ejpmr, 2020,7(2), 247-249

EUROPEAN JOURNAL OF PHARMACEUTICAL AND MEDICAL RESEARCH

www.ejpmr.com

SJIF Impact Factor 6.222

Review Article

ISSN 2394-3211

EJPMR

ITERATIVE IMPLEMENTATION FOR SEGMENTATION OF NORMAL AND ABNORMAL TISSUES OF BRAIN

[1]*Priyanka Banerjee and [2]Prof. Samir Kumar Bandyopadhyay

[1]Lecturer, Department of Computer Science, The Bhawanipur Education Society College, Kolkata, India.
[2]Academic Advisor, The Bhawanipur Education Society College, Kolkata, India.

***Corresponding Author: Priyanka Banerjee**

Lecturer, Department of Computer Science, The Bhawanipur Education Society College, Kolkata, India.

Article Received on 25/11/2019 **Article Revised on 15/12/2019** **Article Accepted on 05/01/2020**

ABSTRACT

Central nervous system (CNS) is the part of the human nervous network which integrates the coordination and processing of receiving neural information. In this paper, an iterative implementation level set methodology has been proposed for the precise segmentation of normal and abnormal tissues in MRI of brain.

KEYWORDS: CNS, Multiple Sclerosis, Segmentation and Gaussian mixture.

INTRODUCTION

CNS is contained by the brain and the spinal cord and constituted by two tissue components: GM, which is the main CNS element and consists in neuronal cell bodies; and white matter tissue WM, which is the second CNS component and it is mainly composed of myelinated axon tracts. CNS may be damaged by different affections caused by infections such as encephalitis, neurodegenerative diseases like Alzheimer or autoimmune and inflammatory diseases such as multiple sclerosis.

Three phase level set is used as a basic segmentation by changing speed function, and introducing the concept of iteration because most of the existing method failed to find much accuracy on MR images. Iteration is used to divide the complex segmentation for easier and accurate segmentation. In the proposed approach, intensity distribution is modeled in the image partitions using Gaussian mixture to form a close approximation to the actual intensity distribution in the image. Anatomical constraints of brain structures especially in borders between tissues and inconsistent adjacent pixels are used to extract brain model characteristics.

Literature Review

Several brain tissue segmentation approaches have been projected over the years. A discriminative semantic segmentation[1] method based on supervised decision forest to segment the brain tissues that achieved good results. Heuristic based Bayesian method[2] was used problem specific information and expert knowledge in segmenting brain MR images. This information allows it to make some up-gradation on misclassified pixels particularly in border areas. The major advantage of using heuristic rules in ameliorating segmentation results is its flexibility in incorporating new knowledge into the algorithm. Further improvement is possible by using adjacent slices in configuring the neighboring system.

An integrated[2] method over the entire domain and in cooperated in to a variational level set formulation has been developed by the energy minimization. This method is robust to initialization and allows automatic applications. The weakness of this method is that it is sensitive to initialization and thereby allowing automatic applications. Later an improved method[3] has been recognized for image segmentation in the presence of intensity in-homogeneities. Another concepts of[4] level set based method on sparse field produced good results and admirable at preventing leakage where other similar methods would struggle. However, level set methods have some problems segmenting images with low variance, causing leakages, which is also present in the implemented sparse field algorithm. These classical snakes[5] evolve using a Lagrangian formulation until an object boundary is delineated. It defines a reasonable initial curve for the model to give meaningful results.

Sometimes cortical gray matter is overestimated because segmenting the small folds of cortical gray matter correctly is more complicated with a probability atlas.[6] Incorporating a hierarchical representation of the tissues in the segmentation process provides a more powerful and more flexible framework not only for tissue classification but also for the segmentation of substructures and abnormal part of the brain. A statistical method[7] with two dynamic statistical features and three 2D wavelet decomposition features were used to segment different tissues. But that method[8] does not work well on different type image in terms of accuracy. Recently Kmeans[9] and FCM[10-13] based methods are used to segment the brain tissues but they are not performed well on different type of brain image in terms of accuracy, specificity and sensitivity. The problem of under and over segmentation are still exists on Kmeans and FCM methods.

Proposed Method

The proposed method is based on brain tissue segmentation that reaches to very good acceptable results. Proposed methodology has the ability to detect abnormality in the brain lesion if any. A level set based minimization scheme for the segmentation model using iterative concepts and changing the speed function of level set. While the popular level set framework has so far only been used for two-region segmentation or segmentation with a fixed number of regions. Sharp peak provides good initializations and it has not any leakage and less sensitive to local minima and maxima than comparable methods. The performance of proposed model with the existing well known method shows that proposed method gives better accurate and stable results for transverse, coronal and sagittal MRI image. Proposed method also removes over and under segmentation problem of other comparable methods. All advantages of the level set framework are preserved, while its main problem has been solved by using proposed method.

The fundamental conception of level set is to completely evolve a higher dimensional level set entrench function $\Phi: \Omega \rightarrow R$ whose zero level set $C: \Phi = 0$ represents dynamic shapes on the surfaces. The growing curve C separates the image into two regions: C_{in} region within the curve, which is enclosed by $\Phi > 0$ and C_{out}, which is the region exterior the curve, i.e., where $\Phi < 0$. Gaussian based on local mean and variance statistics and successfully smoothen the initial pixel wise probabilistic values. That enabled the accurate segmentation of low and high contrast brain structures from the surrounding tissues.

After performed level set segmentation, segmented regions are clearly separated. But for significant accurate segmentation of different tissues of brain and non brain part, iterative or repetitive of level set segmentation is required. The block diagram of the concept of iteration of proposed method has been shown below in Figure 1.

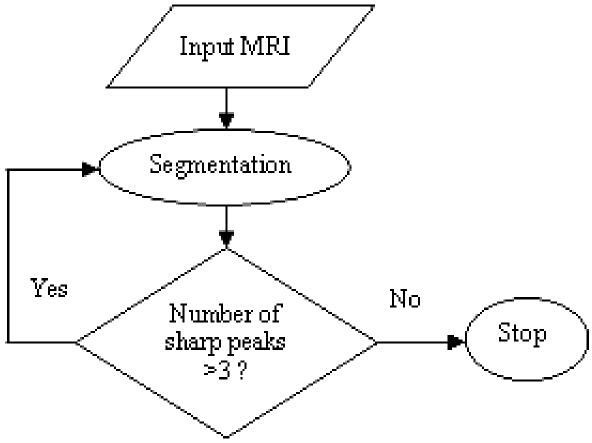
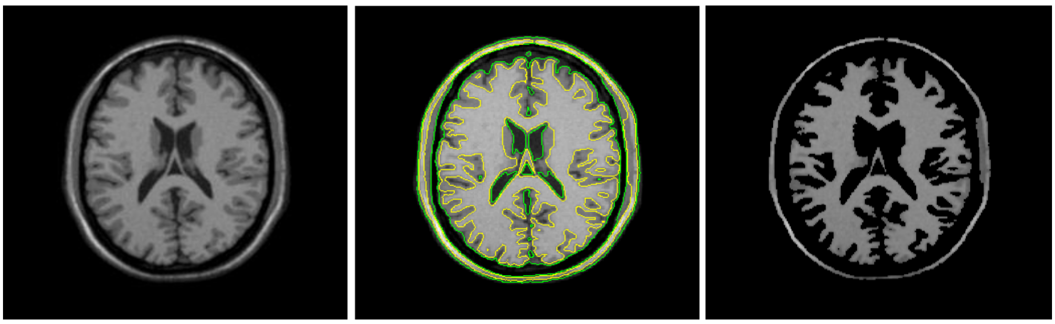


Figure 1: Block diagram of Iterative segmentation method.

The proposed method has been tested with a couple of MRI of brain images.[14-15] BrainWeb is a dataset which provides brain MRI for different acquisition modalities and it ground truth segmentation such as T1, T2, and PD.[14-15] The outputs proposed methodology with almost perfect segmentation for transverse type MRI is shown in Figure 2.



(a) input MRI **(b) after level set** **(c)segmented region**

Figure 2 Results of segmented tissues using proposed method.

CONCLUSIONS

The proposed method is used for brain tissue segmentation. It has also the ability to show abnormality in the brain lesion if any. Proposed method also removes over and under segmentation problem.

REFERENCES

1. Z. Yi, A. Criminisi, J. Shotton e A. Blake, "Discriminative, Semantic Segmentation of Brain Tissue in MR Images," Medical Image Computing and Computer-Assisted Intervention – MICCAI, 2009; 5762: 558-565.
2. Albert Huang, R. Abugharbieh, et al., "A Hybrid Geometric Statistical Deformable Model for Automated 3-D Segmentation in Brain MRI," IEEE Transactions on Biomedical Engineering, 2009; 56(7): 1838-1848.

3. Chunming Li, RuiHuang, Zhaohua Ding, Chris Gatenby, Dimitris Metaxas, and John Gore, “A Variational Level Set Approach to Segmentation and Bias Correction of Images with Intensity Inhomogeneity,” MICCAI 2008, Part II, Springer - LNCS, 2008; 5242: 1083–1091.
4. Chunming Li, Rui Huang, Zhaohua Ding, J. Chris Gatenby, Dimitris N. Metaxas, "A Level Set Method for Image Segmentation in the Presence of Intensity Inhomogeneities With Application to MRI," IEEE Transactions On Image Processing, 2011; 20(7): 2007-2016.
5. Andreas Helmich Hunderi, Neshahavan Karunakaran, Frank Lindseth, Erik Smistad, “Segmentation of Medical Image Data using Level Set Methods,” Department of Computer and Information Science, Norwegian University of Science and Technology, 2013; 1-17.
6. Nishant Verma, Gautam S. Muralidhar, Alan C. Bovik, Matthew C. Cowperthwaite, Mia K. Markey, “Model-driven, probabilistic level set based segmentation of magnetic resonance images of the brain,” Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, IEEE, 2011; 2821–2824.
7. Kilian M. Pohl, Sylvain Bouix, Ron Kikinis, W. Eric L. Grimson, "Anatomical Guided Segmentation with Non-Stationary Tissue Class Distributions In An Expectation-Maximization Framework," IEEE International Symposium on Biomedical Imaging: From Nano To Macro, Arlington, VA, 2004; 81-85.
8. S.Javeed Hussain, C.Venkatesh, S. Asif hussain, L.Chetana and V.Gireesha "Segmentation of Normal and Pathological Tissues in MRI Brain Images Using Dual Classifier," 2011 International Conference on Advancements in Information Technology With workshop of ICBMG 2011, IPCSIT vol.20 (2011), IACSIT Press, Singapore.
9. Jianwei Liu, Lei Guo, "An Improved K-means Algorithm for Brain MRI Image Segmentation," ICMRA, Atlantis Press, 2015; 1087-1090.
10. S. Madhukumar, N. Santhiyakumari, "Evaluation of k-Means and fuzzy C-means segmentation on MR images of brain," The Egyptian Journal of Radiology and Nuclear Medicine, Elsevier, 2015; 46(2): 475–479.
11. Lin D, Vasilakos AV, Tang Y, Yao Y. Neural networks for computer-aided diagnosis in medicine: A review. Neurocomputing, 2016.
12. M. Havaei, A. Davy, D. Warde-Farley et al., “Brain tumor segmentation with Deep Neural Networks,” Medical Image Analysis, 2017; 35: 18–31.
13. A. Bousselham, O. Bouattane, M. Youssfi, and A. Raihani, “3D brain tumor localization and parameter estimation using thermographic approach on GPU,” Journal of Thermal Biology, 2018; 71: 52–61.
14. *Whole Brain Atlas*: MR brain image, 2013.
15. BrainWeb: Simulated Brain MR brain image dataset, 2013.