4-2015

A Novel Segmentation Approach For Brain Tumor in MRI

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ABSTRACT

Brain MRI image segmentation is one of the most important applications of image segmentation technique, and is an important part of clinical diagnostic tools. Segmented image can help physicians to identify tumor tissues in brain, and monitor effectiveness of chemotherapy treatments. However, manual segmentation of muscle regions is not only inaccurate, but also time consuming. In this work, Intensity Space Map (ISM) is used along with fuzzy c-means clustering algorithm to segment tumor regions in color MRI images. Experiments show the proposed ISM-based fuzzy c-means clustering brain MRI image segmentation yields promising results.

KEYWORDS

MRI Image; Segmentation; Intensity Space Map (ISM); Fuzzy C-means Clustering; Brain Tumor.

1 INTRODUCTION

Image segmentation is to group pixels into regions for future process. In each partitioned region of an image, pixels have similar characteristics based on given criteria. Brain MRI image segmentation is one of the most important applications of image segmentation technique, and is an important part of clinical diagnostic tools. Physicians can use magnetic resonance images (MRI) to estimate volume of tumor tissues in brain before and after chemotherapy. The thickness of reconstruction of MRI slices is determined during scanning. If the size of tumor region in MRI can be measured, the volumetric estimation of tumor can be obtained by calculating the sum of the products of the slice thickness and the tumor region size of each MRI slice. Hence, segmenting the tumor region in MRI images becomes the key step in the procedure.

There have been many research endeavors to segment brain tumor in MRI. Stadlbauer et al. used the Gaussian distribution of spatial distribution of choline-containing compounds (Cho), creatine (Cr) and N-acetyl-aspartate (NAA) in brain tumors as threshold in normal brain T2-weighted MRI [1]. The region growing segmentation methods are part of the region-based methods, and are the most commonly used for brain tumor segmentation [2]. Chong et al. [3] used region growing based algorithm to measure the tumor volume demonstrated on pretreatment T2-weighted magnetic resonance data sets.

The *k*-means algorithm is the most commonly used clustering algorithm since it is easy to implement and found to be effective in many applications. The fuzzy version of *k*-means clustering (fuzzy c-means, FCM) is widely adopted for medical image segmentation

[4][5][6]. Unlike the *k*-means clustering method, which forces pixels to belong to one class, FCM classifies pixels to belong to multiple classes with degrees of membership. The advantage of FCM-based segmentation algorithm over thresholding is that there is no need to choose the empirical threshold. This feature is useful especially when large amount of images are processed.

This work uses color fusion MRI methodology to extract color images from longitudinal relaxation time T_1 and transverse relaxation time T_2 images. A previously established standardized acquisition and image processing protocol is used to produce color MRI images of a variety of brain tissues of human subjects. In order to segment tumor tissues, Intensity Space Map (ISM) is introduced to be used by the fuzzy c-mean segmentation algorithm to incorporate both pixel intensity and region spatial connectivity information. The MRI images are from patients who have brain tumor. Experimental results show that the FCM-based image segmentation algorithm incorporated with ISM yields promising results. Segmented tumor regions can be used to estimate volume of brain cancer in order to evaluate effectiveness of chemotherapy.

The remainder of the paper is as follows. Section 2 provides a brief description of the challenges in tumor region segmentation on MRI images and the proposed fuzzy c-means segmentation algorithm using ISM. Section 3 discusses the experimental data preparation and results. Section 4 concludes the paper with an outline for future work.
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2 BRAIN TUMOR SEGMENTATION

2.1 Fuzzy C-mean Clustering

Fuzzy *c*-means (FCM) is a clustering method that allows a data point to belong to more than one cluster. Each point has a degree of belonging to a cluster. The membership function is defined as below:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{2/(m-1)}}, \qquad (2.1)$$

where u_{ij} is the degree of data point x_i in cluster j, $\sum_{j=1}^{C}\mu_{ij} = 1$, c_j is the center of cluster j. $\|x_i - c_j\|$ represents the Euclidean distance between data point x_i and cluster center c_j. C is the total number of clusters. Parameter m is a weighting exponent on each membership and controls the shape of the fuzzy membership function. When the value of m approaches 1, the algorithm becomes similar to *k-means*. The FCM algorithm minimizes the following objective function:

$$\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}\|x_i - c_j\|^2, \ 1 \le m < \infty \qquad (2.2)$$

where N and C are the total number of data points and clusters respectively.

2.2 Challenges of Brain Tumor Region Segmentation in MRI

Figure 1 shows a ColorMRI™ fusion image of axial brain, post gadolinium showing a tumor (glioblastoma) in the left hemisphere. The tumor (pink is active tumor) exhibits some heterogeneity and the adjacent white matter is edematous (pale green). Normal cerebrospinal fluid is also green. Figure 2 shows the segmentation image obtained by fuzzy c-mean clustering using pixel color intensities directly. It shows specific areas of gadolinium uptake in the tumor as well as some non-specific uptake in the posterior orbital fat. Obviously, using Figure 2 can not measure tumor region area correctly. The reason posterior orbital fat regions are included in the segmented image is

because both tumor and fat contain gadolinium element, showing similar colors. Thus pixels in these regions are classified to the same cluster. One way to distinguish them is to incorporate spatial information of pixels in the ROI.

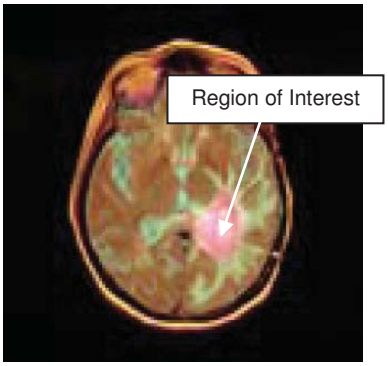

Figure 1. MRI of a Brain Tumor Patient

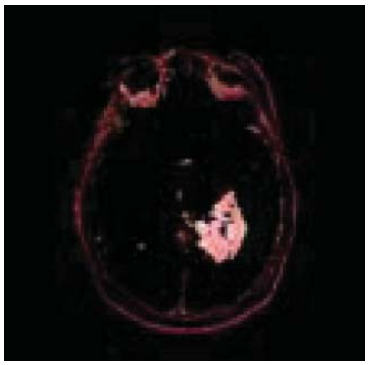

Figure 2. Segmented Tumor and Posterior Orbital Fat Regions of the MRI Image in Figure 1

2.3 Intensity Space Map (ISM)

Region growing segmentation techniques have been used to extract a connected region of similar pixels from an image. Mancas et al. [7] proposed a region growing segmentation method for gray level medical images. For color MRI, there are multiple intensity channels. Hence, an Intensity Space Map (ISG) is proposed for each component in an image. ISM uses both image topological and intensity information. The assumption for ISM is that pixels inside the region of interest not only have similar color intensities but also connect to other pixels inside the region [8]. It is necessary to emphasize that it is not assumed that pixels in other regions have different intensity values from pixels inside ROI. This is important because as we have seen in Figure 2, other tissues have similar values as the region of tumor.

The algorithm starts with a pre-selected seed point inside the region of interest. Initial values of all pixels in the ISM image are set to zero. During each iteration, the ISM values of pixels of each intensity channel which satisfy both of the following conditions are incremented by 1. Condition 1: pixel intensity difference from the seed point is within a threshold T; Condition 2: the pixel belongs to a structure which overlaps the seed point. The ISM values are defined in the following equation for each of the image intensity channels.

$$ISM(i,j)=\sum_{T=0}^{I_{\max}} g(i,j,T)$$

where

$g(i,j,T)=1,\ \text{if}\ (i,j)\in R_T$

AND $\left|I(i,j)-I(seed_x-seed_y)\right|\le T$;

Otherwise, $g(i,j,T)=0$ (2.3)

In equation 2.3, pixel (i,j) belongs to image I with multiple intensity channels. T is a threshold of intensity difference between the seed point and other pixels. Threshold T starts from zero up to the maximum possible value for the pixel value data type $I_{\max}$. If the data type is an unsigned eight bit integer, $I_{\max}$ is 255. R_T is a region overlapping the seed point $(seed_x, seed_y)$ within threshold T. In our calculation, $ISM(i,j)$ is normalized to the range of [0,1]. Pixels connected to the seed point with similar intensities are assigned higher ISM values than other pixels at the end of calculation.

3 EXPERIMENTAL RESULTS

Images used in experiment are extracted from longitudinal relaxation time T_1 and transverse relaxation time T_2 MRI images. The ColorMRI^{tm} methodology generates full color images from the plurality of gray tone images acquired by magnetic resonance imaging. The gray tone images are essentially mappings of biophysical/nuclear magnetic resonance parameters such as longitudinal relaxation time T_1, transverse relaxation time T_2, proton density (PD), magnetic susceptibility, gadolinium contrast media enhancement, etc. Assignment of color masks to each biophysical parameter image and subsequent fusion of the color masked images results in a full color image in which the unique color of each pixel in the RGB color space represents the combination of unique biophysical parameters of the tissue represented by that pixel.

In the RGB color space, differences among colors perceived by the human eye as being of the same entity are not mirrored by similar distances between the points representing those colors in the color spaces. The problem is reduced in the CIE $L*a*b*$ color space [9]. In our experiment, the MRI images are transformed from the RGB space to the CIE $L*a*b*$ space. Only A and B channel images are used in experiments.

Images are first filtered by a 2D Wiener filter to remove noise. To reduce the effect of the initial seed selection, images are dilated. The user chooses an initial seed point within the interested region, i.e. the brain tumor region. ISM is calculated and normalized to range $[0,1]$ in A and B channel respectively. In our experiments, in order to eliminate tissues that are far away and with intensities too much different from the seed point, for each iteration during ISM calculation, standard deviation between the histograms of the current region and the previous one is used. If the difference becomes much larger than it was, it means a heterogeneous is included. For an image of size $i \times j$, $N = i \times j$, $\mathrm{ISM_a}$ and $\mathrm{ISM_b}$ are intensity space maps in a and b channel respectively. The input to the FCM clustering algorithm is an array of $N \times 2$ of p_k, $k = 1 \sim N$, where p_k is the ISM value pair of pixel k in the image from channel a and b. The algorithm is implemented in Matlab 2015a. Figures 3~13 show a set of segmentation results.

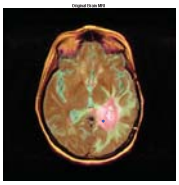

Figure 3. MRI of a Brain Tumor Patient, seed point is shown

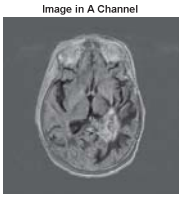

Figure 4. Image in A Channel

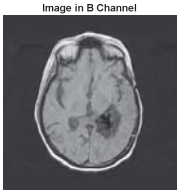

Figure 5. Image in B Channel

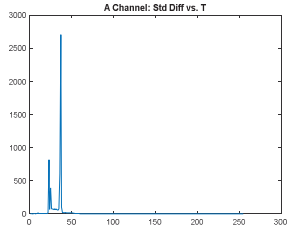

Figure 6. A Channel Difference of Standard Deviation between Histograms of current and previous regions vs. Threshold T in Equation (2.3)

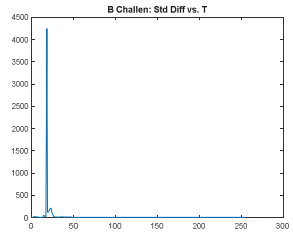

Figure 7. B Channel Difference of Standard Deviation between Histograms of current and previous regions vs. Threshold T in Equation (2.3)

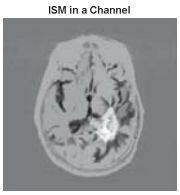

Figure 8. ISM in A Channel

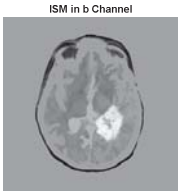

Figure 9. ISM in B Channel

Figure 10. ISM in A Channel, Peak Prominence Threshold of Difference of Standard Deviation between Current and Previous Image Regions = 100

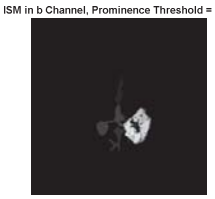

Figure 11. ISM in B Channel, Prominence Threshold of Difference of Standard Deviation between Current and Previous Image Regions = 100

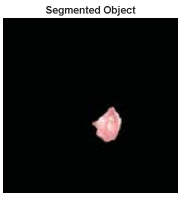

Figure 12. Segmented Tumor Region

Figure 13. MRI with Segmented Tumor Region Highlighted

Figure 3 shows a ColorMRI fusion image of axial brain, post gadolinium showing a tumor (glioblastoma) in the left hemisphere. A seed point is selected in the tumor region by the user. Figures 4 and 5 are the component images in A and B channels respectively. During iteration of calculating ISM's, difference of standard deviation between the current image region and the previous one is used to determine whether heterogeneous regions are included. Figures 7 and 8 illustrate that when thresholds of pixel intensities difference T is large, many heterogeneous pixels are included in the growing region. They should excluded for the purpose of segmentation. Figures 8 and 9 show ISM images in channel A and B without any homogeneous restrictions. Figures 10 and 11 demonstrate that using peak prominence on curves shown in figures 6 and 7 can obtain more accurate ISM's covering the regions of interest. Figures 12 and 13 are the segmented brain tumor and the MRI with tumor region highlighted.

ISBN: 978-1 -941968-10-9 ©2015 SDIWC

4 CONCLUSIONS

In this paper, we use the intensity space map and fuzzy c-means algorithm to perform brain tumor segmentation in MRI images. Both tumor and fat tissues contain gado-linium element, showing similar colors in MRI. Thus using pixel colors alone cannot differentiate tumor from other tissues. ISM utilizes both pixel color intensity and image topological information. It is a promising candi-date as a predicate used for segmentation.

Experimental results show that fuzzy c-means seg-mentation using ISM can effectively segment brain tu-mor regions in MRI. It provides a solid foundation for tumor volume estimation for physicians to evaluate pro-gress of the cancer and effectiveness of chemotherapy treaments. In the future, the technique will be tested on large amount of image data.

REFERENCES

[1] A. Stadlbauer, E. Moser, S. Gruber, R. Buslei, C. Nimsky, R. Fahlbusch, “Improved delineation of brain tumors: an automated method for segmentation based on pathologic changes of 1H-MRSI metabolites in gliomas”, Neuroimage Vol. 23, 2004, pp. 454–61.

[2] J. Yao, “Image processing in tumor imaging”, New techniques in oncologic imaging, 2006, pp. 79–102.

[3] V. Chong, J. Zhou, J. Khoo, J. Huang, T. Lim, “Tongue carcinoma: tumor volume measurement”, International Journal of Radiation Oncology Biology Physics, Vol. 59, Issue 1, May 2004, pp. 59–66 ,

[4] Y. Q. Zhao, Y. L. Zan, X. F. Wang and G. Y. Li, “Fuzzy C-means Clustering-Based Multilayer Perception Neural Network for Liver CT Images Automatic Segmentation,” Control and Decision Conference (CCDC), Xuzhou, China, May 2010, pp. 3423-3427.

[5] X. Li, S. Luo, J. Li, “Liver Segmentation from CT Image Using Fuzzy Clustering and Level Set”, Journal of Signal and Information Processing, Vol. 4, 2013, pp. 36-42.

[6] K. Chuang, H. Tzeng, S. Chen, J. Wu, T. Chen, “Fuzzy c-means clustering with spatial information for image segmentation”, Computerized Medical Imaging and Graphics, Vol. 30, 2006, pp. 9-15.

[7] M. Mancas, B. Gosselin, and B. Macq, “Segmentation Using a Region Growing Thresholding”, Proceedings of the Electronic Imaging Conference of the International Society for Optical Imaging (SPIE/EI), 2005.

[8] M. Oghli, A. Fallahi, M. Pooyan, “Automatic Region Growing Method Using GSmap and Spatial Information on Ultrasound Images”, 18th Iranian Conference on Electrical Engineering (ICEE), 2010.

[9] L. Lucchese and S.K. Mitra, "Color image segmentation: A state-of-the-art survey", Image Process. Vis. Pattern Recog. Proc., Indian Nat. Sci. Acad. (INSA-A), v67 i2, 2001, pp. 207-221.