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Brain Tumor Segmentation using Normalized Graph Cuts

Nancy W, A Celinekavida

Abstract: ***Normalized graph cut algorithm is an efficient method where the technique of graph theory is adopted and in which the images are taken in the form of weighted graph in order to segment the images. This paper comprises of the fundamental concept of Normalized graph cut algorithm and its application towards the segmentation of Brain tumor. Identifying defects such as tumors is a very challenging because differentiating the components is difficult in a complex structure like a human brain. The diagnosis becomes even more complex because the tumor, blood clots and some part of the brain tissues appear as the same Brain tumor is generally detected and analyzed through a comprehensive analysis of the Magnetic Resonance Images of the brain. This technique gives a second opinion regarding the presence or absence of the brain tumor. This paper performs the study of Normalized graph cut algorithm and shows its efficiency in detecting tumors and compares it with other commonly used algorithms.***

Keywords: Brain Tumor, Image Processing, Segmentation and 3D.

I. INTRODUCTION

Image processing is the key way to represent segmentation of the various images such as brain tumors. Segmentation is the process of extracting the required part in the image from the rest of the image. This segmentation becomes more complicated in a complex structure like human brain. The fundamental step in image segmentation is acquiring the image of the subject. There are many imaging techniques such as Magnetic resonance, computerized tomography etc. by which the images of the brain can be obtained There are several techniques for the segmentation. Normalized graph cut algorithm is an extension of the graph theory. In this method the images to be segmented are considered in the form of weighted graph. Those graph are undirected i.e. the node of graph is same as that of the pixel of the image. This method highly adopted since images containing moderate to high noise.

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* Correspondence Author
Nancy W*, Assistant Professor, Jeppiaar Institute of Technology, Chennai, India.
A Celinekavida, Associate Professor, Vel Tech Multi Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Chennai, India.

II. RESEARCH METHODOLOGY

The image to be segmented is obtained from any image database. The segmentation of the image is comparatively simple if the size of the tumor is large. But, the segmentation becomes difficult when the size of the tumor is relatively small because it is hard to find the exact difference between the tumor and the rest of the brain image. The acquired image will be of noise content and hence it must be subjected to preprocessing. The main role of image processing is to provide stable images. These stable images are needed for perfect segmentation. The preprocessing includes removal of noise by a filter called the median filter. Further the image is subjected to enhancements such as resizing. After the preprocessing the image is converted into a weighted graph by considering the pixels as the nodes of the graph. A symmetric similarity matrix and a diagonal matrix consisting of the feature vectors is constructed for the same. These matrices are solved in order to find the smallest eigen value. This eigen value is used to bipartition the graph. The partition is repeated recursively until the Ncut value is less than the threshold value. The proposed techniques of image segmentation as shown in figure 1.

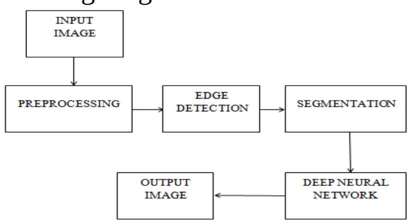

Fig.1 Block diagram of Segmentation

a) Graph Theory: A graph is generally defined in the form of nodes and edges which are represented as V and E that connects with many other nodes G={V,E}. A weighted graph is one in which each edge is always associated with a weight. If every pair of nodes is connected then it is called a connected graph.

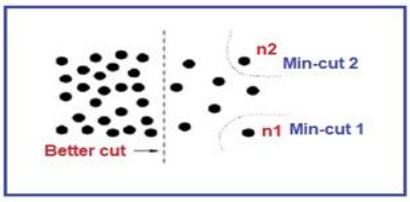

Fig.2 ABAD Partition

In grouping a weighted graph is split into disjoint sets where by some measure the similarity within the group is high and the similarity across the group is low. The dissimilarity between any two groups can be calculated as below:

$$Cut(A,B) = \sum_{i\in A i\in B} Wij \quad \text{------------ } 1$$

The major drawback of graph cuts is that it supports isolated nodes in the graph because of the small values achieved by partitioning such graphs as shown in figure 2.

b) Normalized Graph Cuts: The cut cost is defined as the ratio of the total edge connections to all nodes present in the graph that can be expressed by the help off normalized graph cuts technique as follows:

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

(ie)$assoc(A,V) = \sum_{u\in A, t\in V} w(u,t)$

The various merits of using Normalized graph cuts is that this method 1) it uses unbiased technique 2) it measures the Ncut value with respect to isolated nodes since that particular value will be larger than all other values of nodes.

c) Algorithm: With the given image construct a graph with the by assuming the pixel of the images as node of the constructed graph and ensure the respective weights on each node Construct the similarity matrix and the Diagonal matrix for the same image indicated as W and D respectively. Calculate the smallest eigen value by solving the eigen vector i.e. x=λDx. After obtaining the smallest eigen value consider only the second smallest eigen vector to partition the graph into two groups. In certain cases it can be grouped together again from the partition.

For a given image sequence I. As we discussed earlier assume each node is the pixel of the image I, b y using that construct the weighted graph as G = (V, E), in which N be the number of nodes, i.e. |V |.

Step1: Similarity matrix W is to be constructed with N*N dimensions as follows

$$w_{ij} = \exp\frac{-\|F(i)-F(j)\|_2^2}{\sigma_I^2} \times \begin{cases} \exp\dfrac{-\|X(i)-X(j)\|_2^2}{\sigma_X^2} & if \ \|X(i)-X(j)\|_2 < r \\ 0 & \text{otherwise} \end{cases}$$

Where the spatial location of node I is denoted as X(i) i.e., the coordinates in the original image I, and F(i) is represented as feature vector which is defined as:

Feature vector value	Segmentation types
F(i) = 1	Point sets
F(i)= I(i)	Grey scale images
F(i)=[u•s•sin(h), v•s•cos(h)](i)	Colour images
F(i)−[|I∗f1|,....,|I∗fn|](i)	Various scales and orientations

For texture segmentation,

Let us assume d_i=$P_i w_i$ be the total connection from node from i to all other nodes.
Construct a N × N diagonal matrix D with d on its diagonal.

Step 2: As we assumed earlier take only the second smallest eigen value by solving the generalized eigen system using (D−W)x= λDx. We can also solve the generalized eigen system using the MATLAB **eigs**to function.

Step 3: In this step the graph is bipartition using the previously obtained eigen vector. The two discrete values of eigen vector are considered and the sign of it gives an idea about the partition of the graph for ideal cases [A= {$V_i|y_i$>0}, B={$V_i|y_i$<=0}]. But it is necessary that y should be always real values according to that condition we need to choose the value for splitting the graph. We have many methods to choose the values such as

- Take value can be assumed as 0
- Take value can be obtained by calculating the median
- Ncut(A,B) should be always minimum the splitting point should be selected in such a way.

$$\frac{y^T(D-W)y}{y^T Dy} \text{ ------- } 4$$

Where y = (1 + x) − b(1 − x) where b = k/(1 − k)
Where

$$k = \frac{\sum_{zi>0} di}{\sum_i di} \text{-------}5$$

Where z is an N dimensional indicator vector, zi =1 if node i is in A and -1, otherwise.

We have to assume different splitting values to obtain the minimum value of Ncut. Probably the Ncut value will be minimum around the mean value of eigen vector. It can also be processed by using MATLAB has a function, **fminsearch**.

Step 4: Repeat this process until we get the larger value of Ncut than the threshold value. It can also stopped in the another condition such that total number of nodes is lesser than a threshold value. Finally a deep neural network is trained in order to determine the position and the type of the tumor.

III. RESULTS AND DISCUSSION

The Matlab implementation of the above method is given in the figure 3-6.

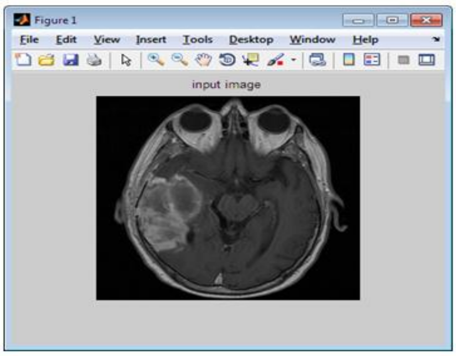

Fig.3 Input Image

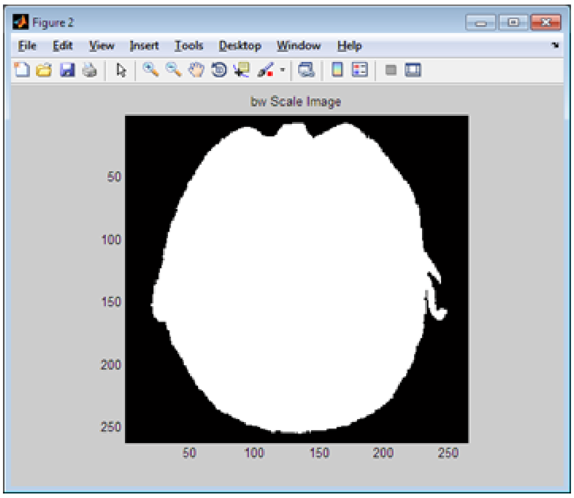

Fig.4 BW Scale Image

The image segmentation of above method implemented in Matlab as shown in the various output fig. 3,4,5 & 6.

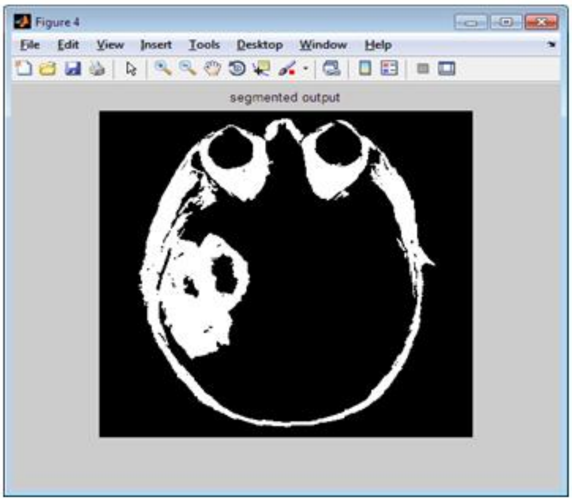

Fig.5 Segmented Output

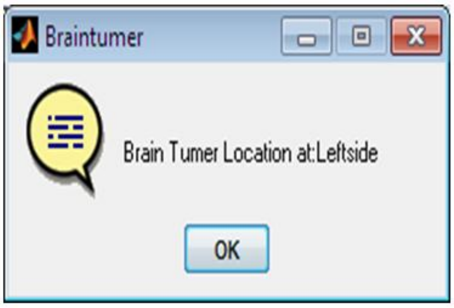

Fig.6 Final Output

IV. CONCLUSION

An algorithm has been presented to get deep information about the normalized cut value. This algorithm can be used in clinical purposes since it has good performance and highly robust in nature. it is cost effective which does not require any hardware constraint. Different type of models can be designed by incorporating the typical shape model into the normal framework. Thus we conclude that this method is robust and more accurate for different set of experiments on medical imaging modalities. This work can be extended in 3D through evaluation process of framework.

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