextual information; it does just represent the number of pixels per gray level information. Sometimes, to recognize the peaks may be difficult job when there are so many variations in peak area. Whether, Energy curve improve the discriminate power to separate the objects and provides better clustering.

Histogram based traditional thresholding techniques do not considered spatial contextual information for selecting the optimum threshold and are effective only to identify single threshold. In this thesis we proposed a novel thresholding technique that mitigated both these limitations. First, we proposed an energy function that computes the energy of the image at each gray value by taking into an account the spatial contextual information of the image. The energy value is computed in such a way that the characteristic of the energy curve is similar to histogram of the image. Thus, by using the energy curve instead of using histogram, we incorporated spatial contextual information in threshold selection process. Second to mitigate multiple thresholds selection problem, here we exploited genetic algorithm. The fitness function of the genetic algorithm is modeled by extending the criterion proposed in [17].

Multi-thresholding is a difficult task as respective to computational effort in image segmentation, but genetic algorithms make it easier. Genetic algorithms results show that it is very promising in this field. We carried out results on 4 images for both methods i.e., Kapur's method [17] and proposed method, and compared the results on the basis of DB index. Result data sets shows that our proposed method is a better technique as compared to Kapur's method [17].

6.2 Future Scope

As energy curve is a better way of representing the information of the image. We can use it in other methods of image thresholding or other research area of image processing; where we need histogram of the image. So, the energy curve can be a substitute of histogram. In our thesis work, we chooses threshold on the basis of DB index i.e., for what no. of thresholds segmentation should be done or for what number of thresholds clustering will be more accurate. In future we can automate a pattern using energy curve by which we can classify the no. of thresholds for which segmentation should be done for a particular image.

REFERENCES

[1] Linda G. Shapiro and George C. Stockman (2001): “Computer Vision”, pp 279-325, New Jersey, Prentice-Hall, ISBN 0-13-030796-3.

[2] N. Senthilkumaran and R. Rajesh, “Edge Detection Techniques for Image Segmentation – A Survey of Soft Computing Approaches”, International Journal of Recent Trends in Engineering, Vol. 1, No. 2, May 2009.

[3] Tranos Zuva, Oludayo O. Olugbara, Sunday O. Ojo and Seleman M. Ngwira, “Image Segmentation, Available Techniques, Developments and Open Issues”, Canadian Journal on Image Processing and Computer Vision Vol. 2, No. 3, March 2011.

[4] Pedro F. Felzenszwalb, “Efficient Graph-Based Image Segmentation”.

[5] J. Serra., “Image Analysis and Mathematical Morphology”, Academic Press, 1982

[6] S.L. Horowitz and T. Pavlidis, “Picture Segmentation by a Directed Split and Merge Procedure”, Proc. ICPR, 1974, Denmark, pp.424-433.

[7] S.L. Horowitz and T. Pavlidis, “Picture Segmentation by a Tree Traversal Algorithm”, Journal of the ACM, 23 (1976), pp. 368-388.

[8] L. Chen, “The lambda-connected segmentation and the optimal algorithm for split-and-merge segmentation”, Chinese J. Computers, 14(1991), pp 321-331.

[9] Prof. Hisham Al-Rawi, Dr. Jane J. Stephan, “Histogram-Based Optimal Multiple Thresholding Using Genetic Algorithm”, College of Information Technology / University Of Bahrain –Bahrain, National Computer Center-Baghdad, Iraq.

[10] T.W. Ridler, S. Calvard, Picture thresholding using an iterative selection method, IEEE Trans. System, Man and Cybernetics, SMC-8 (1978) 630-632.

[11] Nobuyuki Otsu, “A Threshold Selection Method from Gray-Level Histograms”, IEEE transactions on systems, man, and cybernetics, Vol., smc-9, no. 1, January 1979.

[12] T. Pun, “A New Method for Gray-Level Picture Threshold Using the Entropy of the histogram”, Signal Processing, Vol.2 No. 3 (1980) 223-237.

[13] P. K. Sahoo, S. Soltani, and A. K. C. Wong, “SURVEY: A Survey of Thresholding Techniques”, computer vision, graphics, and image processing 41, 233-260 (1988)

[14] T. Pun, “Entropic Thresholding: A New Approach”, Computer Graphics and Image Processing, 16, (1981) 210-239.

[15] G. Johannsen and J. Bille, "A threshold selection method using information measures", in Proceedings, 6th Int. Conf. Pattern Recognition, Munich, Germany, 1982, pp. 140-143.

[16] D.E. Lloyd, "Automatic Target Classification Using Moment Invariant of Image Shapes", Technical Report, RAE IDN AW126, Farnborough-UK, December 1985.

[17] J. N. Kapur and P. K. Sahoo, "A New Method for Gray-Level Picture Thresholding using Entropy of the Histogram", Computer vision, Graphics and Image Processing 29, 273-285(1985).

[18] Kittler, J. and Illingworth, J., 1986, "Minimum error thresholding". Pattern Recognition, 19, pp. 41–47.

[19] M.K. Yanni, E. Horne, "A New Approach to Dynamic Thresholding", EUSIPCO-9: European Conf. on Signal Processing, Vol. 1, Edinburg, 1994, pp.34-44.

[20] Ping-Sung Liao, Tse-Sheng Chen And Pau-Choo Chung, "A Fast Algorithm for Multilevel Thresholding", Journal Of Information Science And Engineering 17, 713-727 (2001).

[21] P. Kanungo, P. K. Nanda and U. C. Samal, "Image Segmentation Using Thresholding and Genetic Algorithm", Image Processing and Computer Vision Lab. Department of Electrical Engineering, NIT, Rourkela.

[22] Ruohui Xiao, "An Image Segmentation Algorithm using Genetic Strategy", 2nd International Conference on Computer Engineering and Technology [Volume-6], V6-607, 2010.

[23] Tam, K.L. 1992, "Genetic Algorithms, Function Optimization and Facility Layout Design", European Journal of Operational Research, 63, pp.322-346.

[24] Tom V. Mathew, "Genetic Algorithm", Assistant Professor, Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai.

[25] S. Rajeskaran , G.A. Vijayalakshmi Pai., "Neural Networks, Fuzzy Logic and Genetic Algorithms synthesis and Applications".