A Fuzzy-C-Means Approach for Tissue Volume Estimation in Brain MRI Images

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ABSTRACT
The paper presents a method for automatic segmentation and calculation of tissue volume in brain MRI images. This is essential for radiologists since different diseases alter the tissue volume. Since the boundaries are complex, Modified Fuzzy C means (MFCM) is used to segment brain MRI image into three tissues namely white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF). The MFCM segmentation results obtained are input to the level set methodology for refinement of results. We have used the methodology on 100 different brain MRI images of both male and female. The percentage of WM, GM and CSF calculation is done using pixel counting method. The results indicate that there is no much difference in the tissue volumes of male and female. This method can be used to estimate the tissue volume in different diseases and in different age groups.

General Terms
Medical image processing, Pattern analysis

Keywords
Brain MRI, Fuzzy Logic, Level Set, Tissue, Segmentation, Volume

1. INTRODUCTION
The progress in the application of computer technology in the medical field has completely changed the world. The various reasons for the use of computer systems are reliability, accuracy, simplicity and ease of use (Masroor M. Ahmed & Dzulkifli Bin Mohammad, 2008). In analysis of medical images, images obtained are converted to digital form. Further, they are processed for doing segmentation and for extracting important information using various features. There are many diagnostic tools namely mammography, magnetic resonance imaging (MRI), X-ray, positron emission tomography (PET) and computed tomography (CT) used by doctors.

MRI is useful for obtaining images of any part of the body. MRI of the brain is a powerful diagnosis technique used by radiologists to detect structural abnormalities responsible for many pathological conditions. MRI helps in quantification of brain tissue volume, and has been used in many applications such as cognitive, clinical and neuroscience. In brain image segmentation, image should be partitioned into non-overlapped, consistent regions which are homogeneous with respect to some features such as intensity, shape or texture. Accurate segmentation of brain MRI images is of interest for many brain disorders. It helps in qualitative as well as quantitative analysis of segmented brain MRI. It is also useful for volume measurements of different tissues such as WM, GM and CSF.

It is to be noted that the brain MRI images are generally analyzed visually and qualitatively by radiologists. But, quantitative information, such as the volume of WM, GM and CSF in brain and size of the various brain structures after a traumatic brain injury is required for diagnosis. It is very essential to take advantage of information technology and develop a methodology for analyzing and measuring various structures in order to provide quantitative information from brain MRI images. However, due to several factors such as noise, imaging artifacts, intrinsic tissue variation and partial volume effects, tissue classification and volume estimation remains a challenging task (Bricq S. et al., 2008).

Radiologists use the manual segmentation to study the brain MRI images for diagnosis. This diagnostic method is tedious, time consuming and also produces inaccurate results. Hence, it is important to have some efficient computer based system that accurately defines the boundaries of important brain tissues along with minimizing manual intervention with the system (Matthew C., 1994). The manual segmentation process also requires too much time to complete (Mancas M., 2005). Because of human inherent limitations, it is necessary to take help of computer technology in assisting the doctors for diagnosis of diseases of human brain from images. In this connection, we have carried out a literature survey and following is the summary of papers cited in the literature related to the present work.

Mohamad F. et al., (2010) have presented a method using modified fuzzy c-means (FCM) algorithm for brain MRI image segmentation. Wells W. et al., (1996) have described a adaptive segmentation method that uses knowledge of tissue intensity properties and intensity in- homogeneities to correct and segment MRI images using expectation-maximization (EM) algorithm. Song T. et al., (2007) have proposed a modified probabilistic neural network (PNN) for brain tissue segmentation with MRI. Seixas F.L. et al., (2007) have proposed automatic brain structure segmentation based on anatomic atlas. Ballester M.A.G. et al., (1998) have presented a method for 3-D segmentation and measurement of volumetric data based on the statistical and geometrical information. Jing-Hao X. et al., (2000) have proposed a automatic method based on fuzzy modeling of knowledge to segment brain structures in MRI images. Cheng C. et al., (2011) have presented an intensity neighborhood based system for segmenting arbitrary biomedical image datasets using supervised learning. Lowry, N. et al.,(2011) have discussed EM and level set image segmentation that combines the advantages of the two algorithms via a geometric prior that encourages local classification similarity. Chuang K. et al., (2006) have proposed a FCM algorithm that includes spatial information into the membership function for segmentation. Ciptadi A. et al., (2009) have estimated the tissue intensity probabilities in 3D images using a non-parametric method.

It is observed from the literature survey that less work is done in the area of tissue volume estimation. The methods proposed are semiautomatic and they require manual intervention from the doctors. Hence, we are proposing a completely automatic method for brain MRI image segmentation and tissue volume estimation. A modified FCM (MFCM) method is used to get WM, GM and CSF approximately and level sets are used for refinement of results to get more accurate boundary. The proposed method helps in reducing time to segment and tissue volume estimation. It also gives good segmentation accuracy.

The paper is organized into four sections. The proposed methodology for tissue volume estimation is described in section two. Section three highlights the results and discussions. Section four presents the conclusion of the work.

2. PROPOSED METHODOLOGY

There are four phases involved in the proposed methodology and are shown in Figure 1. The phases are discussed below.

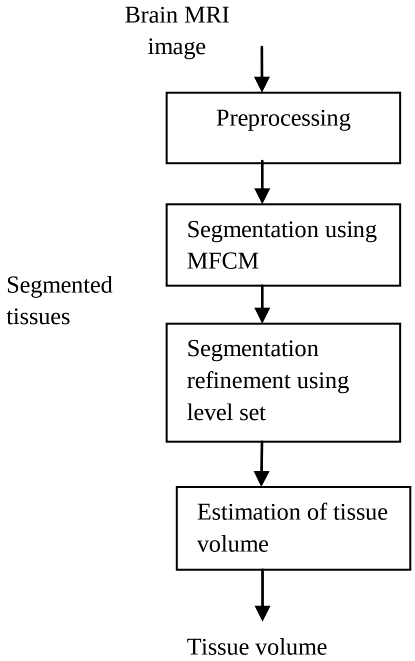


Fig 1: Phases used in the tissue volume estimation of brain MRI images

2.1 Brain MRI Images and Preprocessing

We have used the axial views of brain MRI images both male and female. The images used are in the gif grayscale format. The sample input brain image is shown in Fig. 2. Each image is of size 176*208 pixels. The number of brain MRI images used is 100 (50 male and 50 female). These images are obtained from local hospital authorities. The MRI machine used is GE Sigma Excite of 1.5Tesla. The research is approved by the ethical committee. The patients have given the formal consent for the research in writing and hospital has provided all the resources for the research purpose. The adaptive wiener filter is used to reduce the noise in the image. It is a 2-D noise-removal filter.

2.2 Segmentation using MFCM

Proper measurement of distribution of tissues in brain MRI images is done by image clustering. There are two types of clustering methods viz. hard clustering and fuzzy clustering. In hard clustering, each data element belongs to exactly one cluster. Data elements can belong to more than one cluster in

Fig 2: Input Brain MRI image

fuzzy clustering. FCM algorithm is one of the most widely used fuzzy clustering algorithms (Bezdek 1981). FCM method is applied for segmentation of medical images (Cai W., 2007; Chuang K.S., 2006; Lei W.K., 2007). It originates from the k-means algorithm and is a kind of adaptive thresholding. It is used because the three important brain tissues do not form hard boundaries.

FCM algorithm used for an image segmentation task lacks spatial information. Image noise and artifacts affect the FCM segmentation performance. Hence it is essential to include spatial information into an FCM algorithm. Let the membership function μ_{mn} indicate the degree of membership of the n_{th} object to the m_{th} cluster. The FCM is modified to include spatial information and is called Modified FCM (MFCM) (Chuang K. S.,2006). To include the spatial information into an FCM, a spatial function is defined as

$$h_{ij} = \sum_{k\epsilon w(x_j)} \mu_{ik} \qquad \ldots\ldots\ldots\ldots\ldots \qquad (1)$$

where $w(x_j)$ represents a small square window centered on pixel x_j in the spatial domain. The spatial function h_{ij} represents the probability that pixel x_j belongs to i_{th} cluster. This spatial function is the summation of the membership function in the neighborhood of each pixel under consideration. When the majority of pixel neighborhood belongs to the same clusters, then the the spatial function of a pixel for a cluster is large. We have considered the 5*5 neighborhood for our experimental work.

The segmentation is done in two steps. The modified FCM (MFCM) is used for initial segmentation. The approximate boundaries of interest in a brain MRI image are determined by the MFCM. MFCM yields homogeneous segmented regions and it is less sensitive to noise. The intermediate morphological operations are eliminated by the fuzzy clustering with spatial information. Three clusters viz. WM, GM and CSF of brain MRI are obtained using MFCM method. Fig. 3 shows the result after applying MFCM, which shows three clusters. From Fig. 3, it is evident that the MFCM has given three clusters approximately, since the boundaries are not clear. The results of MFCM are used in the second step for segmentation refinement using level sets. The MFCM

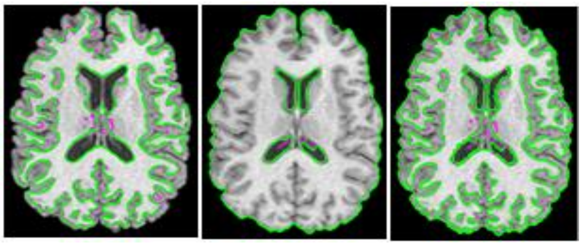
(a) (b) (c)

Fig 3: Segmented clusters after applying MFCM (a) WM (b) CSF (c) GM

is also used to estimate controlling parameters and regularize level set evolution.

2.3 Segmentation Refinement Using Level Sets

The level set method used as numerical technique for tracking interfaces and shapes has been increasingly applied to image segmentation for various applications (Cremers D., 2003). The level set method performance is dependent on proper initialization and configuration of controlling parameters. This requires manual intervention by radiologists. For image segmentation, level set methods use dynamic variational boundaries (Sethian J.A,1999; Osher S., 2003). In this proposed work, level set method uses the resulting images obtained using MFCM. This method helps in overcoming the manual intervention. The estimation of the controlling parameters required for level set segmentation method is also done by the MFCM. This also helps in improving the quality of segmentation and accuracy of segmentation. Fig. 4. shows the images obtained after applying level set method.



(a) (b) (c)

Fig 4: Segmented clusters after applying level set (a) WM (b) CSF (c) GM

2.4 Volume Estimation of Tissues

We have used the pixel counting method for estimating the percentage of CSF, WM and GM. We have counted the pixels in each tissue and found the percentage of each tissue by dividing it by total pixel count. We have done this experiment for both male and female brain MRI images.

3. RESULTS AND DISCUSSIONS

For experimental work, we have used the laptop with Intel(R) Core™ i3-2350M CPU @ 2.3GHz and 4GB RAM. The Operating System used is Microsoft Windows 7. MATLAB Version 7.11 is used to implement the code. We have tested the methodology on 100 different healthy brain MRI images of both male and female. We have not considered the MRI images of brain injured during accidents or suffering from any disease. Fig. 5 shows the average percentage of each tissue for both male and female. Fig. 6 represents tissue average volume for both male and female using pie chart. maximum and minimum values of CSF, WM and GM percentage both for male and female are depicted in the Table 1.

The Figure 5 shows that there is no much difference in the CSF, WM and GM percentage in male and female brain MRI. This result is estimated based on only 50 images in each category. This analysis can be extended to more images in different views and formats. Further, we can estimate tissue volume for the normal and abnormal brain MRI images in diagnosing various diseases. We can also analyze the degradation in tissue volume due to aging.

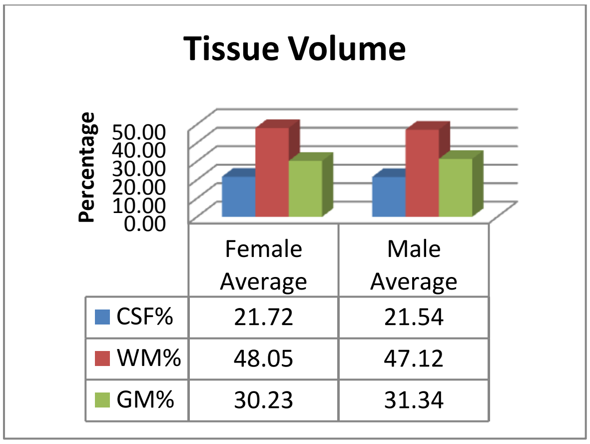


Fig 5: Tissue estimation for male and female

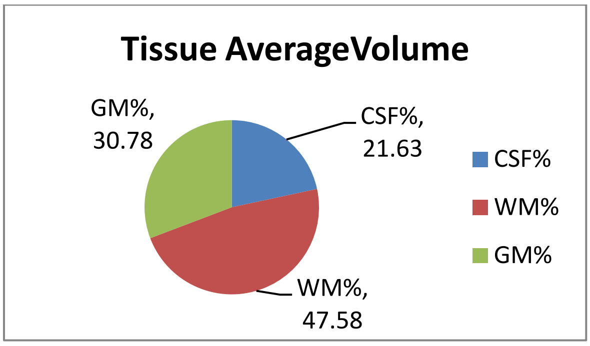


Fig 6: Tissue average volume for both male and female

Table 1: Maximum and Minimum values of tissue estimation for male and female

G	CSF%		WM%		GM%	
	Max	Min	Max	Min	Max	Min
F	29.16	13.82	54.52	41.74	32.41	26.13
M	30.98	15.24	53.21	39.06	33.72	27.77

Legends: G-Gender, M-Male, F-Female

4. CONCLUSION

MFCM, level set and pixel counting based methods are used for segmentation and volume estimation of brain MRI images. GM, WM and CSF are segmented from the brain MRI images and their volumes are estimated in the brain. The proposed method is able to estimate the volumes of different tissues of the brain MRI. The manual intervention is avoided and time required in estimating the tissue volume is reduced in this method. The intermediate morphological operations are eliminated by the fuzzy clustering with spatial information. In summary, this automatic brain MRI image segmentation and tissue volume estimation is useful for further investigation by radiologists. It is suitable for medical experts in the analysis of MRI images in hospitals for diagnosing various diseases related to brain.

5. ACKNOWLEDGMENTS

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