To: Dr. Saundra F. DeLauder, Dean of Graduate Studies and Research

The members of the Committee approved the Thesis of ___Chao Zhang___ as presented on ___April 15, 2015___.

We recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science with a major in ___Applied Mathematics___.

___S Makrogiannis___ Department ___Math___ Date ___4/15/2015___
Advisor

_______ Department ___Math.___ Date ___4/15/2015___
Member

_______ Department ___Math___ Date ___4/15/2015___
Member

_______ Affiliation ___CIS___ Date ___4/15/2015___
Outside Member

APPROVED

_______ Department ___Math___ Date ___4/15/2015___
Program Director

_______ College ___Math Nat Sci Tech___ Date ___4/16/15___
Dean

for Saundra F DeLauder Date ___4/29/15___
Dean, School of Graduate Studies and Research

GRAPH-BASED ANALYSIS IN COMPUTER VISION: PRINCIPLES, ALGORITHMS AND APPLICATIONS

by

CHAO ZHANG

A THESIS

Submitted in partial fulfillment of the requirements for
the degree of
Master of Science
in the
Applied Mathematics
Graduate Program of
Delaware State University

DOVER, DELAWARE
May 2015

COPYRIGHT

DEDICATION

This thesis is dedicated to my beloved wife, Ying Yāng.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my advisor, Dr. Sokratis Makrogiannis, who has provided me with valuable encouragement and guidance in every stage of the writing of this thesis. Without his enlightening instruction, impressive kindness and patience, I could not have completed my thesis.

I would also like to extend my sincere thanks to Dr. Fengshan Liu for all his kindness and help. My special appreciation goes to Dr. Yucui Guo, whose help means a lot to me.

I would also like to thank other members of my thesis committee, Dr. Jinjie Liu, Dr. Xiquan Shi and Dr. David Pokrajac for taking the time to read this thesis and for giving helpful suggestions.

I wish to thank College of Mathematics, Natural Sciences and Technology and Delaware State University for providing me with the opportunity, resources and the scholarships that made this research possible.

My sincere appreciation also goes to the faculty and staff of Department of Mathematical Sciences.

I wish to acknowledge the US Department of Defense through the grant "Center for Advanced Algorithms" (W911NF-11-2-0046) for their support.

Last but not least, my thanks would go to my beloved parents for their loving considerations and great confidence in me through all these years. I also owe my sincere gratitude to my wife who gave me her help and time during the writing of this thesis.

ABSTRACT

Graph theoretic image segmentation enjoys great popularity in the image analysis domain. The image segmentation task may be translated as a graph-based optimization problem for finding the optimal graph partitioning. Normalized cut (N-cut) is an algebraic graph optimization technique applied in image segmentation. Despite the fact that N-cut produces good results for a variety of images, it has some weaknesses, such as high computational cost and over-segmentation. In this paper I adopt the watershed transform to address these problems. Watershed can improve slow computing speed and produce a closed outline of objects. However, watershed itself has the drawback of over-segmentation. Therefore, I propose to first apply watershed, then build a graph from the watershed regions and find the N-cuts of the watershed region graph to improve segmentation accuracy.

The first goal of this thesis is to study graph theoretic algorithms in the literature mainly formulating image segmentation as a graph optimization problem. The second goal is to reduce the complexity of this problem by optimizing region-based graph structures. The third goal is to validate the performance of the existing and the proposed methods and test the hypothesis that region-based analysis reduces the complexity of optimization problem.

I also compare the results produced by watershed, N-cut, and the proposed technique. The results show that the proposed technique in this paper guarantees precision, reduces calculation complexity and improves the problem of over segmentation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES OR ILLUSTRATIONS

ACRONYMS

CT computed tomography

DOOG difference of offset gaussian

GUI graphical user interface

HSV hue, saturation, value

MST minimum spanning tree

N-cuts normalized cuts

NRN the number of regions produced by Normalized cut method

NRW the number of regions produced by Watershed method

NRWC the number of regions produced by Water-cuts RAG method

NRWNC the number of regions produced by Water-cuts Clust method

RAG region adjacency graph

YLGC Yang and Liu's global criterion

YLGCN the value of YLGC after using Normalized cut method

YLGCW the value of YLGC after using Watershed method

YLGCWC the value of YLGC after using Water-cuts RAG method

YLGCWNC the value of YLGC after using Water-cuts Clust method

Chapter 1

INTRODUCTION

1.1 Motivation

This thesis deals with graph-based image segmentation techniques. The first goal is to study graph theoretic algorithms in the literature mainly formulating image segmentation as a graph optimization problem. The second goal is to reduce the complexity of this problem by optimization of region-based graph structures. The last goal is to validate the performance of the existing and the proposed methods and test the hypothesis that region-based analysis reduces the complexity of optimization problem.

1.2 Preview

Image segmentation is a technology that divides an image into a set of meaningful areas or objects that are not overlapping. In general, the accuracy of segmentation depends on whether the required areas are accurately segmented or not. For example, in the automated inspection of electronic assemblies, interest lies in analyzing images of products with the objective of determining the presence or absence of specific anomalies, such as missing components or broken connection paths [12]. Segmentation has been widely applied in aerospace technology, transportation control systems, human-face recognition, finger recognition, machine vision and medical science, such as B ultra-sound, CT, X-ray. By analyzing the medical graphs, it can help locate tumors and other pathologies, assist in measuring tissue volume, and operating computer-guided surgery. It can also be used in anatomy and other fields. The successful segmentation will help us to apply subsequent high level image analysis. Therefore, image segmentation is a very important step for image processing.

Since the introduction of segmentation research, a lot of methods have been proposed for image segmentation. One of these mature methods is: the classic minimum spanning tree put forward by Zahn in 1971. The theory is very simple, which is to map the image into a graph, delete the edges with the smallest weight, and partition the image into different sub-images for segmentation. In the 1970s, Beucher and Lantuéjoul put forward the watershed method, which was successfully applied to grayscale images. This method has attracted a lot of attention. In 2000, Shi and Malik proposed the normalized cut method using graph theory. To attain segmentation, they also measured the difference of different partitioned areas and the similarity in the same area. This solves the flaw of the principle of MST (minimum spanning tree). However, most of the segmentation algorithms are based on one of 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 edges. 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, such as thresholding, graph-based segmentation and, so on [12].

The field of image segmentation is developing and new methods are emerging in an endless stream. In the following sections, this thesis will review image segmentation methods, based on graph theory. At the same time, we will also introduce the main image segmentation methods in recent research and we will also point out those methods advantages and disadvantages.

1.2.1 Edge Detection Algorithms

Edge detection aims to sketch split lines between the image and background through a certain algorithm and partitions the image into several sub-images. The edge of image is one of fundamental characteristics of image. It can provide substantial information of image, such as orientation and shape. Image edge is a local characteristic of discontinuity of reflection, such as gray mutation and color mutation. It indicates the ending of one part and the beginning of another part. It exists between the object and the background, between object and object, between pixel (The minimum elements has some characteristic) and different pixels. The edge is the most important characteristic that image segmentation depends on. In line with the intensity of the changes on grey level, edge detection can be divided into two types: (1) Step edge. Grey level pixel value in different edges is distinctly different, and the second derivative is zero crossed in the edges; (2) Ridge edge. It is located at the turning point of grey value, which changes from higher level to lower level. Second derivative takes the extreme value at the ridge edge. Fundamentally, the basic idea of edge detection algorithm is to calculate local differential operator, such as gradient operator, Sobel operator, Prewitt operator and Laplace operator [12]. Those classical edge operator methods only use individual pixel point as the criterion to edge, therefore they are sensitive to noise and will enhance noise when detecting edges. As a result, the difficulty in edge detection is greatly increased.

1.2.2 Thresholding

Thresholding method employs one or several thresholds to separate grey level of images into different parts, and holds the view that pixels that belong to the same part are of one single object. Thresholding algorithm is categorized into global thresholding algorithm and local thresholding algorithm. The global thresholding utilizes global information to evaluate optimal segmentation threshold of the whole image (for instance, grey level histogram). Optimal segmentation threshold can be a single threshold or multiple thresholds. Local threshold algorithm is to divide the original image into several disjoint, sub images at first and then evaluate optimal segmentation threshold of every sub images. Because of its intuitive properties, simplicity of implementation, and computational speed, image thresholding enjoys a central position in applications of image segmentation [12]. It can be regarded as a classical algorithm.

Thresholding has a number of limitations. If the images we segment have distinct boundaries with the background, then thresholding is simple and accurate. If the image is a more complicated one, it is difficult to get a correct threshold. The result of image segmentation through thresholding depends to a great extent on the choice of threshold. Therefore, thresholding is not suitable for extensive use of image segmentation.

1.2.3 Region-Based Segmentation

Classical region-based segmentation algorithm includes: region growing, region splitting and region merging. Region growing is a procedure that groups pixels or subregions into larger regions based on predefined criteria for growth. The basic approach is to start with a set of "seed" points and from these grow regions by appending to each seed those neighboring pixels that have predefined properties similar to the seed (such as specific ranges of intensity or color) [12].

The result of the region-growing is determined by three factors: (1) Choice of initial point. Choose one or several seed pixels. (2) Choice of rules of growing. (3)

Terminal condition of growing. Artificial choice of seed pixels is the common defect of region-based segmentation. Meanwhile, it is inevitable to set up the same amount of seeds or seeds more than the number of regions in order to get the desired region. At the same time, noise exerts great influences on the process of region growing, or can even segment regions which are originally irrelevant to the region.

Region splitting and region fusion establish the rule for region merging. When the region characteristics in an image are in inconformity, it is required to split the region into several sub regions with equal proportion. When adjacent regions possess unanimous characteristics, they will merge into a bigger region until all the subregions don't meet the condition of region splitting and merging. The shortcomings of this algorithm are as follows: if the degree of splitting is insufficient, the result of it must be unsatisfactory. Whereas when the degree is higher than required, it intensifies the difficulty of splitting and consumes a large amount of time for calculation.

1.2.4 Normalized Cuts

Shi and Malik's normalized cut algorithm is one of the image segmentation algorithms based on graph theory, regarded as a normalized principle in the field of image segmentation. Normalized Cuts is an unsupervised segmentation technique, it does not require initialization and has three main advantages [2]: (1) It approaches the segmentation problem as a graph partitioning problem; (2) It is based on a global criterion; (3) It maximizes both the total dissimilarity between the different groups and the total similarity within the groups. In Chapter 2, the paper will illustrate the principle and method of normalized cut.

Though normalized cut dealt with the defects of minimum cut, normalized cut algorithm itself has some drawbacks: heavy calculation, excessive segmentation, or under-segmentation. In addition, when segmenting color images in using this algorithm, it generally should be converted into a grey level image, and then start image segmentation. If the converted the edge of grey level graph is clear, and the pixel grey level between the object the backdrop is distinct, the result would be a satisfactory one. If the similarity of pixels is distinct, the result would lead to an unsatisfactory one.

1.2.5 Watershed

Watershed algorithm evolves on the basis of mathematical morphology, and has become a relatively mature segmentation algorithm. The basis of watershed is: two space coordinates are regarded as grey level function. The calculation of watershed algorithm is divided into two steps: sorting pass and submerging pass. This algorithm is simple with fast calculating speed. Furthermore, the image after segmentation possesses closed outline. Accurate positioning shows its advantage in dealing with images with unclear edges. Nevertheless, the major defect is over-segmentation. In Chapter 2, the paper will illustrate the principle and method of Watershed.

From the above analysis, it can be seen that even though some achievements have been made, there are still some defects in each method. In view of these defects, this paper has done some study and research. Some major work is as follows: a method of combining normalized cut algorithm and watershed algorithm has been put forward. First, preprocess target image using watershed algorithm, decrease the number of nodes, and reduce the complexity in calculation. Next, form a weighted graph from the pre-processed image as the input image of normalized cut algorithm. In this way, the dimension of weight matrix is greatly lowered, and the calculating time is reduced. Second, this work presents an algorithm combing cluster and average pixel to compare with the result of the combination of normalized cut algorithm and watershed algorithm, which shows a satisfactory effect. 3) This paper has done a simulation of the algorithm on the Windows 7 system on the MATLAB program. The result shows that the two methods produce good results. As for the watershed and normalized cut, the defects of involving too much calculation and taking too much time. A highly accurate segmented image has been achieved. By use of the YLGC (Yang and Liu's global criterion) to compare our proposed approaches with the existing methods, it can be seen that the values are smaller than the existing ones, which indicates that the two methods satisfy the segmentation result to a great extent.

1.3 Thesis organization

Chapter 1: Introduction. This part gives a general introduction of the thesis choosing background, significance and major work. It gives a detailed description of the existing image segmentation method and the merits and drawbacks.

Chapter 2: Algorithm of Image Segmentation Based on Normalized Cuts and Watershed. This paper gives a detailed description of the image basis, normalized cut, the introduction and comparison of the segmentation of major images. It also gives detailed introduction to watershed algorithm based on the mathematical morphology.

Chapter 3: Water-cuts RAG. Based on chapter two and chapter three, this paper comes up with the innovative method of combining watershed and normalized cut, introduces a method of clustering algorithm and uses new method to carry out calculation and analysis. It also compares with the traditional normalized cut in terms of operation time and segmentation results.

Chapter 4: Results and Discussion. We use the MATLAB program on the

Windows system to conduct simulation test based on the new method in chapter four. Analyzing the test result and comparing it with the existing ones to get satisfactory results.

Chapter 5: Conclusion. We summarize the major keypoints in this paper and present some goals for future work.

Chapter 2

ALGORITHM OF IMAGE SEGMENTATION BASED ON NORMALIZED CUTS AND WATERSHED

The basic theory of image segmentation is Graph theory. At the beginning of this chapter, we will introduce some related knowledge of Graph Theory. Secondly, we will introduce the algorithm of graph cuts. Thirdly, in the most important part, we will particularly introduce the concept and method of Normalized Cuts.

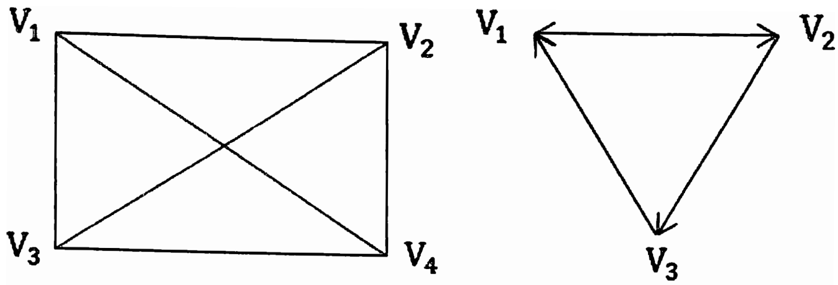
In mathematics and computer science, Graph theory is the study of graphs, which are mathematical structures used to model pairwise relations between objects. A "graph" in this context is made up of nodes and vertices (or edges) that connect them. It's worth noting that the graph is not traditional graph such as triangle, square or image chart. The graph in this thesis is constituted by a number of given vertex and the edges which connect two vertices. This graph is usually used to describe a certain relationship between objects. It uses the vertex to present the object and uses the edges which connect two vertices to present the certain relationship between objects.

2.1 The concept of Graph Theory and Digital Image

2.1.1 Definitions

A graph is a finite set constituted by a set of vertex V and a set of edges E which connects the vertices. Definition by mathematical formula is $G = (V, E)$

For example:



(a) G_A (b) G_B

Figure 2.1: A sample example for Graph.

G_A, G_B is undirected graph and directed graph, respectively. It can be represented as $G_A = (V_A, E_A)$, $G_B = (V_B, E_B)$, where $V_B = \{V_1, V_2, V_3\}$, $E_B = \{(V_1, V_2), (V_2, V_1), (V_2, V_3), (V_3, V_1)\}$

(1) The set of vertex $V \neq \emptyset$, the $|V|$ present the number of vertices

(2) E is a set which contains unordered pairs of any two points at V. In the E a vertex can appear many times. Meanwhile, the degree of correlation between two vertices is present by weight W.

2.1.2 Degree of a vertex

Degree of a vertex is the number of edges that connect to this vertex. If it is weighted graph, the degree of vertex V is change to the sum of weighted for all edges which connect vertex V. Exactly, $d_i = \sum_j w_{ij}$. For example, V_1 is the vertex of G_A, the degree of V_1 can be present as $D(V_1) = 3$. Whether it is undirected graph or directed graph, the relationship between the number of vertex n, the number of edges and degree can be expressed as follows: $e = \frac{1}{2}\sum_{i=1}^{n} D(V_i)$

The degree of a vertex can obviously reflect the degree correlation of vertex and other vertex that is in one set with vertex. If degree of one vertex is zero then the vertex must be an isolated point. The degree of node and weight of edges are important information for image segmentation.

2.1.3 Digital Image

An image may be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the intensity values of f are all finite, discrete quantities, we call the image a digital image [12].

Key Stages in Digital Image Processing: Therefore, we can use the matrix in

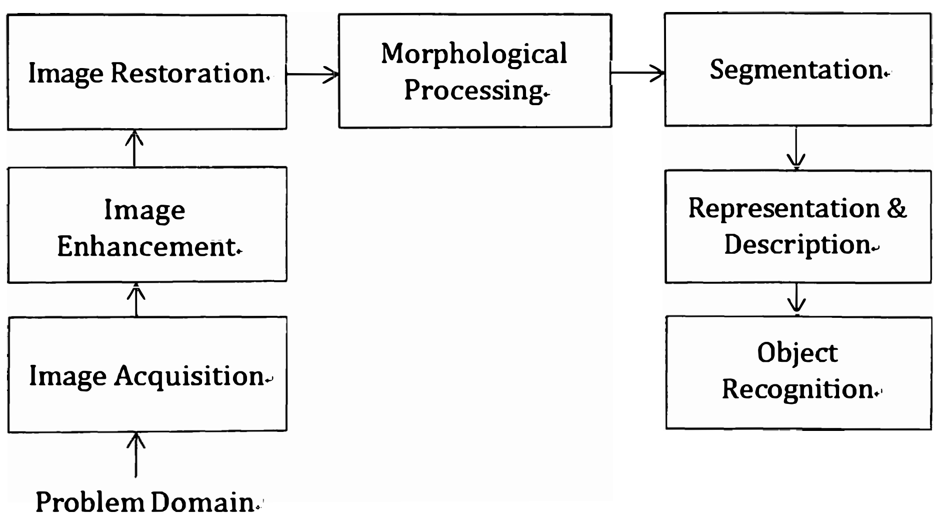


Figure 2.2: Key stage in digital image processing.

mathematics to present the important information in this image.

(1) Adjacency Matrix: it can determine whether or not there is connection between any two points in image. If the target image has n vertices then adjacency matrix must be a $n \times n$ matrix.

It can be presented as:

$$a_{ij} = \begin{cases} 1 & (V_i, V_j) \in E \\ 0 & (V_i, V_j) \notin E \end{cases}$$

Then , the example G_A can be described by adjacency matrix as follow:

$$A_1 = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

Correspondingly, if we have an adjacency matrix then we can reproduce the graph. It is simple to see that the degree of one vertex is a sum of rows in adjacency matrix.

(2) Weight Matrix: It is used to identify the degree of similarity of each vertex. When it has number of n vertex, the dimension must be $n \times n$. It can be expression as follow:

$$W_{ij} = \begin{cases} W(V_i, V_j) & (V_i, V_j) \in E \\ \infty & (V_i, V_j) \notin E \\ 0 & i = j \end{cases}$$

2.2 Graph theoretic image segmentation techniques

2.2.1 Max-flow and Min-cut

In order to analyze the Local Property of image, we will always segment image in the actual problems. The most popular method of image segmentation is Max-flow and Min-cut.

Maximum flow is the maximum "amount of water" that can be sent from the source to the sink by interpreting graph edges as directed "pipes" with capacities equal to edge weights [4].

CUT is the division of a vertex in the network. It divides all vertexes in the network into two sets which is S and T. Source node $s \in S$, sink node $t \in T$. Write as $CUT(S, T)$. The inside is capacity and the outside is flow. Show in the graph: A

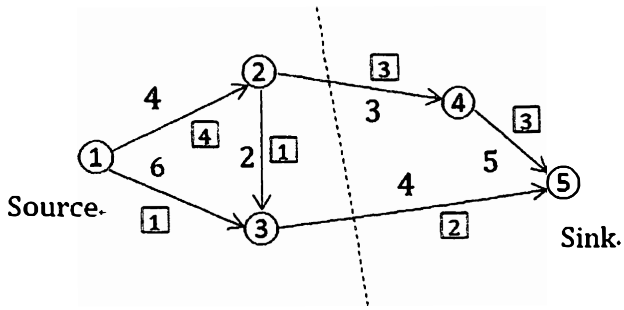


Figure 2.3: Directed example graph.

set of vertex $S = \{1, 2, 3\}$ and a set of $T = \{4, 5\}$ constitute to a cut. If two vertices in a strip of arc belongs to S and T respectively, it can be called CUT.

Max-flow and Min-cut is based on CUT. The relationship between Max-flow and Min-cut is showed below: Min-Cut-Max-Flow Theorem [7]:

Let $g =< V, E >$ consist of a set of nodes, or vertices, $v \in V$ and a set of edges or arcs $e \in E$, and let $s, t \in V$ be the two terminal nodes. Then the three statements are equivalent:

(1) f is a maximal flow (f is a flow in the network $f(X, Y)$, it expresses all arc which is from the vertex of X point to the vertex of Y);

(2) There is no path in the residual graph g_f from s to t that could be augmented;

(3) $|f(g)| = c(C)$ for some cut C.

Min-cut is a common method in CUT. The minimum cut problem on a graph is to find a cut that has the minimum cost among all cuts. To put it simply, the Min-cut method is changed from minimum the interval similar to minimum the CUT.

Wu and Leahy have already used the Min-cut method at image segmentation in a simple way. First, use the Min-cut method to divide the target image into two parts. Second, use loop iteration to divide the target image into suitable numbers of sub-graph. Meanwhile, we should make sure that CUT between many sub-graph is the minimum value [24, 3].

The advantage of Min-cut method is simplicity. However, it also has disadvantages. This method just considered the difference of vertices between the sets but neglected similarity.

In this way, we find an approach to the shortest route to obtain the minimum value capacity of the two subgraph. And this method will result in the smallest value on the shortest side. Usually the noise point and isolation point are the smallest in this condition. From the above chart, we can clearly see that it is a wrong segmentation.

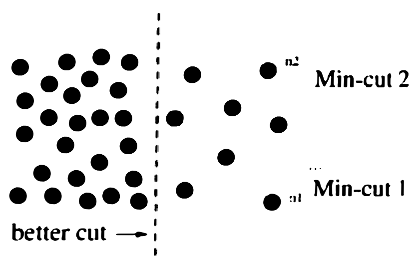


Figure 2.4: A case where minimum cut gives a bad partition [21].

The result is not a best segmentation that we are looking for.

2.2.2 Graph cut

Graph cut is a very useful and popular energy optimization algorithm. In general, the Graph cut algorithm is using Max-flow-Min-cut to improve the model. In fact, the Graph cuts is an effective global optimization method which is used to solve combinatorial optimization problems. Graph cuts can be treated as a two-value mark problem, which is applied to pixel level. 1 is to mark the object pixel and 0 is mark the background pixel. Let [25] $A = \{A_1, \cdots, A_p, \cdots, A_{|P|}\}$ be a binary vector whose components A_p specify assignments to pixels p in P. Each A_p can be either "object" or "background". $|P|$ is the number of pixel, A_p is the mark of p^{th}, then the vectors A defines a segmentation of image.

The expression of vectors A is showed in below [25]:

$$E(A) = \lambda R(A) + B(A) \tag{2.1}$$

where, $R(A) = \sum_{p \in P} R_p(A_p)$ (Data item or area term), $B(A) = \sum_{\{p,q\}} B_{\{p,q\}} \delta(A_p, A_q)$ (Smooth item or Boundary term) and $\delta_{A_p} \neq \delta_{A_q} = \begin{cases} 1 & A_p \neq A_q \\ 0 & A_p = A_q \end{cases}$.

$\lambda \geq 0$ the importance of weight area item and boundary item

$R_p(\cdot)$ may reflect how the intensity of pixel p fits into a known intensity model of the object and background. Coefficient $B_{\{p,q\}} \geq 0$ should be interpreted as a penalty for a discontinuity between p and q. $B_{\{p,q\}}$ is large when pixels p and q are similar and $B_{\{p,q\}}$ is close to zero when the two are very different.

Graph cuts is an implicit optimized method. It needs to construct relevant image first, use max-flow/min-cut to find the min cut of this image, mark each vertex with two-value, express object and background respectively, and then achieve the image segmentation finally.

The details of Boykov's interactive segmentation are shown in Figure 2.5 [25, 26]:

(a) O is the target point of interactive, B is the background point of interactive;

(b) it is weight flow that is built on energy function which is from equation (2.1);

(c) it uses max-flow/min-cut method to segmentation the flow which is built on

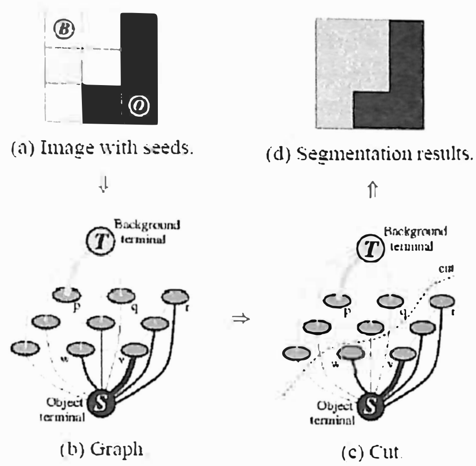


Figure 2.5: A simple 2D segmentation example for a 3×3 image.

(b);

(d) it is the result after segmentation; it is like two-value divided the image into target and background.

2.2.3 RAG-Minimax algorithm

In [15] a method is presented that incorporates the main principles of region-based segmentation and cluster-analysis approaches - A multiresolution color image segmentation approach. The outline of the proposed algorithm is depicted in Figure 2.6:

The RAG-Minimax algorithm is based on fuzzy similarity relations. The final segmentation is produced by applying lambda cuts to produce a crisp relation that embraces the similar regions. In literature define $[x_i] = \{x_j, |(x_i, x_j) \in ER\}$ as the equivalent class of x_i on a universe of data points, X. This class is contained in a special relation ER, known as equivalence relation. The equivalence relation is defined as a mathematical relation that possesses the properties of reflexivity, symmetry and

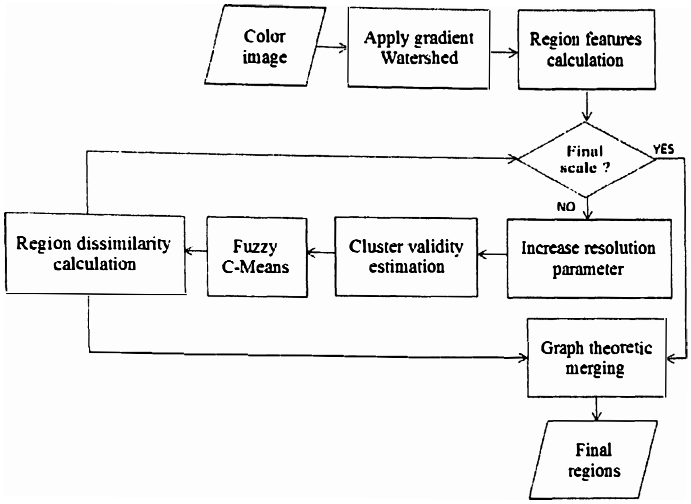


Figure 2.6: Flowchart of the proposed algorithm.

transitivity:

$Reflexivity : \mu_{ER}(x_i, x_i) = 1$

$Symmetry : \mu_{ER}(x_i, x_j) = \mu_{ER}(x_j, x_i)$

$Transitivity : \mu_{ER}(x_i, x_j) = \lambda 1, \mu_{ER}(x_j, x_k) = \lambda 2 then \mu_{ER}(x_i, x_k) = \lambda, \lambda \geq min(\lambda 1, \lambda 2)$

When only reflexivity and symmetry requirements are fulfilled, it is called a tolerance relation.

This process is completed in the following steps:

1. Map the Watershed regions onto RAG.
2. Form a forest that comprises of subtrees.
3. Repeat until subtrees are formed.
4. Find the minimum cost link between subtrees.
5. Merge the corresponding subtree-regions and reduce total population by 1.
6. Calculate the new merging costs between the resulting subtree and its neighbors.

For each pair of subtrees:

7. Calculate the dissimilarity values of the regions-members between the examined subtrees.
8. Find the maximum dissimilarity value.
9. Assign the maximum value to the cost between the subtrees.
10. Map the final subtrees onto the region map.

2.3 Normalized Cuts

Based on the disadvantage of Min-cut, Shi and Malik have posted an unsupervised image segmentation method. This method change image segmentation to optimize image segmentation Normalized Cuts. Normalized Cuts method has three characteristics [2]:

(1) It approaches the segmentation problem as a graph-partitioning problem;

(2) It is based on a global criterion;

(3) It maximizes both the total dissimilarity between the different groups and the total similarity within the groups.

2.3.1 N-cuts algorithm implementation [21, 20]

A graph $G = (V, E)$ can be partitioned into two disjointed sets, $A, B, A \cap B = \emptyset$. The degree of dissimilarity between these two parts can be computed as total weight of the edges that have been removed. In graph theoretic language it is called the cut:

$$cut(A, B) = \sum_{u \in A, v \in B} w(u, v) \tag{2.2}$$

where $w(u, v)$ is the weight of the edges connecting the u, v. It represents the similarity degree between two points.

For example:

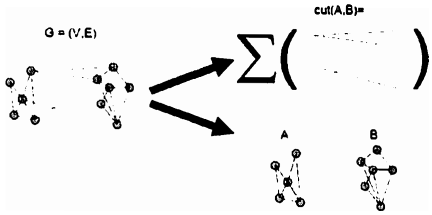


Figure 2.7: A simple example for cut.

An optimized dichotomy of an image is the minimum value of Cut. However , minimum cut is not optimal value. Aimed at this problem, Shi and Malik point out non-similarity measure in difference organization, which is Normalized Cut.

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \tag{2.3}$$

where $assoc(A,V) = \sum_{u \in A, t \in V} w(u,t)$ is the total connection from nodes in A to all nodes in the graph, and $assoc(B,V)$ is similarly defined.

As well ,we can identify similarity measure function in the same group Nassoc:

$$Nassoc(A,B) = \frac{assoc(A,A)}{assoc(A,V)} + \frac{assoc(B,B)}{assoc(B,V)} \tag{2.4}$$

Where $assoc(A,A)$ and $assoc(B,B)$ are total weights of edges connecting nodes within A and B respectively.

Therefore, we can get the conclusion that they are naturally related:

$$Ncut\,(A,B) = 2 - Nasso(A,B) \tag{2.5}$$

According to what has been mentioned above, we can see that in image segmentation algorithm, minimizing the disassociation between the groups and maximizing the association within the group are in fact identical.

Let x be an $N = |V|$ dimensional indicator vector $x_i = \begin{cases} 1 & i \in A \\ -1 & otherwise \end{cases}$ and let $d(i) = \sum_j W(i,j)$ be the total connection from node i to all other nodes.with the definitions x and d we can rewrite:

$$\begin{aligned} Ncut(A,B) &= \frac{cut(A,B)}{asso(A,V)} + \frac{cut(A,B)}{asso(B,V)} \\ &= \frac{\sum_{(x_i>0,x_j<0)} -w_{ij}x_ix_j}{\sum_{x_i>0} d_i} + \frac{\sum_{(x_i<0,x_j>0)} -w_{ij}x_ix_j}{\sum_{x_i<0} d_i} \end{aligned} \tag{2.6}$$

let $D = diag(d_1, d_2, ...d_N)$ be an $N \times N$ diagonal matrix with d on its diagonal, W be an $N \times N$ symmetrical matrix with $W(i,j) = w_{ij}$.

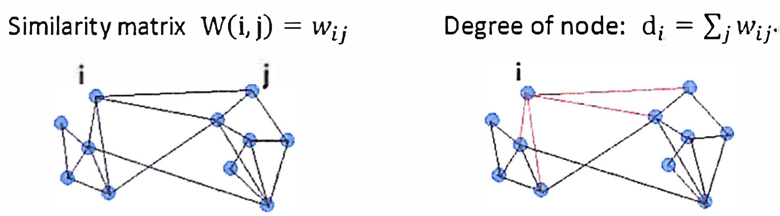


Figure 2.8: Similarity matrix W and Degree of node d.

Let I be an $N \times 1$ vector of all ones, and $k = \frac{\sum_{x_i>0} d_i}{\sum_i d_i}$, corresponding, we can rewrite:

$$4[Ncut(x)] = \frac{(1+x)^T(D-W)(1+x)}{kI^TDI} + \frac{(1-x)^T(D-W)(1-x)}{(1-k)I^TDI} \tag{2.7}$$

Setting $y = (1+x) - b(1-x)$ and $b = \frac{k}{1-k}$. In this way, to find the optimized value in all can be simplified as below:

$$min_x Ncut(x) = min_y \frac{y^T(D-W)y}{y^T Dy} \tag{2.8}$$

where $y_i \in \{1, \frac{-\sum_{x_i>0} d_i}{\sum_{x_i<0} d_i}\}$ and $y^T DI = y^T \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix} = 0.$

Note that the above expression is the Rayleigh quotient [11]: If y is relaxed to take on real values, we can minimize equation (2.8) by solving the generalized eigenvalue system

$$(D-W)y = \lambda Dy \tag{2.9}$$

However, we have two constraints on y:

(1) $y^T DI = y^T \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix} = 0$

(2) y it can be discretized into two values automatically.

Rewrite equation (2.9) as:

$$D^{-\frac{1}{2}}(D-W)D^{-\frac{1}{2}}z = \lambda z \tag{2.10}$$

Where λ is eigenvalue and $z = D^{-\frac{1}{2}}y, z_0 = D^{-\frac{1}{2}}I$ is an eigenvector of equation (2.10) with eigenvalue of 0. $(D-W)$ is Laplacian matrix, it is also semi-positive definite therefore $D^{-\frac{1}{2}}(D-W)D^{-\frac{1}{2}}$ is symmetric semi-positive definite. Hence z_0 is the smallest eigenvector of equation (2.10), and all eigenvectors of equation (2.10) are perpendicular to z_0. Translating this statement back into the general eigensystem

(2.9) we have:

(1) $y_0 = I$ corresponding with eigenvalue 0, is the smallest eigenvector;

(2) $y_1^T DI = z_1^T z_0 = 0$ where y_1 is the second smallest eigenvector of (2.9).

So we can have

$$y_1 = arg.min_{y^t DI} \frac{y^T(D-W)y}{y^T Dy} \tag{2.11}$$

Based on what was mentioned above. Since y_1 is the second smallest eigenvector of (2.9) and it is meet the specification. Thus the eigenvector corresponding to the second smallest eigenvalue has significant meaningful for Nut-cuts. But each element of eigenvalue has consecutiveness. Next, we should identify a separation point. In general we can choose one of the follows: 1) 0; 2) median; 3) Search for a splitting point which results in minimized $Ncut(A, B)$. The splitting point which minimizes Nut-cuts value can be found by repeating calculation of $\frac{y^T(D-W)y}{y^T Dy}$ where y, b, k, x by our definitions. Finally, we can have the optimal segmentation of image.

Based on the research above, the algorithm can be summarized as follows:

1. Given a set of features, set up a weighted graph $G = (V, E)$. Compute the weight on each edge, and summarize the information into W and D;

2. Solve $(D-W)y = \lambda Dy$ generalized eigensystem and get the eigenvectors with the smallest eigenvalues;

3. Use the eigenvector with second smallest eigenvalue to bipartition the graph by finding the splitting point such that N-cuts is maximized;

4. Decide if the current partition should be subdivided by checking the stability of the cut, and if necessary, recursively repartition the segmented parts.

2.3.2 The research based on N-cuts

N-cuts can change image segmentation problem to divide image. First we construct the weighted graph $G = (V, E)$, by taking each pixel as a node, the weight of edges that connect i and j is $W(i, j)$. The similarity of two points can be expressed as:

$$w_{ij} = e^{\frac{-\|F(i)-F(j)\|_2}{\sigma_I}} * \begin{cases} e^{\frac{-\|X(i)-X(j)\|_2}{\sigma_X}} & if\|X(i) - X(j)\|_2 < \gamma \\ 0 & otherwise \end{cases}$$

Where $\|X(i) - X(j)\|_2 < \gamma$ present the Euclidean distance to i and j, $X(i)$ is the spatial location of node i, σ_X decided space similarity, σ_I can decide the level of similarity for selected information, $F(i)$ is the feature vector based on intensity, color, or texture information at that node define as:

1. $F(i) = 1$ for segmenting point sets;

2. $F(i) = I(i)$ the intensity value, for segmenting brightness images;

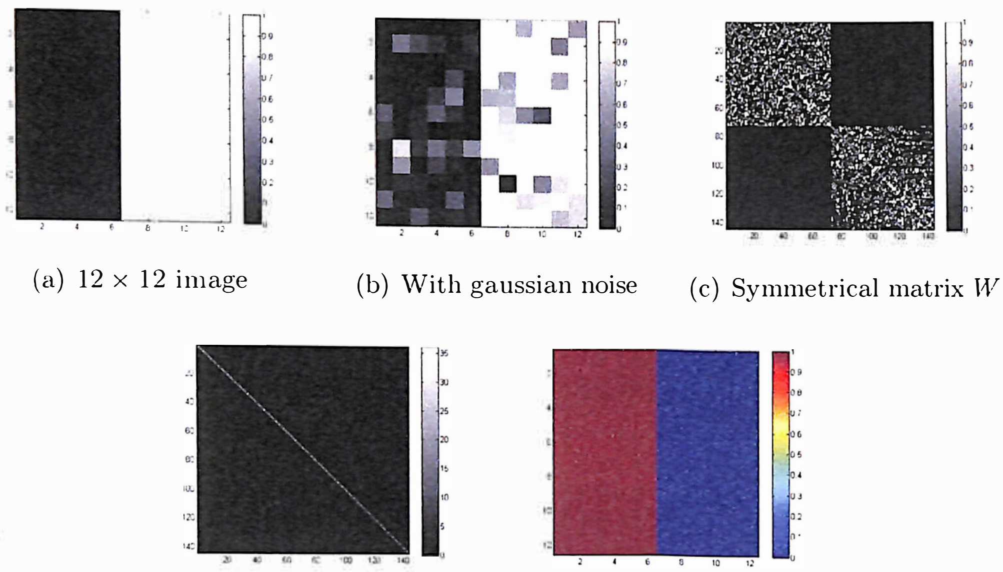
3. $F(i) = [v, v \cdot s \cdot \sin(h), v \cdot s \cdot \cos(h)](i)$ where $h.s.v$ are the HSV values for color segmentation;

4. $F(i) = [|I * f_1|, ...|I * f_n|](i)$ where the f_i are DOOG(Difference Of Offset Gaussian) filters at various scales and orientations as used in [16], in the case of texture segmentation.

A sample example for N-cuts, we do N-cuts for a 12×12 Image:

In order to show how N-cuts works on image segmentation, we have chosen some result pictures from our research and show it in Figure 2.10.

After we use Normalized Cuts method to process image, then we can have a better result than using other image segmentation method. But it also has some shortcomings, such as the image segmentation processing is really slow, because if the image is $N \times M$, then the weight matrix W is a $NM \times NM$ big matrix. Meanwhile, from the definition of W, we can see that W is a symmetric sparse matrix. When the



(a) 12 × 12 image (b) With gaussian noise (c) Symmetrical matrix W

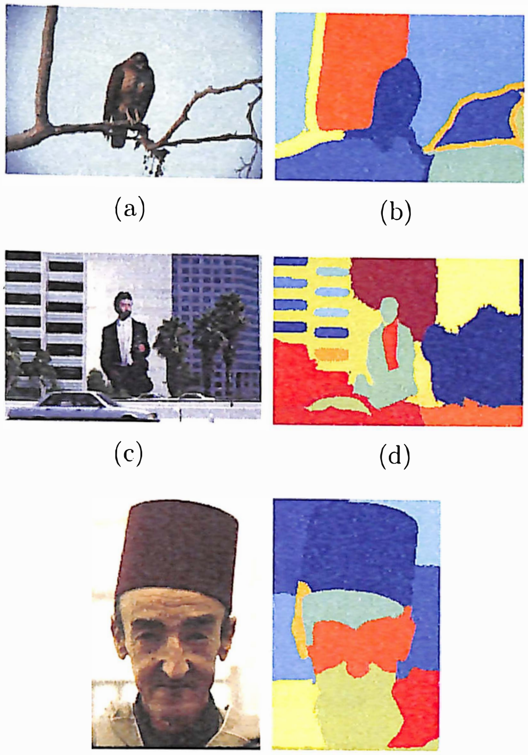
(d) Diagonal matrix D (e) Segmentation result

Figure 2.9: (a) is a sample image (12 × 12); (b) with gaussian noise; (c) is the symmetrical matrix W; (d) is the diagonal matrix D; (e) is the segmentation result. All the results shown above are produced by Shi's code.

distance between i and j is more than γ, $W_{ij} = 0$. At the same time, Normalized Cuts method also has other problems such as over- segmentation and under-segmentation.

2.4 The basics of Morphology [12]

The word morphology commonly denotes a branch of biology that deals with the form and structure of animals and plants. We use the same word here in the context of mathematical morphology as a tool for extracting image components that are useful in the representation and description of region shape, such as boundaries, skeletons, and the convex hull. In this paper, we have mainly used erosion, dilation, opening and closing methods. Now we will simply introduce the basic principles of those four methods below.



(a) (b) (c) (d) (e) (f)

Figure 2.10: (a),(c),(e) are original image(Berkley's dataset),(b),(d),(f) are N-cuts results. All the results shown above are produced by Shi's code.

2.4.1 Erosion

Erosion method can be used to reduce the size of image and it can also remove some parts of image. With A and B as sets in Z^2, the erosion of A by B, denoted $A \ominus B$, is defined as

$$A \ominus B = \{z | (B)_z \subseteq A\}$$

in common, B is structural element, this equation indicates that the erosion of A by B is the set of all points z such that B, translated by z, is contained in A.

For example:

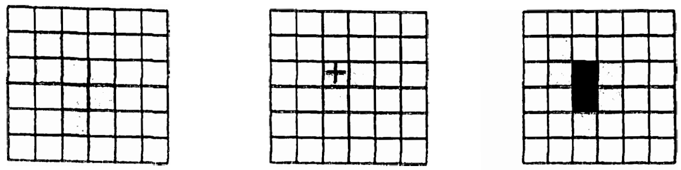


Figure 2.11: (a) Set A; (b) Element B; (c) The result after erosion. Two black grids shown in the figure is the result after erosion.

2.4.2 Dilation

Dilation can be used to expend part of image. With A and B as sets in z^2, the dilation of A by B, denoted $A \oplus B$, is defined as

$$A \oplus B = \{z|(\hat{B})_z \cap A \neq \emptyset\}$$

This equation is based on reflecting B about its origin, and shifting this reflection by z. The result of B is dilation by A can be treated as the set of after translation fellowship, which is the intersection, is not empty. In other words, $\hat{B}$ intersection A exist one element at least. The processing is shown in below:

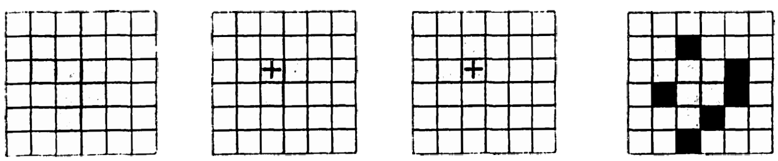


Figure 2.12: (a) Set A; (b) Element B; (c) B's mapping; (d) The result after dilation. The sum of grey parts and black parts in the picture is the result.

2.4.3 Opening

Opening generally smooths the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions. The opening of set A by structuring element B, denoted

$$A \circ B = (A \ominus B) \oplus B$$

Opening can be explained as geometric method. As shown in the picture [12] B is a graphic entity. The processing of opening can be achieved by translations of B in A. The boundary point of $A \circ B$ can be looked as a set that is all elements in B which are can closely reach the boundary of A.

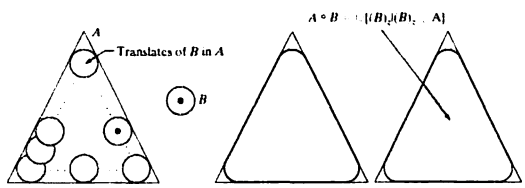


Figure 2.13: (a) Structuring element B "rolling" along the inner boundary of A (the dot indicates the origin of B); (b) Structuring element B; (c) The heavy line is the outer boundary of the opening; (d) Complete opening (shaded).

2.4.4 Closing

Closing also tends to smooth sections of contours but, as opposed to opening, it generally fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour. The closing of set A by structuring element B, denoted $A \bullet B$, is defined as

$$A \bullet B = (A \oplus B) \ominus B$$

Closing method can be explained by the following Figure [12]:

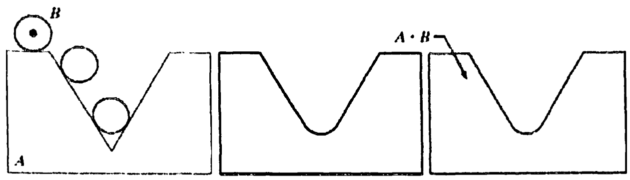


Figure 2.14: (a) Structuring element B "rolling" on the outer boundary of set A; (b) The heavy line is the outer boundary of the closing; (c) Complete closing (shaded).

2.5 Watershed

Watershed method is a traditional segmentation method. At the beginning, it is pointed out for Terrain mathematical Elevation Model. In 1978, H.Digabel and C.Lantuejoul firstly used watershed method in digital image processing area [9]. After further study by Beucher and Vincent, a complete watershed theory system was built up. Since 1980s, the watershed method has been used to segment grey images [5]. Main concept: the image gradient magnitude is considered to be a topographic surface as a function of two spatial coordinates of the image plane. The watershed segmentation is performed in two stages: sorting and flooding of gradient minima.

As shown in the Figure 2.15 [23]:

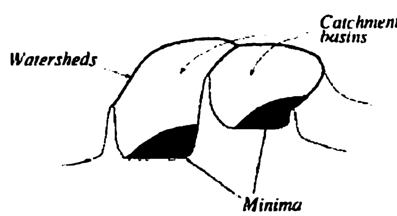


Figure 2.15: Minima, catchment basins, and watersheds.

2.5.1 Watershed Segmentation Algorithm [12]

Let $M_1, M_2, \cdots, M_R$ be sets denoting the coordinates of the points in the regional minima of an image $g(x, y)$. Let $C(M_i)$ be a set denoting the coordinates of the points in the catchment basin associated with regional minimum M_i.

Let $T[n]$ represent the set of coordinates (s,t) for which $g(s,t) < n$. That is $T[n] = \{(s,t)|g(s,t) < n\}$.

Let $C_n(M_i)$ denote the set of coordinates of points in the catchment basin associated with minimum M_i that are flooded at stage n. And given by $C_n(M_i) = C(M_i) \cap T[n]$.

Let $C[n]$ denote the union of the flooded catchment basins at stage n: $C[n] = \bigcup_{i=1}^{R} C_n(M_i)$.

The processing of flooding for watershed method can be explained as water level increased slowly from the minimum point of gradient image by units whole number to maximize. So $g(x,y) = n$ can be regarded as a horizontal plane, $T[n]$ is a point coordinate set that is located at a horizontal plane.

The notation min and max will be used to denote the minimum and maximum values of $g(x,y)$. To construct a watershed is a recursion process. The algorithm for finding the watershed lines is initialized with $C[min+1] = T[min+1]$, and Let Q denote the set of connected component $q \in Q[n]$, there are three possibilities:

(1) $q \cap C[n-1]$ is empty;

(2) $q \cap C[n-1]$ contains one connected component of $C[n-1]$;

(3) $q \cap C[n-1]$ contains more than one connected component of $C[n-1]$.

Construction of $C[n]$ from $C[n-1]$ depends on which of these three conditions holds. Condition 1 occurs when a new minimum is encountered; Condition 2 occurs when q lies within the catchment basin of some regional minimum; Condition 3 occurs when all, or part, of a ridge separating two or more catchment basins is encountered.

In other words, two or two more connected component will become one connected component. At this time, it should build watershed in q to protect connected component merge connected component. If it has many connected components, then more watersheds are needed.

The result of Watershed is shown in Figure 2.11:

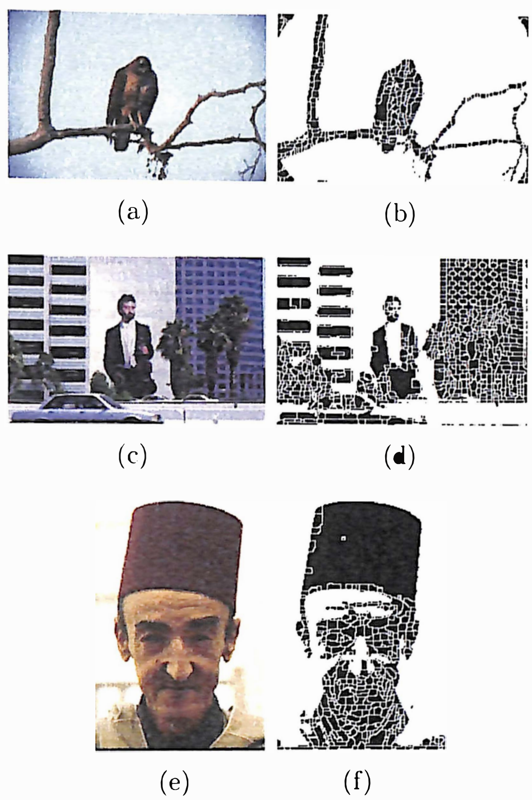


Figure 2.16: (a),(c),(e) are original image(Berkleys dataset),(b),(d),(f) are Watershed results.

The Watershed method has used many Terrain concepts. In fact, Watershed [23] is a region growing method. But it also has difference with region growing method; the difference is the watershed methods growing is from the location of minimum value in the detected part of image. Due to the effect by noise and dark texture, the image will have a number of false minimum values; that false minimum value will become false hydrops basin. Therefore, the false minimum value and the real minimum value will be regarded as an independent area through Watershed - it will cause over-segmentation problem finally, as shown in the above picture. Meanwhile, Watershed has the following advantage: (1) It is computationally efficient;(2) Watershed regions have closed boundaries;(3) It produces accurate delineation.

Chapter 3

WATER-CUTS RAG

Most traditional segmentation methods, such as the N-cut method process directly the greyscale image. Alternatively they transform a color to greyscale image, then apply the segmentation algorithm. If the region indicator function, which is produced by segmentation, has preserved the object boundaries and has separated object from background successfully, then the segmentation is considered accurate. However, if segmentation has produced disconnected boundaries between objects, or overly segmented regions, the result is considered erroneous and segmentation needs to be improved.

Watershed is a spatial domain segmentation method that is based on the combination of edge and spatial information. However, due to the fact that the watershed method is very sensitive to noise in the image, the watershed method has an over-segmentation problem [22, 13, 8]. At present, two methods can solve the over-segmentation problem in watershed method. The first one is processing the image before using watershed method. This method is based on markers to detect the watershed regions [10, 17]. Every marker corresponds to an object in the image. So the point of solving the over-segmentation problem for watershed method is based on processing image before is effective selected marks. Second, processing image after watershed method. This method aims at the result after using watershed method. It is based on any standards then process to merge region [14, 19, 18]. To achieve goals to reduce the computational complexity and reduce the computing time. In this paper, I will introduce water-cuts RAG method. The water-cuts RAG method belongs to processing techniques after watershed method. It has concentrated the advantages of N-cuts and watershed method. That is to say, use the watershed method first to segment the target image, preprocessing the image, reduce the number of nodes, reduce the computational complexity and use the image which is after preprocessing to construct a piecewise constant image. Then weight image will be used as the input image at N-cuts method. In this way, we will not only solve the over-segmentation under the watershed method but also solve the long calculation time and the request of edges under the N-cuts method.

The processing is shown below:

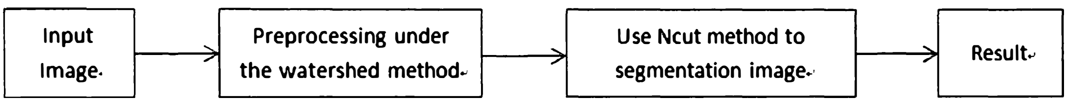


Figure 3.1: The processing of segmentation that combine watershed method and N-cuts method.

Based on this method, I will propose another method that combines water-cuts RAG method and clustering method. The calculation using the pixel values on average in each area in the image that preprocessing by use of watershed algorithm. Then use those average values in clustering algorithm. The difference between these two algorithms is the combination of water-cuts RAG method and clustering method has use average intensity of pixel into clustering algorithm. But the watershed algorithm directly uses average intensity of pixel into N-cuts algorithm. The result shows that the combined method of water-cuts RAG method and clustering method will make a better segmentation result.

3.1 Filter preprocessing

The disadvantage of watershed method is over-segmentation. It is due to the effect of the noise in the image and the quantization error, the result will split out many small regions that should be formed a region surrounded by a large margin. And it is also because gradient information in the next step is very sensitive to noise. These reasons will cause the real edge be divided into many false edges, which is over-segmentation. In order to avoid this over-segmentation phenomenon, we can use the filter preprocessing method to filter the noise in the image before use the watershed method. I will mainly use the Gaussian filter method in this paper [12]:

$$H(u,v) = e^{-D^2(u,v)/2D_0^2}$$

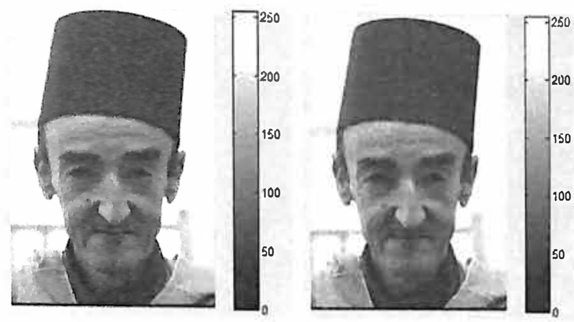
The implementation process of this method is shown below:

```
G=gfilt(size(A),varargin{2});
FG=fftshift(fft2(G,size(G,1), size(G,2)));
FA=fftshift(fft2(A,size(A,1), size(A,2)));
FGA=FA.*FG;
GA=fftshift(real(ifft2(ifftshift(FGA),size(FGA,1), size(FGA,2))));
```

Figure 3.2: Gaussian filter's code.

The result after use Gaussian filter is shown below:

Compare the image that is after using Gaussian filter with the original image. The result shows that the image that is after use Gaussian filter is very smooth and reduces the noise. It has made a good foundation for the next watershed method, and it is effective to decrease the over-segmentation phenomenon in watershed.



(a) (b)

Figure 3.3: (a) Original image; (b) The result after Gaussian filter and $\sigma = 1$.

3.2 The implementation of water-cuts RAG

In this paper, the main process of water-cuts RAG method is use the image that is after use Gaussian filter as the enter image to watershed segmentation, then use the preprocessing result by watershed method as the new target image to N-cuts segmentation.

The key stage is shown below:

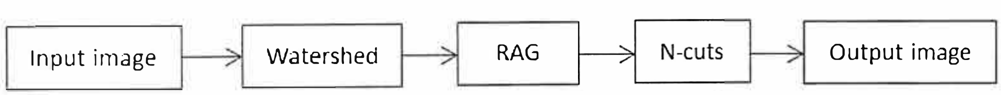


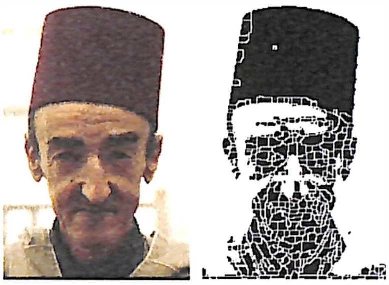
Figure 3.4: The idea of water-cuts.

We will introduce this method by these processes in the following parts.

3.2.1 The preprocessing of watershed method

In practical problemsthe image that need to deal with is very large. Then the dimensions of the weighted matrix must be very large. For example, there are N pixels in the image, so we will have an $N \times N$ system in the calculation. If the image size is 256×256 then the dimensions of the weighted matrix is $(256 \times 256) \times (256 \times 256)$.

It is obvious that the image size is big then the amount of calculation is big. It will increase computational complexity; increase the amount of calculation, and increase the time of calculation. Therefore, in order to meet precision requirements we can use watershed method to preprocess the image. In this way, we can reduce the number of nodes and decrease computational complexity. The result of preprocessing is shown in Figure 3.5(b):



(a) (b)

Figure 3.5: (a) Original image; (b) The result after watershed method.

In the Figure 3.5(b), after dealing with the watershed, the image is divided into 493 areas. We can treat the 493 areas as 493 pixels. Then use it to compare with 241×161 pixels in Figure 3.5(a). We can see that under the condition of keeping the original pixel values, it has reduced the number of node in weight image, reduced the amount of calculation and reduced the time of calculation.

3.2.2 Structural weight matrix

After using the filter method to smooth preprocessing the image, it has effectively eliminated the detail and noise in the image. Reducing the over-segmentation has produced a good foundation for N-cuts. However, before using N-cuts method we also need to use the image that is after processing by watershed method to structure a weight matrix. The form of weight in this paper is show in below:

$$w_{ij} = e^{\frac{-\|F(i)-F(j)\|_2}{\sigma_I}} * \begin{cases} e^{\frac{-\|X(i)-X(j)\|_2}{\sigma_X}} & if \|X(i) - X(j)\|_2 < \gamma \\ 0 & otherwise \end{cases}$$

Where $\|X(i) - X(j)\|_2 < \gamma$ present the Euclidean distance to i and j, $X(i)$ is the spatial location of node i. This method adopts the method of identifying adjacency matrix, in the picture if the two small area are identified as adjacency then calculate their similarity level the same as weight. If the two small areas are non-adjacent then weight is zero. The value of σ_x and σ_I will have effect for the research results. In addition, the factor of calculation weight matrix γ is a constant number that is approved in advance. If the value of γ is small then the weight matrix will become sparse, the speed of segmentation will become quickly. But we will have a bad result. On the contrary, if the value of γ is big then the result will be better. But the amount of calculation will increase. Therefore, we should choose the appropriate value [6].

In this paper, through calculation the average intensity of pixel ,which is after using watershed method to preprocessing then build a weight image. In this way, we effectively reduce the number of nodes and save amount of calculation time. The processing detail is shown below:

The result is shown in Figure 3.7:

In the Figure 3.7 above, Figure 3.7(a) is the result of N-cuts and Figure 3.7(b) is the result of water-cuts RAG. For the same parameterin the segmentation result of water-cuts RAG, we can see that the segmentation for persons face is very meticulous and the background is closer to the entirety. Meanwhile, it reduces a lot of calculation time.

What are said reproted are the implementation processing and the result of water-cuts RAG. In order to have a more clear segmentation result, We will introduce

```
n_watershed_regions = length(mean_intensity);
Adjacency_Matrix = zeros(n_watershed_regions, n_watershed_regions);

[nr,nc,nb] = size(I);

for i=2:nr-1
    for j=2:nc-1
        if B(i,j)==0
            VN=B(i-1:i+1,j-1:j+1);
            VN2=unique(VN);
            if length(VN2) > 2
                Adjacency_Matrix(VN2(2),VN2(3)) = 1;
                Adjacency_Matrix(VN2(3),VN2(2)) = 1;
            end
        end
    end
end

[W,Dist] = compute_relation(mean_intensity');

Adjacency_Graph =  W .* Adjacency_Matrix;

nbSegments = nb1;

[NcutDiscrete,NcutEigenvectors,NcutEigenvalues] = ncutW(Adjacency_Graph,nbSegments);
```

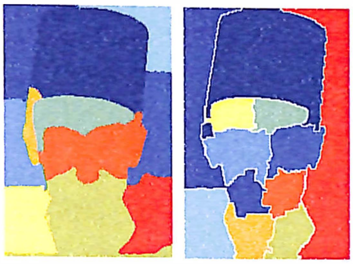
Figure 3.6: Water-cuts RAG's code: use N-cuts method to segment image after watershed method.

another method, which combines by water-cuts RAG method with clustering method. The details are described in the following section.

3.3 Combine water-cuts RAG method with clustering method

Clustering is the processing of dividing a set of data into different groups. It can make the data in the same groups have the same label but the data in the different group have different labels. The process of clustering is shown below:

Clustering-based segmentation algorithms in general also have a serious drawback. Pixels from disconnected areas of the image can be grouped together, if there is an overlap in their feature space values. As a consequence, several noisy areas and incomplete region borders are produced in the segmentation results [15].



(a) (b)

Figure 3.7: (a) The result of N-cuts method; (b) The result of water-cuts RAG method.

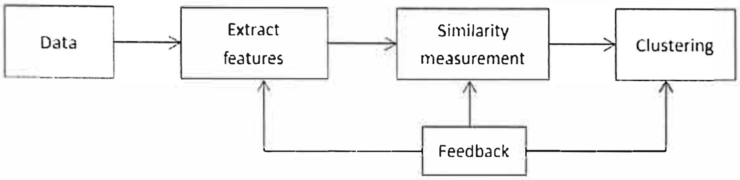
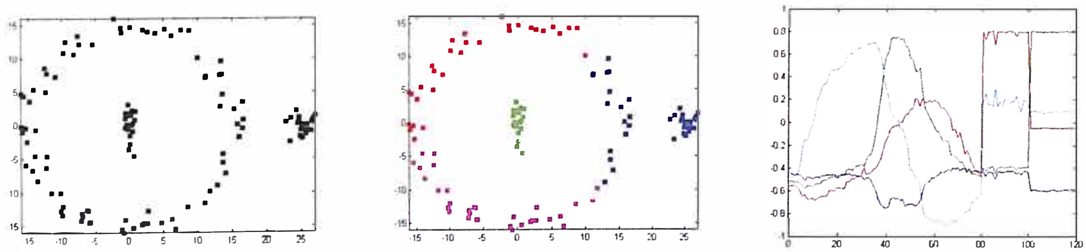


Figure 3.8: The process of clustering.

The picture shown in Figure 3.9 will give a typical example of clustering: Figure 3.9(a) the input data for clustering analysis Figure 3.9(b) the result after using clustering method that based on similarity measurement. The same color points present the same group. The original data has been divided into four groups. Figure 3.9(c) is the eigenvector that corresponding to the point in Figure 3.9(b).



(a) (b) (c)

Figure 3.9: (a) This is the input data points to be clustered; (b) Clustering result; (c) Eigenvectors.

From the literature [15] idea, in this paper, we will combine the clustering method with water-cuts RAG method. This means that using the image that is after use watershed method to preprocessing then use combined clustering method with N-cuts method to do the segmentation.

The key stage is shown below:

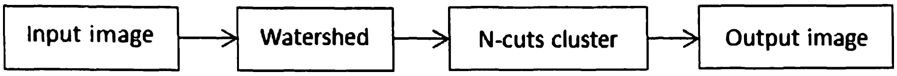


Figure 3.10: The idea of water-cuts clust.

The processing is shown below:

```
[W,Dist] = compute_relation(mean_intensity');

nbCluster = nb2;

[NcutDiscrete,NcutEigenvectors,NcutEigenvalues] = ncutW(W,nbCluster);

RegionLabels = zeros(size(NcutDiscrete,1), 1);
for i=1:size(NcutDiscrete,1)
   RegionLabels(i) = find(NcutDiscrete(i,:));
end
```

Figure 3.11: Water-cuts RAG with clustering code.

The result is shown in the Figure 3.12:

From the result, we can see that it has an over-segmentation phenomenon. Therefore, we have done some corresponding processing for over-segmentation. The detailed processing is: the image that after watershed will have a corresponding number label in each area. After using clustering method, it will merge many similar areas and relabel them. In this way, it has reduced the number of areas produced by watershed method and marked the edge as 0. Therefore, we can compare the mark value of pixel a_{ij} with adjacent mark value. If there are two values between this pixel and adjacent

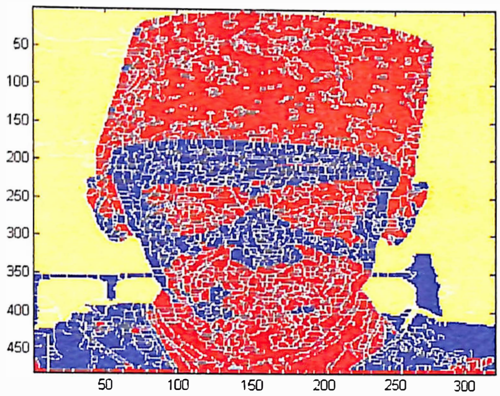


Figure 3.12: The result of water-cuts clust.

pixel, then relabel the value of a_{ij} as the same with adjacent value. If there are more than two values, then a_{ij} keep the same value.

For example:

3	3	3
3	0	3
3	3	3

(a)

1	0	2
1	1	0
1	0	2

(b)

Figure 3.13: Example for removing over-segmentation.

In the Figure 3.13(a), $a_{ij} = 0$ and there are just 0 and 3 so remark $a_{ij} = 3$

In the Figure 3.13(b), $a_{ij} = 1$ and mark value is 0, 1 and 2, it is more than two, so a_{ij} keep the same value.

The implementation code is shown below:

The result is shown Figure 3.15:

```
for i=2:nr-1
    for j=2:nc-1
        if B(i,j)==0
            V=Seglabel(i-1:i+1,j-1:j+1);
            V2=unique(V);
            if length(V2)==2
                SegLabel_NcutCluster(i,j)=V2(2);
            end
        end
    end
end
```

Figure 3.14: Remove over-segmentation code.

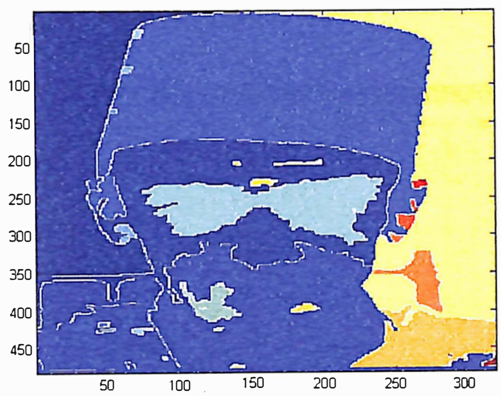


Figure 3.15: The result after removing over-segmentation.

From the result above ,we can see that we have improved the over-segmentation problem.

3.4 GUI (Graphical User Interface)

GUI is the abbreviation of Graphical User Interface. It is a graphical user interface development environment, which is provided by MATLAB. It can vividly show the simulated calculation results. However, GUI just has a shell. There is no real substance in it. Therefore, we need to add our development program into GUI. In this way, we can have more benefit for our research. In order to control experimental parameters, compare the segmentation result that is based on difference method and test amount of data, we improve the GUI that is provided by MATLAB in this paper.

In this interface, we input different filtering parameters and segmentation param-eters first. Second, we transfer those parameters to different segmentation methods. Finally, we can get results based on different methods and we can also have other research data. In this way, we can clearly analyze the results produced by differ-

ent segmentation methods. The details are shown the picture below. Now, I will particularly introduce our GUI.

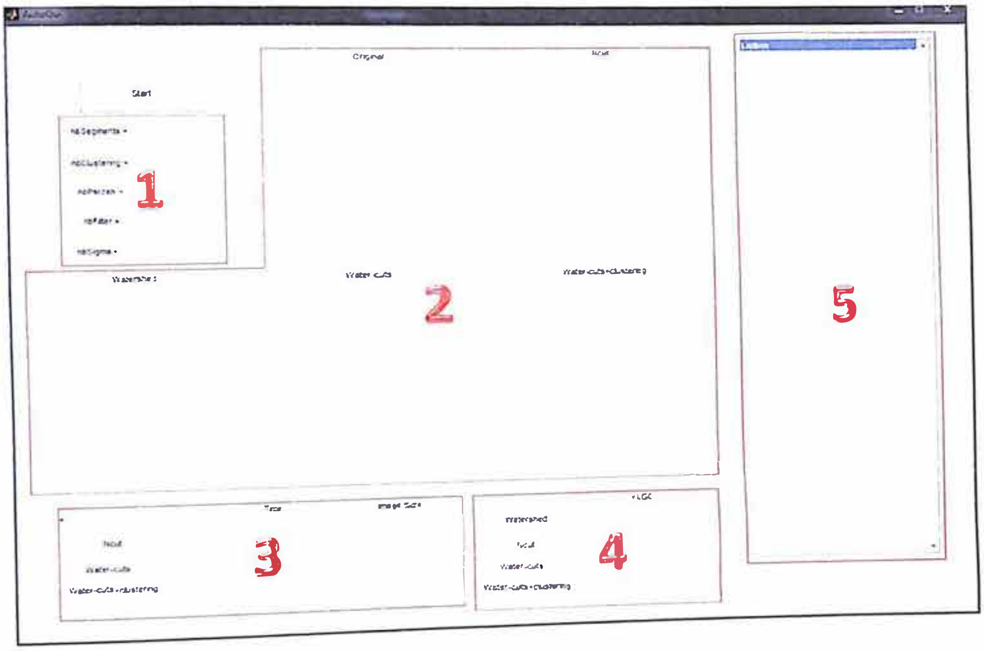


Figure 3·16·GUI-Graphical User Interface.

In Figure 3.16, the interface has been divided into five areas. In the area 1, we can input the research parameter. And the *nbsegment* is the number of subrange that uses N-cuts method and water-cuts RAG method segment the image. This determines how many regions in the segmentation result. *nbClustering* is the number of categories that is used in clustering method to divide the pixels in the image. *nbParzen* is the radius of the parzen, *nbfilter* and *nbsigma* are the parameters that are needed in Gaussian Filter. In the area 2, we can clearly see that it consists of five parts ,which is the original image, the result based on N-cuts method, the result based on watershed method, the result based on water-cuts RAG method and the result based on water-cuts and clustering method. In area 3, it is mainly presenting the calculation time and the size of test image, which is based on N-cuts method, water-cuts RAG method and water-cuts clustering method. In area 4, it is mainly presenting the number of YLGC that is based on four different segmentation methods.

YLGC is Yang and Liu's global criterion. YLGC quantifies the error between the piecewise constant image model after segmentation and the original image. Smaller YLGC values indicate more accurate segmentation with smaller number of regions and larger region areas.

The YLGC measure is expressed by the relation [15]:

$$YLGC = \sqrt{\frac{N_R}{h \cdot w \cdot c}} \cdot \sum_{i=1}^{N_R} \frac{\sigma_i^2}{\sqrt{card_i}}$$

In this equation, h, w and c are the height, width, and number of the image channels, respectively. N_R is the number of final regions, σ_i^2 is the color over region i, and $card_i$ is the number of pixels inside region i.

In area 5, are displayed the names of all test images in the specified folder and the image is that current in testing.

In the Figure 3.17 we can directly see results after using four different segmentation methods. In the same parameter environment ($nbsegments = 11, nbClustering = 3, nbParzen = 15, nbFilter = 3, nbSigma = 0.5$). Segment a 241×161 size image

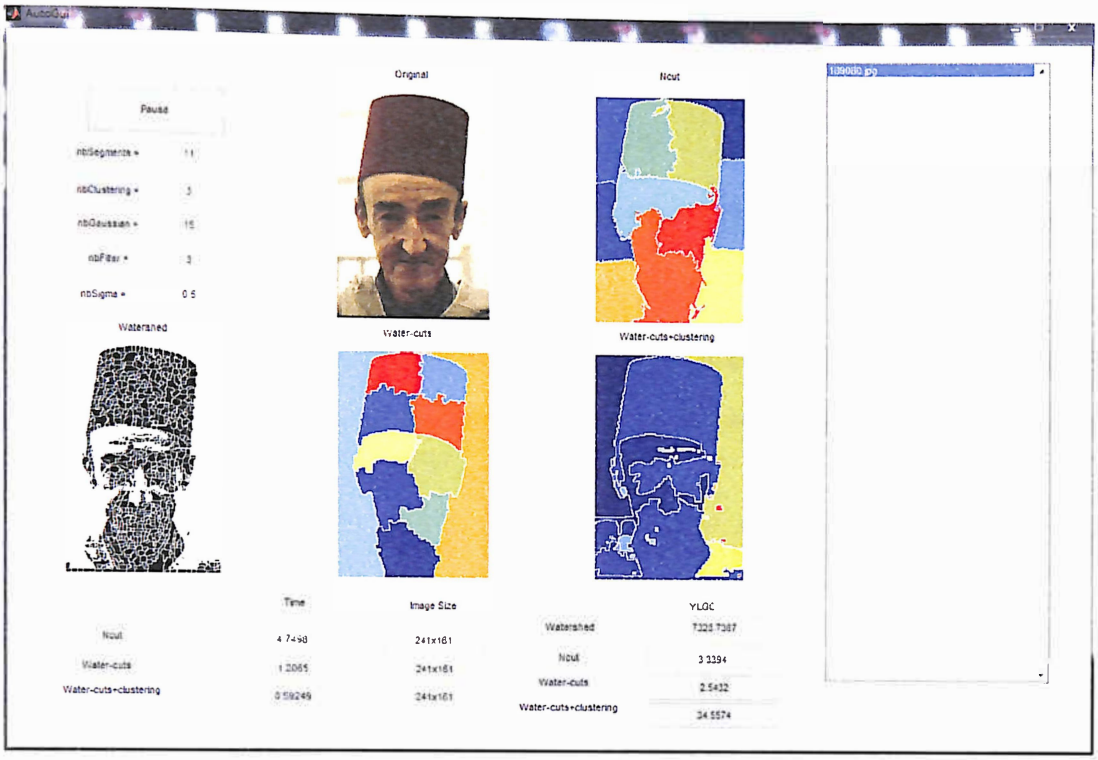


Figure 3.17: The result after using GUI.

, the calculation time for N-cuts is $4.7498s$ water-cuts RAG is $1.2065s$, water-cuts clust is $0.59249s$. Based on those numbers, we can see that the calculation time has been improved. The value of YLGC for N-cuts is 3.3394. The value of YLGC for water-cuts RAG is 2.5432. In the same segmentation area that is in the eleven sub-region condition, the value of YLGC for water-cuts RAG is lower. It is powerfully proved that the improved result of water-cuts RAG method. What's more from the segmentation result, we can directly see that using water-cuts RAG method combined with clustering method will have the best result.

This paper introduced two kinds of improved method of image segmentation. We will mainly discuss the results produced by two newly introduced methods. We will also compare the method that we already have.

Chapter 4

RESULTS AND DISCUSSION

In this chapter, a large number of experimental data will be used to prove that the proposed algorithm has a relative improvement compared with the past algorithm in different problems.

4.1 Time comparison.

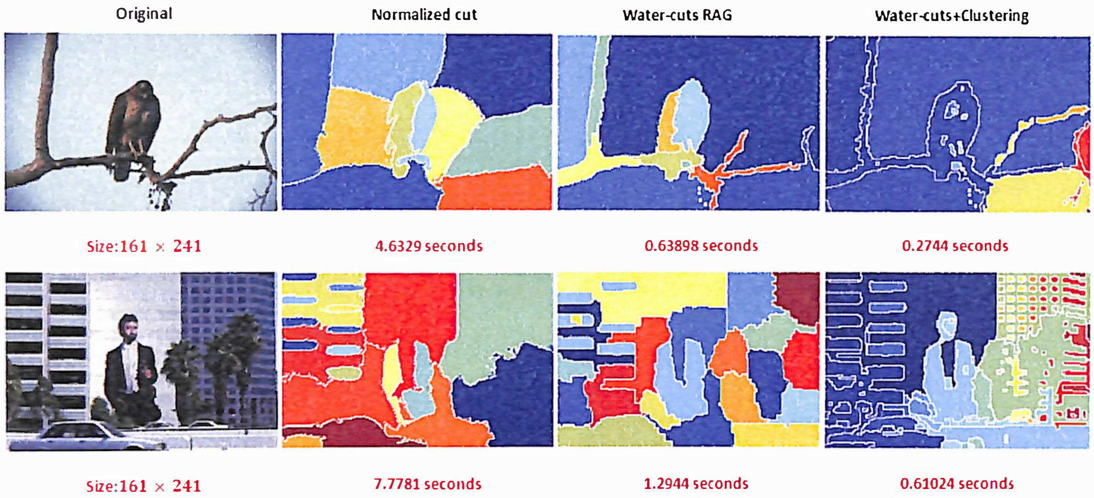


Figure 4.1: Time comparison.

A sample table to compare time:

Table 4.1: Time comparison.

	Normalized cut	Water-cuts RAG	Water-cuts Clust
Image 1 (Top)	4.6329s	0.63898s	0.2744s
Image 2 (Bottom)	7.7781s	1.2944s	0.61024s

From the results in Figure 4.1 and Table 4.1, it is clear that the two methods in this thesis have a larger amount of calculation and enjoy improvement in problem of time length. For example, in Figure 4.1, Image 1, N-cuts takes 4.6329 seconds, while Water-cuts RAG take merely 0.63898 seconds. Because solved a standard eigenvalue problem for all eigenvectors takes $O(n^3)$ time, n is the number of pixel in the image. However, the watershed method just takes $O(n^2)$. Therefore we can save the time. Meanwhile, it is clear to see that in the segmentation results, the two methods mentioned in this thesis have also made improvements.

4.2 Comparison in Calculation Complexity.

Figure 4.2: Comparison in Calculation Complexity.

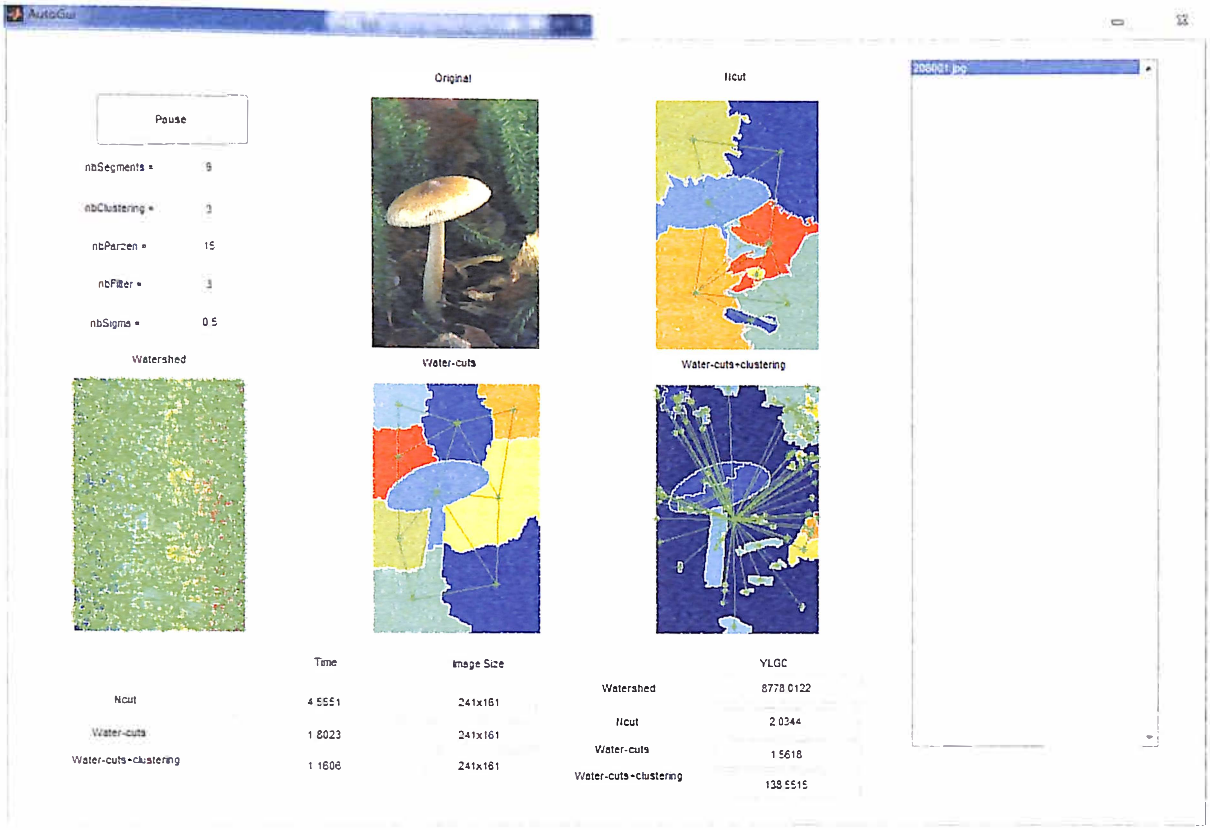


Figure 4.3: Comparison in Calculation Complexity.

We can visually observe through the two experimental results that the two mentioned calculation methods have made improvements in the segmentation results. It demonstrated that we have lowered the complexity of calculation. Connect the midpoints of the two neighboring sub-sections (sharing the same side) and then we can directly compare the complexity of the centralized algorithm, and this has solved the problem of over-segmentation. For example, in Figure 4.3, the segmentation in Watershed has connected almost all the pixels in pictures, which has fully proved the problem of over-segmentation. In our calculation, we have reduced over-segmentation, without affecting the accuracy. Thus, this method has lowered calculation complexity, saved time and obtained a relatively satisfactory segmentation result.

4.3 YLGC (Yang and Liu's global criterion) values comparison.

Table 4.2: YLGC values comparison when regions=10.

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
101085.jpg	1462	4459.038852	10	6.612651443	10	4.350396147	107	127.3660733
101087.jpg	746	2063.898901	10	1.441639693	10	1.997075592	62	48.45759147
102061.jpg	765	1619.5499	10	1.327016299	10	3.866544513	81	76.71929147
103070.jpg	1278	1824.098851	10	1.828089795	10	2.219193677	44	26.15395909
105025.jpg	1213	3003.803367	10	3.916996771	10	3.326853859	146	178.2052387
106024.jpg	594	1131.0962	10	3.074454631	10	2.31711896	43	61.78439424
108005.jpg	1553	3787.707448	10	2.076821018	10	1.961964896	110	156.3862185
108070.jpg	1724	3910.235553	10	2.569569981	10	1.990143309	127	190.9954054
108082.jpg	1129	2770.021562	10	1.744562681	10	2.869749934	114	202.3997086
109053.jpg	1261	1659.88248	10	1.437226602	10	1.340215079	108	84.63875571
119082.jpg	1002	3992.752066	10	2.236670696	10	3.680723161	121	180.4750289
12084.jpg	1632	2764.577656	10	1.414994644	10	1.229676041	234	242.5923961
123074.jpg	1498	2508.009528	10	2.280491773	10	2.056101667	110	59.71384376
126007.jpg	632	937.330477	10	3.097868634	10	3.765556208	53	46.07724528
130026.jpg	1293	3790.791667	10	2.886246193	10	4.237123332	130	253.6586484
134035.jpg	1582	7169.763812	10	5.118928856	10	3.978412172	338	1005.787135
14037.jpg	579	564.128357	10	1.377574613	10	1.319852202	32	20.67628111
143090.jpg	538	500.7862833	10	1.081743313	10	1.042909297	28	3.677841299
145086.jpg	973	2458.52386	10	7.691318192	10	2.702139288	88	162.9091351
147091.jpg	837	2708.554676	10	4.21483053	10	4.00122836	96	225.6598672
148026.jpg	1422	6111.845619	10	3.303445789	10	3.698330062	210	387.689182
148089.jpg	1504	4431.765111	10	2.622284394	10	2.506058046	235	470.3532035
156065.jpg	1313	2219.830678	10	2.039214261	10	2.426440483	137	122.66972
157055.jpg	1122	2823.108547	10	2.500024085	10	3.276985344	134	169.5157434
159008.jpg	1154	6732.920097	10	5.438496494	10	6.004046038	190	634.7981505
160068.jpg	772	2036.412202	10	1.041537974	10	3.375384435	173	280.0261124
16077.jpg	1126	3152.885822	10	2.936289363	10	4.007359639	137	183.0302029
163085.jpg	1201	1601.214206	10	1.554053298	10	1.391001347	152	86.36854209
167062.jpg	350	685.4944914	10	0.822630338	10	5.10185144	36	98.97854525
167083.jpg	1503	7715.091844	10	3.809319581	10	4.380887751	249	799.8364334

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
170057.jpg	1510	1981.454758	10	2.022719937	10	1.463915873	115	88.42343881
175032.jpg	2016	3985.263652	10	1.842317032	10	1.4239029	340	297.7718876
175043.jpg	1867	5075.423858	10	1.663369801	10	1.648116232	246	285.9459943
182053.jpg	843	2358.289013	10	3.054512789	10	6.863538823	66	76.28830959
189080.jpg	493	1631.276724	10	3.00644967	10	3.058277065	53	118.0697033
19021.jpg	1186	3096.880374	10	2.382312457	10	2.601042839	91	143.2138538
196073.jpg	1363	450.9580497	10	0.138305399	10	0.196102062	33	26.8759108
197017.jpg	1063	2290.770542	10	1.74340452	10	1.581084146	47	74.50146819
208001.jpg	1370	2001.25038	10	1.86367739	10	1.573016024	72	32.98443583
210088.jpg	812	1906.626621	10	2.305601778	10	3.071174043	193	262.2567517
21077.jpg	1023	3251.439426	10	8.404654671	10	4.271956656	103	158.7648391
216081.jpg	1100	2658.064517	10	3.572677975	10	3.815260728	101	121.2143725
219090.jpg	806	1909.133809	10	2.918953814	10	2.21458789	91	170.7857638
220075.jpg	1151	4315.980814	10	3.300236284	10	3.487605526	185	473.5713127
223061.jpg	1464	5114.112066	10	2.277589427	10	1.418875067	132	361.4520283
227092.jpg	580	183.9550192	10	0.5364781	10	0.911991563	34	4.359286332
229036.jpg	1643	5441.190404	10	4.654938715	10	4.126182009	204	375.9505826
236037.jpg	1769	3377.443403	10	2.225099626	10	1.56291121	61	37.24615372
24077.jpg	1171	6586.889012	10	2.581738555	10	4.25261261	209	564.1490066
241004.jpg	672	1846.342772	10	1.942255495	10	2.603372731	18	6.329999727
241048.jpg	1311	3567.731294	10	2.894726694	10	3.256216993	116	145.0025739
253027.jpg	1407	3761.930428	10	0.875883649	10	1.461643403	145	216.0783924
253055.jpg	724	1358.926062	10	0.964749732	10	1.615126964	42	92.38044463
260058.jpg	951	586.5687677	10	0.949865382	10	0.847642625	55	28.40556885
271035.jpg	1226	2654.735854	10	4.242941633	10	3.420696233	160	176.3366913
285079.jpg	1458	5394.252112	10	3.623544661	10	3.723192575	144	392.5575418
291000.jpg	1918	4780.218802	10	2.818934518	10	2.23019997	223	306.8441283
295087.jpg	1007	973.0664025	10	0.832132621	10	1.156328344	121	61.22315617
296007.jpg	798	457.9159813	10	0.479559472	10	1.07396935	76	22.26186981
296059.jpg	772	766.5473701	10	1.108810297	10	1.796984834	51	36.33194045
299086.jpg	811	354.8147129	10	0.43197164	10	0.598382833	96	27.797624
300091.jpg	776	1144.278115	10	1.462147696	10	2.607632341	52	75.73142579
302008.jpg	654	3691.273901	10	2.884090616	10	5.140408864	157	401.3807512
304034.jpg	1757	6510.811321	10	2.782822162	10	3.893646181	216	449.1603183
304074.jpg	1493	3932.347653	10	2.648117209	10	2.417644886	165	220.0041843

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
306005.jpg	971	3015.340076	10	4.20834502	10	4.686217923	106	179.5255069
3096.jpg	206	149.5137425	10	1.169845477	10	2.054745966	28	13.67870754
33039.jpg	1770	10599.49286	10	6.943575232	10	4.969616398	389	1162.028895
351093.jpg	1170	5359.964398	10	3.748986976	10	3.733629756	53	78.25471604
361010.jpg	1105	2519.155531	10	4.725238562	10	2.24185897	78	165.052685
37073.jpg	609	556.5093111	10	0.622595402	10	1.043045097	40	28.98454219
376043.jpg	1669	3481.975713	10	2.604317797	10	2.852911578	87	88.23981302
38082.jpg	1553	2063.978909	10	1.521070314	10	1.566825872	78	32.44682015
38092.jpg	1077	3348.257229	10	5.325858756	10	2.96017398	97	135.7437119
385039.jpg	1030	3367.504621	10	4.255668077	10	2.409927433	139	250.4655104
41033.jpg	1144	2590.762031	10	2.674720868	10	1.458544204	93	141.6848215
41069.jpg	1755	2568.748952	10	1.757995797	10	1.25269236	148	103.1438815
42012.jpg	1191	2429.570657	10	3.225526456	10	3.18557005	98	103.8458467
42049.jpg	332	1034.002545	10	2.824786286	10	3.418524966	85	105.6548292
43074.jpg	1060	712.4855877	10	0.447705313	10	0.806358827	93	30.44427631
45096.jpg	294	372.2186529	10	1.395233146	10	3.503917203	15	11.95737328
54082.jpg	938	718.0327851	10	1.234375211	10	1.176841941	86	30.02521021
55073.jpg	1712	5508.721617	10	4.986893731	10	2.846702049	136	225.5938128
58060.jpg	1396	3235.000036	10	0.921512259	10	1.542967008	178	191.3430426
62096.jpg	935	5695.879963	10	2.999058272	10	4.370493134	120	519.389533
65033.jpg	1580	3814.284184	10	4.908090175	10	2.762718172	105	119.854935
66053.jpg	1372	1992.226258	10	2.663875041	10	2.031702684	52	18.96573007
69015.jpg	1195	2129.845456	10	1.710412546	10	2.387325678	78	58.05884074
69020.jpg	1565	1921.961181	10	2.258882085	10	1.522070376	34	15.19594645
69040.jpg	1971	2794.546194	10	1.839960098	10	0.967807159	164	93.98774733
76053.jpg	1355	1961.592974	10	2.213782483	10	1.770400225	58	37.26601839
78004.jpg	950	2308.134626	10	3.223757948	10	1.90073404	43	31.97505569
8023.jpg	1581	2154.594959	10	0.854495564	10	0.843024723	89	44.07585383
85048.jpg	1379	4989.556449	10	6.766614125	10	4.361585149	165	291.389224
86000.jpg	1040	2145.954108	10	1.618399828	10	2.629948886	178	205.7746148
86016.jpg	1978	1902.673829	10	0.4989062	10	0.355262288	205	71.91071026
86068.jpg	1491	1344.468875	10	1.092489171	10	0.843437756	142	93.10549882
87046.jpg	1498	5306.339497	10	3.419759584	10	4.218342322	208	372.5246924
89072.jpg	1149	2574.694171	10	3.982910056	10	2.986760705	150	150.3189623
97033.jpg	1210	4551.142666	10	5.199996191	10	4.250897088	141	246.4491116

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
mean		2917.524147		2.647802234		2.637201466		183.6760808
std.dev.		1890.982214		1.654097691		1.333306016		198.6627919

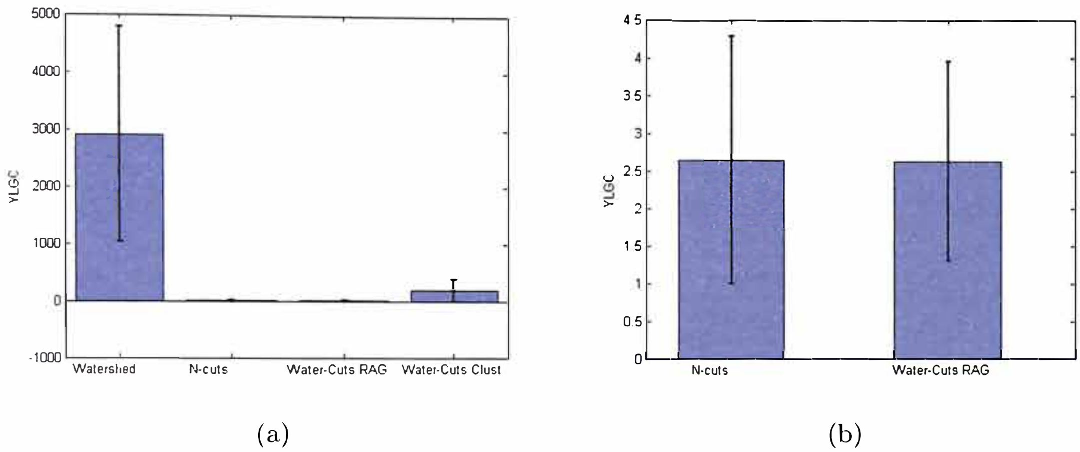


Figure 4.4: Plots of YLGC values for 10 regions..

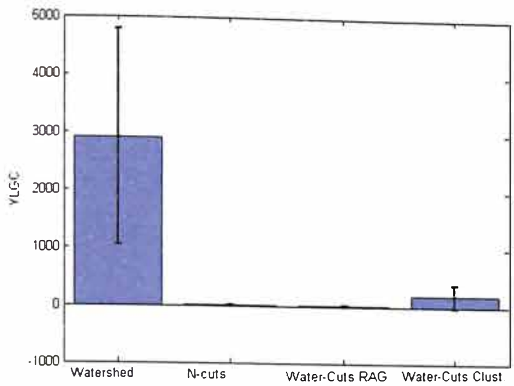
Table 4.3: YLGC values comparison when regions=20.

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
101085.jpg	1462	4459.038852	20	9.558760594	20	10.01615362	81	67.25593397
101087.jpg	746	2063.898901	20	5.699227829	20	6.952102975	66	63.01609789
102061.jpg	765	1619.5499	20	4.423759827	20	7.986375675	76	69.65285914
103070.jpg	1278	1824.098851	20	4.966239932	20	6.701562755	27	11.73749473
105025.jpg	1213	3003.803367	20	11.75856928	20	9.231829354	146	178.2052387
106024.jpg	594	1131.0962	20	9.150322877	20	6.098057848	43	61.78439424
108005.jpg	1553	3787.707448	20	6.926755788	20	7.242678342	110	156.3862185
108070.jpg	1724	3910.235553	20	6.941059092	20	6.766917723	67	91.87273654
108082.jpg	1129	2770.021562	20	5.825925938	20	8.53088278	113	208.2430261
109053.jpg	1261	1659.88248	20	4.095410154	20	5.129383125	94	69.87160063

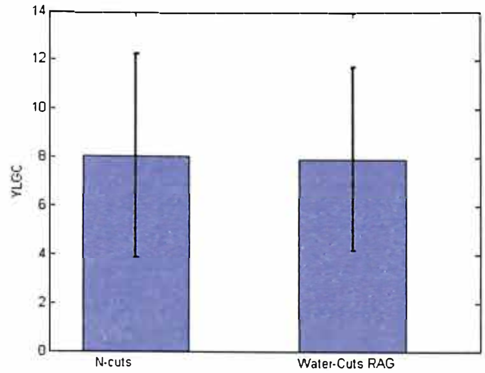
Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
119082.jpg	1002	3992.752066	20	11.88144028	20	11.47298221	119	178.3646614
12084.jpg	1632	2764.577656	20	4.43989874	20	4.695818727	245	255.9873433
123074.jpg	1498	2508.009528	20	7.422341988	20	6.11931917	111	60.55466387
126007.jpg	632	937.330477	20	5.444163642	20	8.430290471	54	48.25830186
130026.jpg	1293	3790.791667	20	8.006028236	20	11.34810679	133	258.1950349
134035.jpg	1582	7169.763812	20	17.75608488	20	11.15584239	339	1008.01674
14037.jpg	579	564.128357	20	2.865726568	20	3.484711126	32	20.67628111
143090.jpg	538	500.7862833	20	3.855181405	20	3.311662389	28	3.677841299
145086.jpg	973	2458.52386	19	14.5570011	20	7.595193662	88	162.9091351
147091.jpg	837	2708.554676	20	10.70924169	20	10.30619581	96	225.6598672
148026.jpg	1422	6111.845619	20	9.168282566	20	11.53108879	210	387.689182
148089.jpg	1504	4431.765111	20	10.0806689	20	9.48433817	235	470.3532035
156065.jpg	1313	2219.830678	20	7.183921568	20	8.188325082	135	122.8370829
157055.jpg	1122	2823.108547	20	6.806303807	20	9.828801109	134	169.9310366
159008.jpg	1154	6732.920097	20	13.15069302	20	14.82479456	192	645.5640987
160068.jpg	772	2036.412202	20	9.961960934	20	12.34429016	173	280.0261124
16077.jpg	1126	3152.885822	20	8.41719794	20	9.452431964	137	183.0302029
163085.jpg	1201	1601.214206	20	4.833950389	20	5.342380707	152	86.36854209
167062.jpg	350	685.4944914	20	3.248302974	20	13.72381365	36	98.97854525
167083.jpg	1503	7715.091844	20	16.09946694	20	11.20455668	248	865.0936552
170057.jpg	1510	1981.454758	20	9.679351575	20	4.319378833	109	73.65622576
175032.jpg	2016	3985.263652	20	5.952689452	20	4.704597367	338	295.3701176
175043.jpg	1867	5075.423858	20	7.062429455	20	6.354999451	181	199.6011817
182053.jpg	843	2358.289013	20	11.16426234	20	16.94919173	68	72.7531178
189080.jpg	493	1631.276724	20	17.47000036	20	7.7413932	53	118.0697033
19021.jpg	1186	3096.880374	20	9.471173467	20	8.202056783	126	207.4307501
196073.jpg	1363	450.9580497	20	0.610087054	20	0.779089503	33	26.8759108
197017.jpg	1063	2290.770542	20	5.361312105	20	5.130785227	47	74.50146819
208001.jpg	1370	2001.25038	20	7.625736341	20	6.073090876	72	32.98443583
210088.jpg	812	1906.626621	20	9.076604295	20	11.4784937	193	262.2567517
21077.jpg	1023	3251.439426	20	20.5019509	20	15.07660978	103	158.7648391
216081.jpg	1100	2658.064517	20	8.359020025	20	10.02850557	96	113.0429951
219090.jpg	806	1909.133809	20	8.442336459	20	9.203540216	91	170.3919395
220075.jpg	1151	4315.980814	20	12.41487739	20	12.26810712	185	473.5713127
223061.jpg	1464	5114.112066	20	14.86413027	20	5.211202392	132	361.4520283

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
227092.jpg	580	183.9550192	20	3.731355448	20	2.90728158	34	4.359286332
229036.jpg	1643	5441.190404	20	14.4572563	20	8.907716471	212	382.5563382
236037.jpg	1769	3377.443403	20	6.590110965	20	5.911472464	61	37.24615372
24077.jpg	1171	6586.889012	20	10.55602919	20	18.06137742	209	564.1490066
241004.jpg	672	1846.342772	20	6.073410615	20	6.505118555	18	6.327899914
241048.jpg	1311	3567.731294	20	9.238795663	20	8.211911071	115	143.2347836
253027.jpg	1407	3761.930428	20	4.169791061	19	4.201223006	145	216.2380939
253055.jpg	724	1358.926062	20	4.068694515	20	4.089691504	42	92.37146143
260058.jpg	951	586.5687677	20	4.183248393	20	2.626513384	54	36.17599479
271035.jpg	1226	2654.735854	20	12.27967559	20	9.351204732	160	176.3366913
285079.jpg	1458	5394.252112	20	15.35276052	20	13.03080765	144	392.5575418
291000.jpg	1918	4780.218802	20	9.531319059	20	6.91363447	215	296.1297228
295087.jpg	1007	973.0664025	20	3.143584861	20	4.21366326	121	60.26074322
296007.jpg	798	457.9159813	20	2.209890687	20	3.826085987	76	22.26186981
296059.jpg	772	766.5473701	20	3.868606245	20	4.25680216	51	36.33076152
299086.jpg	811	354.8147129	20	1.219578315	20	2.664696198	96	27.81292182
300091.jpg	776	1144.278115	20	4.313514028	20	7.040496076	52	75.81395802
302008.jpg	654	3691.273901	20	8.58455705	20	19.65574016	156	399.5842216
304034.jpg	1757	6510.811321	20	11.11002326	20	10.07699607	216	449.1603183
304074.jpg	1493	3932.347653	20	6.191814656	20	6.846657479	164	219.7605662
306005.jpg	971	3015.340076	20	10.5597659	20	15.59471661	95	147.9922043
3096.jpg	206	149.5137425	20	4.041883882	20	4.595630081	29	14.35546169
33039.jpg	1770	10599.49286	20	16.97918181	20	17.09874158	393	1190.262646
351093.jpg	1170	5359.964398	20	11.7490618	20	12.39633964	53	78.25471604
361010.jpg	1105	2519.155531	20	9.975943624	20	8.190425897	78	164.9542503
37073.jpg	609	556.5093111	20	1.581152432	20	3.378439619	40	28.98454219
376043.jpg	1669	3481.975713	20	8.429443965	20	9.079588475	86	87.2018895
38082.jpg	1553	2063.978909	20	5.384359384	20	5.056215221	146	66.87794986
38092.jpg	1077	3348.257229	20	9.450361203	20	9.344495194	97	135.7437119
385039.jpg	1030	3367.504621	20	10.56956759	20	9.347168417	139	250.4655104
41033.jpg	1144	2590.762031	20	7.089450813	20	6.086329831	93	141.6891176
41069.jpg	1755	2568.748952	20	6.452772075	20	4.279472456	147	102.3214193
42012.jpg	1191	2429.570657	20	7.131222422	20	9.442734715	98	103.8458467
42049.jpg	332	1034.002545	20	7.776392532	20	10.73026451	85	105.6548292
43074.jpg	1060	712.4855877	20	1.366006143	20	3.077370261	91	29.33066064

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
45096.jpg	294	372.2186529	20	4.824399347	20	9.67601323	28	22.21981633
54082.jpg	938	718.0327851	20	3.290245383	20	4.467529024	86	30.02521021
55073.jpg	1712	5508.721617	20	9.631260691	20	8.817134429	136	225.5938128
58060.jpg	1396	3235.000036	20	3.467173732	20	5.163989045	180	201.3045066
62096.jpg	935	5695.879963	20	15.25676638	20	12.60000198	120	519.389533
65033.jpg	1580	3814.284184	20	16.95270702	20	6.53485348	105	119.854935
66053.jpg	1372	1992.226258	20	7.792761076	20	6.172039713	52	18.96573007
69015.jpg	1195	2129.845456	20	9.028624872	20	8.134693809	61	31.14809579
69020.jpg	1565	1921.961181	20	6.067240714	20	6.052635323	34	15.19594645
69040.jpg	1971	2794.546194	20	4.54969056	20	3.147627423	162	92.50660174
76053.jpg	1355	1961.592974	20	5.191346517	20	4.968602216	58	37.26601839
78004.jpg	950	2308.134626	20	8.718809736	20	6.00641845	43	31.70448657
8023.jpg	1581	2154.594959	20	3.626703664	20	3.626162321	89	44.07585383
85048.jpg	1379	4989.556449	20	13.37038315	20	9.229950753	165	291.389224
86000.jpg	1040	2145.954108	20	6.420195676	20	9.61242763	174	198.7167875
86016.jpg	1978	1902.673829	20	1.783387306	20	1.14858364	218	94.80089487
86068.jpg	1491	1344.468875	20	2.86066178	20	2.552752249	142	93.07573198
87046.jpg	1498	5306.339497	20	13.01142918	20	12.62922742	208	372.5246924
89072.jpg	1149	2574.694171	20	8.720798917	20	6.954148212	153	160.8571813
97033.jpg	1210	4551.142666	20	12.29096324	20	9.928216936	138	244.6839257
mean		2917.524147		8.095559813		7.964419591		182.8282199
std.dev.		1890.982214		4.218116805		3.803244349		202.7474744



(a)



(b)

Figure 4.5: Plots of YLGC values for 20 regions.

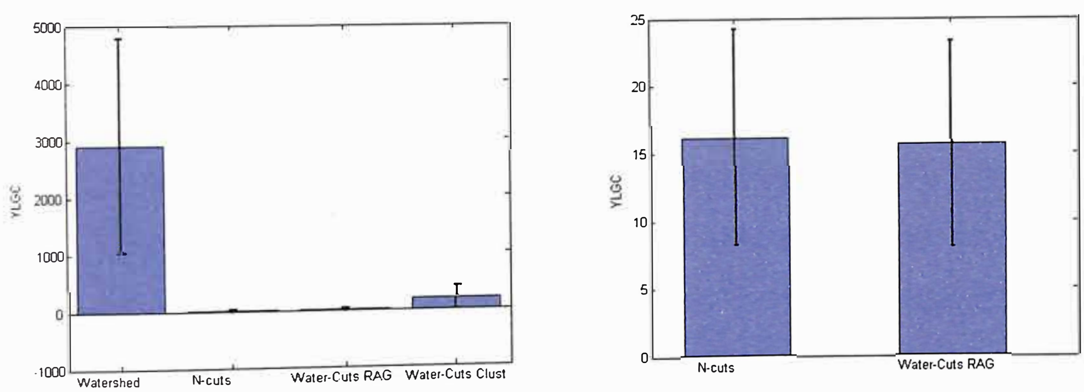
Table 4.4: YLGC values comparison when regions=30.

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
101085.jpg	1462	4459.03885	30	20.75857272	30	21.19645766	107	127.3660733
101087.jpg	746	2063.8989	30	10.86602198	30	12.64797016	68	65.30421228
102061.jpg	765	1619.5499	30	8.519071036	30	18.53951647	76	69.65285914
103070.jpg	1278	1824.09885	30	10.7606218	30	11.70377697	44	26.15395909
105025.jpg	1213	3003.80337	30	19.73769556	30	18.54924284	146	178.2052387
106024.jpg	594	1131.0962	30	15.26270812	30	11.67398232	43	61.78439424
108005.jpg	1553	3787.70745	30	12.93989857	30	15.61221008	104	170.7971345
108070.jpg	1724	3910.23555	30	13.40892557	30	13.77610645	61	77.51449104
108082.jpg	1129	2770.02156	30	10.73086768	30	16.06070497	117	212.9525407
109053.jpg	1261	1659.88248	30	7.038542832	30	9.302588451	104	81.8788876
119082.jpg	1002	3992.75207	30	28.49741427	30	21.56462192	121	180.4750289
12084.jpg	1632	2764.57766	30	8.55183975	30	9.074732154	224	222.7092147
123074.jpg	1498	2508.00953	30	14.85287237	30	12.1086	110	66.08119499
126007.jpg	632	937.330477	30	13.49758754	30	14.29725505	54	47.37484995
130026.jpg	1293	3790.79167	30	13.92529744	30	21.02152662	130	253.6586484
134035.jpg	1582	7169.76381	30	35.06079451	30	24.5414119	339	1008.01674
14037.jpg	579	564.128357	30	6.575411068	30	8.348742418	32	20.66507743

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
143090.jpg	538	500.786283	30	6.122757692	30	6.153586031	28	3.677841299
145086.jpg	973	2458.52386	30	19.63453914	30	13.44926084	88	163.6657304
147091.jpg	837	2708.55468	30	15.1188396	30	23.03006061	96	225.6598672
148026.jpg	1422	6111.84562	30	17.46055117	30	23.35928087	209	380.6909295
148089.jpg	1504	4431.76511	30	21.73096994	30	18.28279097	230	466.8259941
156065.jpg	1313	2219.83068	30	12.51620561	30	13.66115018	137	122.66972
157055.jpg	1122	2823.10855	30	15.6379309	30	15.30140228	134	169.5157434
159008.jpg	1154	6732.9201	30	24.34746955	30	27.87585098	192	645.5640987
160068.jpg	772	2036.4122	30	15.11944853	30	24.37725296	173	280.0261124
16077.jpg	1126	3152.88582	30	20.64326055	30	19.41141424	137	183.0302029
163085.jpg	1201	1601.21421	30	10.46208559	30	11.44165898	153	88.97638392
167062.jpg	350	685.494491	30	6.462879692	30	21.94535665	36	98.97854525
167083.jpg	1503	7715.09184	30	29.69046734	30	24.11377944	249	868.7227677
170057.jpg	1510	1981.45476	30	14.23792585	30	7.975875815	115	88.42343881
175032.jpg	2016	3985.26365	30	13.04761629	30	10.21119107	338	295.3701176
175043.jpg	1867	5075.42386	30	15.88458913	30	13.11017098	246	285.9459943
182053.jpg	843	2358.28901	30	21.03958202	30	29.26805034	66	76.45878524
189080.jpg	493	1631.27672	30	27.15149667	30	17.65593404	53	118.0697033
19021.jpg	1186	3096.88037	30	20.15174685	30	15.23727214	126	207.4307501
196073.jpg	1363	450.95805	30	1.605263779	30	1.562410798	28	13.86236283
197017.jpg	1063	2290.77054	30	13.73395621	30	8.834629605	49	75.76156178
208001.jpg	1370	2001.25038	30	14.17481305	30	10.53450461	73	33.45594298
210088.jpg	812	1906.62662	30	21.23122316	30	23.77100518	196	262.3353513
21077.jpg	1023	3251.43943	30	34.11562349	30	26.13554329	103	158.7648391
216081.jpg	1100	2658.06452	30	16.94230393	30	16.32767746	101	121.2143725
219090.jpg	806	1909.13381	30	14.79824417	30	17.19563349	126	249.814327
220075.jpg	1151	4315.98081	30	25.84094046	30	27.92794847	191	490.5314982
223061.jpg	1464	5114.11207	30	30.72041176	30	10.48690307	130	359.6593382
227092.jpg	580	183.955019	30	6.948703126	30	6.048066693	35	5.053446491
229036.jpg	1643	5441.1904	30	24.65057288	30	20.10478811	205	367.9809758
236037.jpg	1769	3377.4434	30	13.56062625	30	11.60584411	47	24.28399309
24077.jpg	1171	6586.88901	30	21.09340498	30	34.34597759	209	564.1490066
241004.jpg	672	1846.34277	30	15.03175824	30	11.25943748	18	6.329999727
241048.jpg	1311	3567.73129	30	18.62327039	30	15.78780182	115	145.4363074
253027.jpg	1407	3761.93043	30	8.616660962	30	10.20736089	145	216.2380939

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
253055.jpg	724	1358.92606	30	10.50763307	30	8.481973985	43	93.39157767
260058.jpg	951	586.568768	30	7.167213422	30	4.93240211	56	27.91579579
271035.jpg	1226	2654.73585	30	27.89463073	30	19.03873562	160	176.3366913
285079.jpg	1458	5394.25211	30	27.77880681	30	27.77352228	144	392.5575418
291000.jpg	1918	4780.2188	30	17.77147849	30	12.24252809	215	296.1297228
295087.jpg	1007	973.066403	30	7.312288358	30	7.646635007	121	61.22315617
296007.jpg	798	457.915981	30	5.219127091	30	6.153148851	72	20.87690283
296059.jpg	772	766.54737	30	8.190954832	30	7.076291333	51	36.33076152
299086.jpg	811	354.814713	30	2.582472537	30	3.796890368	90	26.62139639
300091.jpg	776	1144.27812	30	8.080730937	30	14.39581718	52	75.73142579
302008.jpg	654	3691.2739	30	16.00413413	30	42.89515041	157	401.3807512
304034.jpg	1757	6510.81132	30	23.03209476	30	20.84206713	215	445.5341587
304074.jpg	1493	3932.34765	30	14.80218701	30	15.07463291	165	220.0041843
306005.jpg	971	3015.34008	30	21.75390303	30	25.43988632	106	179.5255069
3096.jpg	206	149.513743	30	9.168466113	30	8.887204618	28	13.67870754
33039.jpg	1770	10599.4929	30	34.14008898	30	37.19887928	382	1141.536169
351093.jpg	1170	5359.9644	30	31.90378971	30	26.17192941	54	83.80317278
361010.jpg	1105	2519.15553	30	27.69520757	30	18.08430152	78	165.052685
37073.jpg	609	556.509311	30	3.616207401	30	7.794460685	40	28.98454219
376043.jpg	1669	3481.97571	30	22.04329843	30	16.21279401	87	88.23981302
38082.jpg	1553	2063.97891	29	10.85394477	30	11.04287982	150	79.0603222
38092.jpg	1077	3348.25723	30	21.64435293	30	22.861577	97	135.7437119
385039.jpg	1030	3367.50462	30	20.57241501	30	16.09431364	139	250.4655104
41033.jpg	1144	2590.76203	30	11.84977398	30	11.27291502	95	147.1746392
41069.jpg	1755	2568.74895	30	11.53359152	30	8.936223088	148	95.87780124
42012.jpg	1191	2429.57066	30	12.34068668	30	15.88521028	98	103.8458467
42049.jpg	332	1034.00255	30	17.28088576	30	25.10549263	85	105.6548292
43074.jpg	1060	712.485588	30	5.646093351	30	5.59818713	91	29.33066064
45096.jpg	294	372.218653	30	13.10613857	30	20.98230911	28	22.21981633
54082.jpg	938	718.032785	30	6.336446096	30	9.446316232	84	29.94485143
55073.jpg	1712	5508.72162	30	21.08557028	30	17.92284581	146	253.5688952
58060.jpg	1396	3235.00004	30	7.986055522	30	10.56054144	182	200.988938
62096.jpg	935	5695.87996	30	37.22602605	30	26.76224867	120	519.389533
65033.jpg	1580	3814.28418	30	26.57344001	30	17.76725125	116	131.5661554
66053.jpg	1372	1992.22626	30	15.06141044	30	11.85939944	52	18.96573007

Name	NRW	YLGCW	NRN	YLGCN	NRWC	YLGCWC	NRWNC	YLGCWNC
69015.jpg	1195	2129.84546	30	16.85257154	30	14.62187156	37	16.01728089
69020.jpg	1565	1921.96118	30	9.691657694	30	11.30199694	34	15.19594645
69040.jpg	1971	2794.54619	30	8.430874632	30	6.742054893	162	92.50660174
76053.jpg	1355	1961.59297	30	14.53839708	30	8.030870929	58	37.26601839
78004.jpg	950	2308.13463	30	25.53464809	30	11.99868266	43	31.97505569
8023.jpg	1581	2154.59496	30	7.49848691	30	6.923516488	89	44.07585383
85048.jpg	1379	4989.55645	30	28.64631403	30	21.65225117	165	291.389224
86000.jpg	1040	2145.95411	30	15.0834316	30	17.38467529	191	223.9795532
86016.jpg	1978	1902.67383	30	5.340363073	30	2.459407839	222	92.92388521
86068.jpg	1491	1344.46888	30	8.242691678	30	5.464249634	142	93.10549882
87046.jpg	1498	5306.3395	30	25.03255663	30	22.28005166	208	372.5246924
89072.jpg	1149	2574.69417	30	17.66717589	30	11.86732774	150	150.3189623
97033.jpg	1210	4551.14267	30	22.41333127	30	20.64859837	138	244.6839257
mean		2917.52415		16.29866326		15.71628835		185.3977909
std.dev.		1890.98221		8.076534288		7.712174375		200.4808565



(a) (b)

Figure 4.6: Plots of YLGC values for 30 regions.

In Tables 4.2, 4.3, 4.4 and Figure 4.4, 4.5,4.6. NRW is the number of regions after use Watershed method, YLGCW is the value of YLGC that after using Watershed method. NRN is the number of regions after use Normalized cut method, YLGCN is the value of YLGC that after using Normalized cut method. NRWC is the number of regions after use Water-cuts RAG method, YLGCWC is the value of YLGC that after using Water-cuts RAG method. NRWNC is the number of regions after use Water-cuts Clust method, YLGCWNC is the value of YLGC that after using Water-cuts Clust method.

In the above three Figure 4.4, 4.5, 4.6 and Table 4.2, 4.3, 4.4, we have set in N-cuts and Water-cuts RAG the same number of region (100 images), which is under the condition of changing the *nbsegments* only. Table 4.2 is the result of segmenting the original image into 10 regions, Table 4.3 20 regions and Table 4.4 30, which means nbsegments takes 10,20 and 30. Graph 4.4, 4.5, 4.6 show the bar graphs. Here we only compare YLGC value of N-cuts and Water-cuts RAG because we can not precisely control or predict the regions of the segmentation results. Thus it is meaningless to compare YLGC value under the condition of different regions. So we adopt line chart and YLGC mean value and standard deviation to compare N-cuts and Water-cuts RAG. In Table 4.2, when the segmentation has 10 sections, the YLGC mean value and standard deviation calculated by N-cuts are 2.648 and 1.654, while the YLGC mean value and standard deviation calculated by Water-cuts RAG are 2.637 and 1.333; both are smaller than the former two numbers. In Table 4.3, when the segmentation results have 20 sub-sections, then the YLGC mean value and standard deviation calculated by N-cuts are 8.096 and 4.218, while YLGC mean value and standard deviation calculated by Water-cuts RAG are 7.964 and 3.803; both are smaller than the former two numbers. In Table 4.4, when the segmentation results have 30 sub-sections, the YLGC mean value and standard deviation calculated by N-cuts are 16.299 and 8.077, while the YLGC mean value and standard deviation calculated by Water-cuts RAG are 15.716 and 7.712; both are smaller than the former two numbers. This has further proved that the Water-cuts RAG methods proposed in this thesis had made relative improvement compared with past calculation methods.

All the images are from UC Berkley Segmentation dataset [1].

Chapter 5

CONCLUSION AND FUTURE WORK

Image segmentation has been a popular topic in the past few decades. Successful segmentation is useful for identifying and interpreting the features of images. This paper has proposed a combined approach of using Watershed and N-cuts together, which is Water-cuts RAG to segment images. The Watershed approach preprocesses the input image, structures a weighted image and then uses N-cuts to segment the pictures. In addition, this paper has proposed a method to integrate clustering algorithm, which has achieved a relatively good segmentation result.

The following major work has been done in this paper: the first is to study graph theoretic algorithms in the literature mainly formulating image segmentation as a graph optimization problem. The second is to reduce the complexity of this problem by optimization of region-based graph structures. The last is to validate the performance of the existing and the proposed methods and test the hypothesis that region-based analysis reduces the complexity of optimization problem.

Meanwhile, the large amount of experiments done by using these two calculation methods have demonstrated that these two methods have achieved satisfactory results in execution time and segmentation results. These two methods are of practical value.

Due to factors such as limited time, calculation complexity and so on, there is still much room of study for this paper in regard of this topic. The main targets are to lower calculation complexity, reduce calculation time, and more precise segmentation results. In the future work, emphasis will be on the following aspects:

(1) To try other approaches to preprocess the input images and even techniques in other domain to segment the visual scene.

(2) To start from the feature vector and eigenvalue to optimize calculation results and reduce calculation time length.

(3) To improve N-cuts method by using image magnitude and phase.

REFERENCE LIST

[1] http://www.eecs.berkeley.edu/research/projects/cs/vision/bsds/.

[2] Julio Carballido-Gamio abd Serge J. Belongie and Sharmila Majumdar. Normalized cuts in 3d for spinal mri segmentation. *IEEE Trans, Medical Imaging*, 23(1):36–44, 2004.

[3] Y. Boykov, O. Veksler, and R. Zabih. Fast approximate energy minimization via graph cuts. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(11):1222–1239, 2001.

[4] Yuri Boykov and Vladimir Kolmogorov. An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(9):1124–1137, September, 2004.

[5] Ting Chen and Zhenqiang Shen. An adaptive image segmentation method using region growing. *In the Computer Engineering and Technology*, pages 78–80, 2010.

[6] Timothee Cour, Florence Benezit, and Jianbo Shi. Spectral segmentation with multiscale graph decomposition. *IEEE Computer society Conferenc on Computer Vision and Pattern Recognition*, 2:1124–1131, 2005.

[7] O. Demetz. Graph cuts in computer vision. *Master's thesis*, 2009.

[8] Wang Demin. Unsupervised video segmentation based on watersheds and temporal tracking. *IEEE Transactions on Circuits and Systems for Video Technology*, 8(5):539–546, 1998.

[9] H. Digabel and C. Lantuejoul. Iterative algorithms. *In J.-L. Chermant, editor, 2nd European Symposium on Quantitative Analysis of Microstructures in Material Science, Biology and Medicine*, pages 85–99, 1977.

[10] Hai Gao, Wan-Chi Siu, and Chao huan Hou. Improved techniques for automatic image segmentation. *IEEE Transactions on Circuits and Systems for Video Technology*, 11(12):1273–1280, 2001.

[11] Golub and Van Loan. *Matrix computations.* 1989.

[12] R. C. Gonzalez and R. E. Woods. *Digital Image Processing (3rd Edition)*. Aug, 2007.

[13] Xu Haifeng, Akmal A Y, and Mansur R K. Automatic moving object extraction for content based applications. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(6):796–812, 2004.

[14] Haris K, Efstratiadis S.N, Maglaveras N, and Katsaggelos A.K. Hybrid image segmentation using watersheds and fast region merging. *IEEE Transactions on Image Processing*, 7(12):1684–1699, 1998.

[15] Sokratis Makrogiannis, George Economou, Spiros Fotopoulos, and Nikolaos G.Bourbakis. Segmentation of color images using multiscale clustering and graph theoretic region synthesis. *IEEE Transactions on Systems, Man, and Cyberneticspart Part A: Systems and Humans,*, 35(2):224–238, March 2005.

[16] J. Malik and P.Perona. Preattentive texture discrimination with early vision mechanisms. *Optical Society of American*, 7(2):923–932, May 1990.

[17] Salembier P and Pardas M. Hierarchical morphological segmentation for image sequence coding. *IEEE Transactions on Image Processing*, 3(5):639–651, 1994.

[18] Paul R.H, Canagarajah C.N, and David R.B. Image segmentation using a texture gradient based watershed transform. *IEEE Transactions on Image Processing*, 12(12):1618–1633, 2003.

[19] O'Callaghan R.J and Bull D.R. Combined morphological spectral unsupervised image segmentation. *IEEE Transactions on Image Processing*, 14(1):49–62, 2005.

[20] J. Shi and J. Malik. Normalized cuts and image segmentation. *IEEE Xplore*, pages 731–737, 1997.

[21] J. Shi and J. Malik. Normalized cuts and image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(8):888–905, 2000.

[22] Yaakov T and Amir A. Automatic segmentation of moving objects in video sequence: A region labeling approach. *IEEE Transactions on Circuits and Systems for Video Technology*, 12(7):597–612, 2002.

[23] Luc Vincent and Pierre Soille. Watersheds in digital spaces: An efficient algorithm based on immersion simulations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13(6):583–598, June 1991.

[24] Z. Wu and R. Leahy. An optimal graph theoretic approach to data clustering: Theory and its application to image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11:1101–1113, 1993.

[25] Yuri Y.Boykov and Marie-Pierre Jollu. Interactive graph cuts for optimal boundary & region segmentation of objects in $n-d$ images. *Internation Conference on Computer Vision*, I:105–112, July 2001.

[26] Yuri Y.Boykov and Olga Veksler. Graph cuts in vision and graphics theories and applications. *Mathematical Models in Computer Vision*, 2006.

CURRICULUM VITAE

Chao Zhang
1300 S Farmview Dr Apt.G33
Dover, DE 19904
(302) 698-7582

Education

Masters: Fall 2012 - Spring 2015, Department of Applied Mathematics and Mathematical Physics, Delaware State University, Dover, Delaware. Major in Applied Mathematics.

Bachelor of Science: Fall 2008- Spring 2012 :Department of Computer Science, Jilin Business and Technology College, Changchun, Jilin, China. Major in Computer Science

Learning experience: exchange student– fall semester 2011 study in Delaware State University (08/2011 01/2012) Study Achievement: excellent

Awards and Presentations

The Mathematical Association of America. "Finding Water-Cuts: Image Segmentation using Watershed and Graph Optimization", October 25, 2014.

Excellent Graduate Student of Jinlin Province, 2012.

Other Experience

The Host of the Chinese New Year celebration for Great Dover Area, U.S.A for years 2013, 2014.

Computer Skills

C/C++

Matlab

Latex

MS-Office

Delaware State University
Mass Communication Dept.
1200 N. DuPont Hwy
Dover, DE 19901
ETV building room 125
302.857.6584
Fax 302.857.6589

News Release

FOR IMMDIATE RELEASE

WDSU radio "The Hive" radio station is hosting the weekly show "Breakn N Entern" for up and coming artist on campus and local artist. The interviews with the guest will take place on 4/21/2015 at the station location from 4:30 to 6:30 pm. from the radio show.

Dover, Delaware (April 20,2015)- WDSU radio station "The Hive" is hosting their weekly show to promote inspiring artist of all diversifications. "Breakn N Entern" is mutually beneficial to the artists on the rise and the hive station. The station and artists obtain exposure. The show will be hosted by Marquell "Quell" Tate, who is the Music Director and Label Representative. The co-host is Lonjae "LonnieJ" Williams who is the hive's operation manager.

"Breakn N Entern" has interviewed emerging artist " Lee Mazin" who is the first female contracted artist of Dream chasers record label, as well as another artist under Jahlil Beats music group. Our shows helps the artist get a following from our students." -Marquell Tate

WDSU Radio, "The Hive," is a closed-circuit campus radio station of Delaware State University. This station airs on all campus televisions on channel 15. The Hive is by the students, for the students with the advisement of professor Ava Perrine.

This organization is open to all students at DSU regardless of the major as long as they are in good academic standings. The WDSU radio station aims to promote student opportunities to gain hands on experience with radio production before they graduate and enter the production industry.

For more information on WDSU Radio
https://vimeo.com/user33133172
https://instagram.com/wdsuradio/
https://www.facebook.com/media/set/?set=o.52562646477&ref=mf
http://websta.me/n/wdsuradio
https://blogwdsuradio.wordpress.com/2013/03/26/about-wdsu-radio/

###