Proceedings of the Federated Conference on
Computer Science and Information Systems pp. 183–186

ISBN 978-83-60810-51-4

Graph Partitioning based Automatic Segmentation Approach for CT Scan Liver Images

Walaa H. Elmasry
and Hossam M. Moftah
Faculty of Computers and
Information, Cairo University
Scientific Research Group in Egypt
(SRGE)
http://www.egyptscience.net/
Cairo - Egypt
Email: walaa.elmasry@egyptscience.net,
hossam.moftah@egyptscience.net

Nashwa El-Bendary
Arab Academy for Science,
Technology, and Maritime Transport
Scientific Research Group in Egypt
(SRGE)
http://www.egyptscience.net/
Cairo - Egypt
Email: nashwa.elbendary@ieee.org

Aboul Ella Hassanien
Faculty of Computers and
Information, Cairo University
Scientific Research Group in Egypt
(SRGE)
http://www.egyptscience.net/
Cairo - Egypt
Email: abo@egyptscience.net

***Abstract*—Manual segmentation of liver computerized tomography (CT) images is very time consuming, so it is desired to develop a computer-based approach for the analysis of liver CT images that can precisely segment the liver without any human intervention. This paper presents normalized cuts graph partitioning approach for liver segmentation from CT images. To evaluate the performance of the presented approach, we present tests on different liver CT images. Experimental results obtained show that the overall accuracy offered by the employed normalized cuts technique is high compared to the well known K-means segmentation approach.**

I. Introduction

IMPROVING healthcare through anatomical knowledge coupled with image processing techniques is considered a direct outcome for development of computer-aided diagnosis systems [1]. Computer-based systems for the analysis of computerized tomography (CT) medical images have many advantages over human interpreters, such as speed, large knowledge base for diagnostic information, and non-sensitivity to fatigue [2]. Organ segmentation is often the first step in computer-aided diagnosis. Segmentation of abdominal organs, such as the liver, kidneys, and spleen, from CT scan imagery has been attracting a fair amount of research recently [1]. Image segmentation is the process of partitioning a digital image into multiple segments to simplify or change the representation of an image into something that is more meaningful. Result of the segmentation process is a set of segments that cover the entire image or an extracted set of contours from the input image. All pixels in the resulted regions are similar with respect to some computed characteristics, such as color, intensity, or texture. However, considering the same characteristics, adjacent regions are significantly different [3].

Technologies such as magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and other imaging modalities provide an effective means for non-invasively mapping the anatomy of a subject and have greatly increased knowledge of normal and diseased anatomy for medical research as a critical component in diagnosis and treatment planning. With the increasing size and number of medical images, the use of computers in facilitating their processing and analysis has become necessary. Particularly, image segmentation computer algorithms that are used for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks.

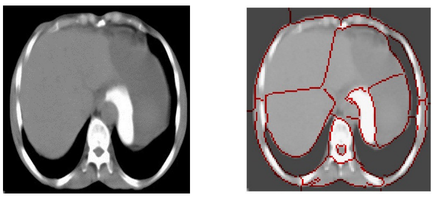
Image segmentation algorithms play a vital role in numerous biomedical imaging application [4]. Segmentations methods vary widely depending on different factors like the specific application, imaging modality, and other factors [5]. Thus, there is no single segmentation method that yields better results for every medical image. Graph partitioning methods can effectively be used for image segmentation. In these methods, the image is modeled as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define the dissimilarity between the neighborhood pixels. The image is then partitioned according to a criterion designed to model good clusters. Each partition of the nodes (pixels) output from these algorithms are considered an object segment in the image. Normalized cuts algorithm is one of the popular graph partitioning algorithms [6].

This paper presents an approach for liver segmentation from CT images based on the normalized cuts graph partitioning algorithm. The normalized cuts algorithm models each pixel in the image as a node in the graph and treats segmentation as a graph partitioning problem. In normalized cuts algorithm, the optimal solution of splitting points is easily computed by solving a generalized eigenvalue problem.

A collection of clinical CT images with reference segmentations was provided to test the accuracy of the normalized cuts. The remainder of this paper is organized as follows. Section II an overview of the normalized cuts segmentation algorithm. Section III presents experimental results. Finally, Section IV addresses conclusions and discusses future work.

II. Normalized Cuts: Preliminaries

In 1997, Shi and Malik [6] proposed the normalized cuts algorithm for image segmentation problem, which is based on Graph Theory [5]. Normalized cuts models the image into a graph. It models each pixel of the image as a node in the graph and set an edge between two nodes if there are similarities between them. The normalized cuts is composed of two steps: (1) similarity measurement and (2) normalized cuts process [7]. The purpose of the first step is to compute the similarity between pixels and this value is set as the weight on the edge. In order to model all the similarities of an image, all pairs of pixels will contain an edge, which means if an image contains N pixels, there will be totally $(N-1)N/2$ edges in the corresponding graph. This kind of graph is called "complete graph" and needs a large memory space. To simplify the problem, sometimes we set edges between two nodes only when their distance is smaller than a specific threshold. For example, in fig. 1, we show an example for modeling an image into a graph.



(a) Original image (b) Segmented image

Fig. 1. An example for modeling an image into a graph

For the resulted connected graph, each pixel goes through the edges to reach all other pixels. The term "cut" means eliminating a set of edges to make the graph "unconnected" and the cut value is the total weights on this set of edges. For example, if we eliminate all the red edges in fig. 1, then the nodes with white color will be "unconnected" to the nodes with dark color, and now we say the graph has been separate into two connected graph (the outside dark group and the inner white group). So, from the graph theory, the image segmentation problem is modeled as graph cut problem. But there are many kinds of cutting path we can adopt to separate the image into two parts. The weights on edges have the similarity meaning between pixels, so if we want to separate two pixels into two different groups, their similarity is expected to be small. Three kinds of cutting criteria have been proposed in recent years: (a) minimum cut, (b) minimum ratio cut, and (c) minimum normalized cuts. The normalized cuts has been proved to maintain both high difference between two segments and high similarities inside each segment.

A graph $G=(V,E)$ can be partitioned into two disjoint sets, A and B. The degree of dissimilarity between these two pieces can be computed as shown in equation (1).

$$cut(A,B)=\sum_{u\in A,v\in B} w(u,v) \tag{1}$$

where $w(u,v)$ is the similarity between node u and v. The optimal bipartition of a graph is the one that minimizes this cut value. Finding the minimum cut is a well-studied problem and there are efficient algorithms proposed for solving it. However, the minimum cut criteria favors cutting small sets of isolated nodes in the graph, and gives bad partition in some cases. Shi an Malik [6] proposed a new measure of disassociation that is named the normalized cuts (Ncuts) and is calculated as shown in equation (2).

$$Ncut(A,B)=\frac{cut(A,B)}{assoc(A,V)}+\frac{cut(A,B)}{assoc(B,V)'} \tag{2}$$

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 defined similarly.

Let $d(i)=\sum_j w(i,j)$ be the total connection from the node i to all other nodes. Moreover, let D be an $N\times N$ diagonal matrix with d on its diagonal. Also, let W be an $N\times N$ symmetric matrix with $W(i,j)=w(i,j)$. Then it turns out that we can minimize $Ncuts(A,B)$ by following equation (3).

$$\min_{A,B} Ncut(A,B)=\min_{y}\frac{y^T(D-W)y}{y^TDy} \tag{3}$$

If y (the value of the eigenvector) is relaxed to take real values, then equation (3) can be minimized by solving the generalized $eigen$ value system, presented in equation (4), where λ is a scalar eigenvalue.

$$(D-W)y=\lambda Dy \tag{4}$$

Amazingly, the second smallest eigenvector y gives the solution of the normalized cuts problem because the second smallest is the real valued solution to the Ncuts problem [6]. Algorithm (1) shows steps of the normalized cuts segmentation algorithm.

In algorithm (1), for step (3), there are several ways to choose a splitting point, such as: Take 0, $median$ and search a splitting point which results in that $Ncuts(A,B)$ is minimized. The splitting point that minimizes $Ncuts$ value also minimizes:

$$\frac{y^T(D-W)y}{y^TDy} \tag{5}$$

where $y=(1+x)-b(1-x)$, $b=k/(1-k)$, $k=\frac{\sum_{x_i>0} d_i}{\sum_i d_i}$, x is an N dimensional indicator vector, where x_i = 1 if node i is in A and x_i= -1 otherwise.

III. Experimental Results and Analysis

This section presents the simulated results for segmenting liver CT medical images using normalized cuts segmentation algorithm. The original images used in our experiments were collected from the CT scans of patients' Livers with general intrinsic tissue variation. In this paper, we applied the normalized cuts algorithm to gray-scaled images. The images size was 431×339 . Examples for segmentation results for four sample liver CT images are shown in fig. 2.

Algorithm 1 Normalized cuts Segmentation Algorithm

1: Construct a weighted graph G = (V,E), compute the weight of each edge (reflecting the likelihood that the two pixels belong to one object), and construct D and W as:

$$W_{ij} = exp\frac{-||F(i) - F(j)||_2^2}{\sigma_I^2} * L \quad (6)$$

where

$$L = \begin{cases} exp\frac{-||X(i)-X(j)||_2^2}{\sigma_x^2}, & \text{if } ||X(i) - X(j)||_2 < r; \\ 0, & \text{Otherwise.} \end{cases} \quad (7)$$

where X(i) is the spatial location of node i (the coordinates in the original image I) and F(i) is a feature vector and Let $d_i = \sum_j w_{ij}$ be the total connection from node i to all other nodes. Construct an N x N diagonal matrix D with d on its diagonal.

2: Solve a generalized eigen system, $(D - W)y = \lambda Dy$, and get an eigenvector with the smallest eigenvalue.

3: Use the eigenvector with the smallest eigenvalue to bipartition the graph. Therefore, a splitting point is needed to be chosen. There are several ways for doing this, such as:
- Take 0
- Take median
- Search a splitting point, which results in that N-cuts(A, B) is minimized.

The splitting point which minimizes N-cuts value also minimizes the output value of equation (5)

$$\frac{y^T(D - W)y}{y^T Dy}$$

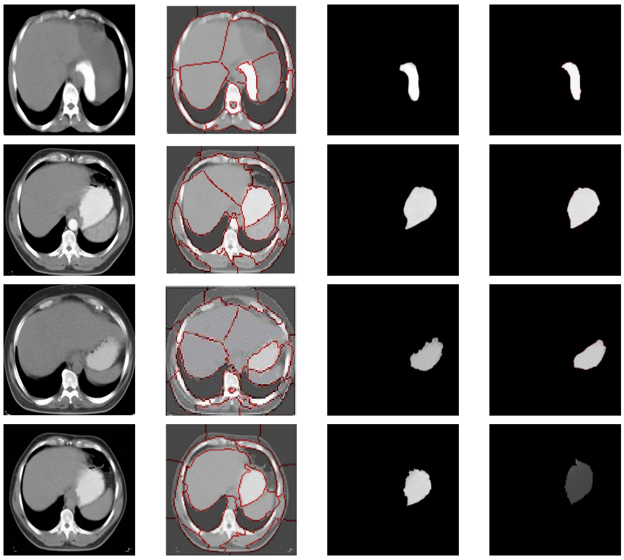
4: REPEAT: (Bipartition recursively)

5: UNTIL:
- N-cuts value $>$ a pre-specified threshold value (Large N-cuts value means that there is no clear partition point any more)

or
- The total number of nodes in the partition (area) $<$ a pre-specified threshold value.

6: STOP

In medical research, supervised evaluation is widely used. It computes the difference between the ground truth and a segmentation result using a given evaluation metric [8]. In this paper, we used the manual segmentation to reflect the ground truth [9]. Furthermore, we evaluated segmentation algorithms by comparing the result from a segmented image against the result from a manual segmented, which is often referred to as a gold standard [10] or "ground truth." The degree of similarity between the manual segmented and machine segmented images reflects the accuracy of the segmented image. Betanzos in [11] defined an accuracy measure with multi types of object. Suppose that an image contains N types of objects, the accuracy measure is computed as shown in equation (8).



(a) (b) (c) (d)

Fig. 2. Normalized cuts segmented images results: (a) Original images, (b) Normalized clustered cuts (c) Desired manual segmented region (d) Normalized segmented results

TABLE I
RESULTS FOR NORMALIZED CUTS SEGMENTATION FOR 4 SAMPLES

	S1	**S2**	**S3**	**S4**
Number of desired pixels for ideal image	11802	25629	17703	19494
Number of pixels for segmented image	11049	24380	16459	23433
Accuracy%	93.62%	94.04%	92.97%	83.19%

$$Accuracy = \sum_{i=1}^{N} \frac{CSP}{TNP} \quad (8)$$

Where CSP is the correct segmented pixels in i^{th} object and TNP is the total number of pixels in i^{th} object. The accuracy measure that determines how far is the actually segmented image from the manually segmented region by expertise. Table I shows experimental results that highlight segmentation accuracy, using normalized cuts algorithm, for 4 **samples:** (**S1**, **S2**, **S3**, and **S4**). It is based on the images of the segmented regions, which represent the affected part in the liver as shown in fig. 2. On the other hand, table II presents segmentation accuracy using K-means segmentation algorithm.

According to the fact that we are focusing on the region of interest (ROI), which is the part that contains the tumor, fig. 2 (c) and (d) show manually segmented (ROI) and

TABLE II
RESULTS FOR K-MEANS SEGMENTATION FOR 4 SAMPLES

	S1	S2	S3	S4
Number of desired pixels for ideal image	11802	25629	17703	19494
Number of pixels for segmented image	10319	22494	16235	15002
Accuracy%	87.44%	87.77%	91.71%	76.96%

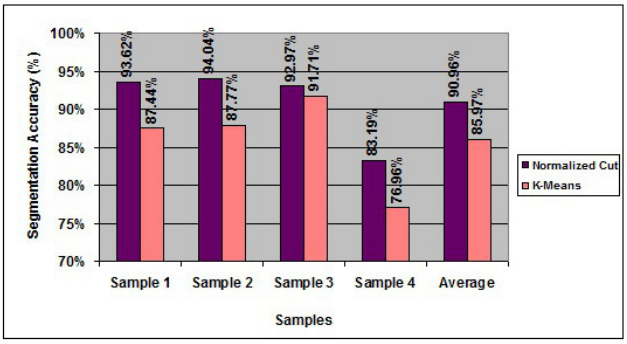


Fig. 3. A comparison between K-means and Ncuts results

segmented part using normalized cuts for images 1, 2, 3, and 4, respectively. As presented in table I and table II, for image 1, the manually segmented part (ROI) with number of pixels = 11802, the segmented part using normalized cuts with number of pixels = 11049 resulted in segmentation accuracy= 93.62% and the segmented part using K-means with number of pixels = 10319 resulted in segmentation accuracy= 87.44%. For image 2, the manually segmented part (ROI) with number of pixels = 25629, the segmented part using normalized cuts with number of pixels = 24380 resulted in accuracy= 94.04 % and the segmented part using K-means with number of pixels = 22494 resulted in segmentation accuracy= 87.77%. For image 3, the manually segmented part (ROI) with number of pixels = 17703, the segmented part using normalized cuts with number of pixels = 16459 resulted in accuracy= 92.97% and the segmented part using K-means with number of pixels = 16235 resulted in segmentation accuracy= 91.71%. Finally, for image 4, the manually segmented part (ROI) with number of pixels = 19494, the segmented part using normalized cuts (Ncuts) with number of pixels = 23433, with accuracy= 83.19% and the segmented part using K-means with number of pixels = 15002 resulted in segmentation accuracy= 76.96%.

Fig. 3 depicts a comparison between the k-means and Ncuts results according to the accuracy of performance. This concludes that the Ncuts has obtained higher average accuracy (90.96%) compared to the k-means results, which is (in average) 85.97%. Therefor, the Ncuts has proved its efficiency and its competency according to the accuracy measure.

IV. CONCLUSIONS AND FUTURE WORKS

This paper presents an approach for liver segmentation from CT images based on the normalized cuts segmentation algorithm. All results were obtained using two measures that highlight segmentation accuracy to asses strength of normalized cuts algorithm for segmenting the affected part in the liver.The two measures are time complexity and segmentation accuracy. In general, normalized cuts algorithm reached high accuracy, however with the cost of high time complexity. According to our experiments the method can efficiently segment the liver in many cases, however, it is still recommended to use more features, additional to the color feature used in this paper, such as shape and texture. Currently, our future work is dedicated to use the multi-objective concept via adding more features to apply other segmentation approaches such as k-means clustering algorithm for various medical images. Moreover, computer-assisted reading of medical images is a relatively new concept, which has been developed during the last 10 years and which is growing into diagnostic radiology. Especially in liver fibrosis, image processing techniques was applied to assist radiologists in the interpretation of liver fibrosis. Accordingly, we are planning to investigate an intelligent diagnosis system for diagnosing features derived from the computer tomography images of liver in Chronic Hepatitis C.

REFERENCES

[1] L. R. Varshney. (2000, August), Abdominal organ segmentation in CT scan images: A Survey. *Cornell University* [Online]. pp. 1-4. Available: http://www.mit.edu/ lrv/cornell/publications/ Abdominal%20Organ%20Segmentation.pdf

[2] A. P. Reeves and W. J. Kostis, "Computer-aided diagnosis for lung cancer. " *Radiologic Clinics of North America*, vol. 38, no. 3, pp. 497–509, 2000.

[3] F. SUN and J. P. HE, "A normalized cuts based image segmentation method. " in *Proc. Second International Conference on Information and Computing Science*, Manchester, UK, 2009, pp. 333–336.

[4] D. L. Pham , C. Xu, and J. L. Prince, "A survey of current methods in medical image segmentation. " *Annual Review of Biomedical Engineering*, vol. 2, pp. 315–337, 1998.

[5] S. E. Schaeffer, "Graph clustering, " *Computer Science Review*, pp. 27–64, 2007.

[6] J. Shi and J. Malik, "Normalized cuts and image segmentation, " *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 888–905, 2000.

[7] S. S. Tabatabaei, M. Coates, and M. Rabbat, "GANC: Greedy agglomerative normalized cuts for graph clustering. " *Pattern Recognition*, vol. 45, no. 2, pp. 831–843, 2012.

[8] N. Situ, X. Yuan, G. Zouridakis, and N. Mullani, "Automatic segmentation of skin lesion images using evolutionary strategy. " in *Proc. IEEE International Conference on Image Processing*, San Antonio, Texas, USA, 2007, vol. 6, pp. 277–280.

[9] X. Li, B. Aldridge, J. Rees, and R. Fisher, "Estimating the ground truth from multiple individual segmentations with application to skin lesion segmentation. " in *Proc. Medical Image Understanding and Analysis Conference*, UK, 2010, MVA Press, vol. 1, pp. 101–106.

[10] C. Graaf, A. Koster, K. Vincken, and M. Viergever, "Validation of the interleaved pyramid for the segmentation of 3D vector images, " *Pattern Recognition Letters*, vol. 15, no. 5, pp. 467–475, 1994.

[11] A. A. Betanzos, B. A. Varela, and A. C. Martnez, "Analysis and evaluation of hard and fuzzy clustering segmentation techniques in burned patient images, " *Image and Vision Computing*, vol. 18, no. 13, pp. 1045–1054, 2000.