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# Two Segment Approach to Find Tumor Affected Area from Brain MRI

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***Abstract***

*Two region graph cut image partitioning after mapping entire image of brain in brain MRI. It is seen that piecewise constant model of the graph cut formulation becomes applicable when the image data is transformed by a main function. The proposed function contains data term to evaluate the deviation of the transformed data within two segmentation region, from the piecewise constant model, and a smoothness boundary preserving regularization term. Using a common function, energy minimization typically consists of iterating image partitioning by graph cut iterations and evaluations of region parameters via fixed point computation. The method results in good segmentations and runs faster the graph cut methods. The segmentation of MRI image is challenging due to the high diversity in appearance of tissue among the patient. An automatic interactive brain MRI image segmentation system with the ability to adjust operator control is achieved through this method.*

***Keywords****: Graph cuts, Image segmentation, Brain tumor, MRI*

## 1. Introduction

Segmentation is referring to the process of partitioning an image. Energy minimization formulations can be divided into two categories: continuous and discrete. Continuous formulations, which seek a partition of the image domain by active curves via a level set representation, have segmented accurately a variety of difficult images. Discrete formulations use objective functions which contain terms similar to those in continuous formulations, generally a data term which measures the conformity of segmentation to the image data, and a regularization term. Image segmentation occurs in many important applications [1]. The piecewise constant data term model, and it's Gaussian generalization, have been intensively used in the context of supervised graph cut methods, the data term can be written in the form required by the graph cut algorithm. Minimization by graph cuts of objective functional with a constant data term produce nearly global optima and less sensitive to initialization [3]. Several interactive graph cut methods have used models more general than the Gaussian by adding a process to learn the region parameters at any step of the graph cut segmentation process.

## 2. Graph Cut Segmentation

Combinatorial optimization methods use graph cut algorithms as an efficient method. Very fast methods have been implemented for image segmentation motion and stereo segmentation and region is a group of connected pixels with similar properties. Graph cut is a partition of the vertices in the graph. this algorithm assigns each pixel as a grey level label in the set of all possible labels. Graph cut objective functional typically contain a

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data term to measure the conformity of the image data and it can minimize an energy function of data term [2, 4].

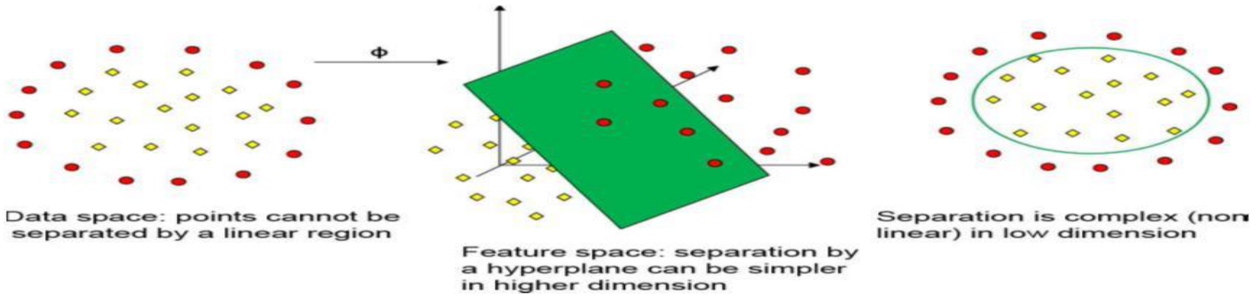


**Figure 1. Illustration of Nonlinear 3-D Data Separation with Mapping. Data is Nonlinearly**

**Separable in the Data Space. The Data Is Mapped to A Higher Dimensional Feature (Kernel)**

**Space So as to Have a Better Separability**

Using a common kernel function, the minimization is carried out by iterations of two consecutive steps:

1) Minimization with respect to the image segmentation by graph cuts and

2) Minimization with respect to the regions parameters via fixed point computation.

## 3. Segmentation in the Kernel Induced Space

The use of kernel functions is to transform image data rather than seeking accurate (complex) image models and addressing a non linear problem. Using the Mercer's theorem, the dot product in the feature space suffices to write the kernel-induced data term as a function of the image, the regions parameters, and a kernel function.

*A. Proposed Algorithm*

In the proposed algorithm graph cut applied over MRI images to find tumor area.

*Step of algorithm execution*

1. read image
2. normalize between 0 and 255
3. detect skull
4. creating images and masks
5. start of the vertical scan and end of the vertical scan
6. Top-down search: Computing the Bhattacharya coefficient-based score function
7. histogram bin size, an important parameter
8. scale for finding maxima and minima of the vertical score function
9. Score plot for horizontal direction
10. Stop

A data term to measure the conformity of image data within the segmentation regions to a statistical model and a regularization term (the prior) for smooth regions boundaries. The kernel trick consists of using a linear classifier to solve a nonlinear problem by mapping the original nonlinear data into a higher dimensional space.

 

*B. Optimization*

Function is minimized with an iterative two-step optimization strategy .Using a common kernel function, the first step consists of the fixing the labeling (or the image partition) and the second step consists of finding the labeling of the image.
The algorithm iterates these two steps until convergence. The algorithm is guaranteed to converge at least to a local minimum. The steps are:

1) Update of the Region Parameters
2) Update of the Partition with Graph Cut Optimization

Let g =(v,e) be a weighted graph, where v is the set of vertices (nodes) and e the set of edges, it contains a node for each pixel in the image and two additional nodes called terminals. Commonly, one is called source and the other is called sink. The minimum cut problem consists of finding the cut, in a given graph, with the lowest cost. The graph weights need to be set dynamically when ever region parameters and pair of labels changes.

## 4. Results

In this paper the graph cut method is used over MRI images to find tumor area.

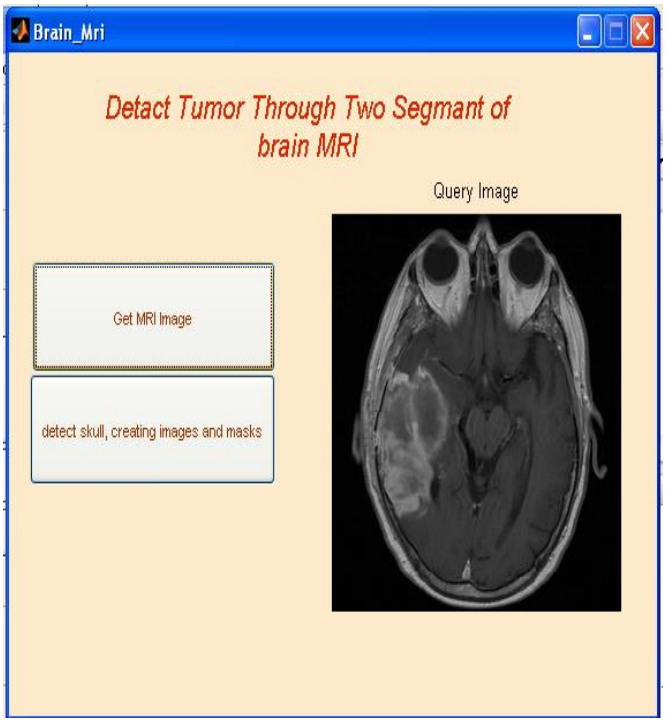


**Figure 2. Brain MRI Original Images**

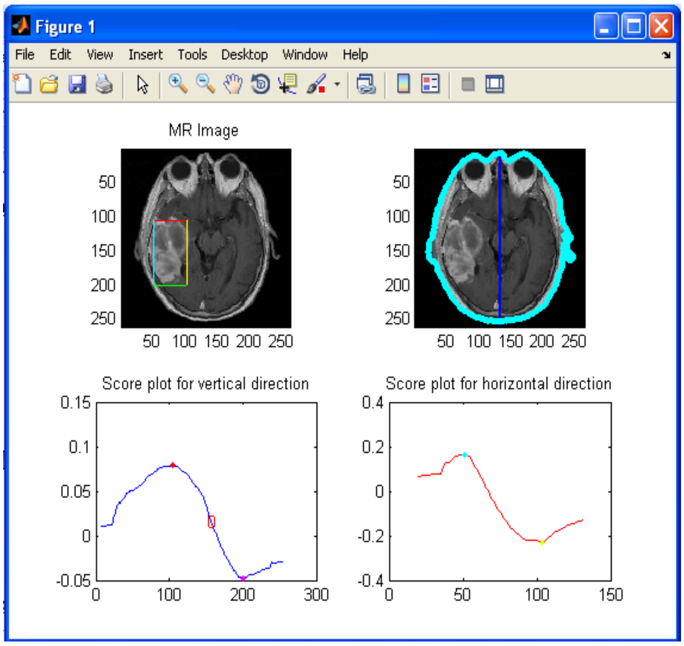


**Figure 3. Segmentations at Convergence & Analytic Result**

The brain image, shown in Fig. 3, was segmented into two regions. In this case, the choice of the number of regions is based upon prior medical knowledge. Segmentation at convergence and final labels are displayed as in previous examples. And it depicts a spot of very narrow human vessels with very small contrast within some regions. These results with gray level images show that the proposed method is flexible. Detection of anatomical brain tumors plays an important role in the planning and analysis of various treatments including radiation therapy and surgery.

## 5. Conclusions

The two regional graphs cut image segmentation in an induced space method consists of minimizing a functional containing an original data term which references the image data transformed in main proposed function. The optimization algorithm iterated two consecutive steps: graph cut optimization and fixed point iterations for updating the regions parameters. The flexibility and effectiveness of the method were tested over medical and natural images. A flexible and effective alternative to complex modeling of image data.

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