Automated Brain Tumor Detection and Segmentation from MRI Images using Adaptive Connected Component Pixel Segmentation

J. Martin Sahayaraj, N.Subash, S.Jaya Pratha, N. Tamilarasan

Abstract- Magnetic resource imaging (MRI) imagesare used in examining the soft tissues which include brain tumors, ligament and tendon injury, spinal cord injury. Gray scale image processing is good for basic segmentation application.The exact location of brain tumor and its length is hard to find.This paper proposes an efficient method to segment the brain tumor. The result shows good segmentation accuracy.

Keywords- Connected component, PixelSegmentation, Image morphology, Brain tumor, Brain cancer, Medical images, MRI images

I. INTRODUCTION

The unnatural growth of tissues in the brain is called brain cancer. Malignant euplastic disease is the term reserved for malignant tumors. Two types of cancers are primary and metastatic. Both Primary and metastatic brain canceroccurs in the body. But it will affect the brain. This is the second biggest cancer to death.Secondary (metastatic) brain tumors are cancer that has spread (metastasizes) to the brain that begins elsewhere in the torso. People with malignant euplastic disease often have the chance of getting secondary tumors. In very rare cases, the first signal of cancer may be a metastatic brain tumor which initiate elsewhere in the body.Compared to the primary brain neoplasm, a secondary brain tumor is found to be more common.

II. LITERATURE SURVEY

Image processing helps in extracting beneficial information by transferring image in to digital form.The most commonly used medical imaging method is MRI.

A. Brain MR Images

Brain tissues are one such type of soft tissue, and hence MRI can be used for brain segmentation, whenever delineation of soft tissue is necessary. Image segmentation in medical modalities helps to differentiable various tissue typesfor the purpose of visualization and volume measurement.

Revised Manuscript Received on November 30, 2019.
* Correspondence Author
J. Martin Sahayaraj*, Department of Electronics and Communication Engineering, Sri Indu College of Engineering and Technology, Hyderabad, 501510, T.S, India
N.Subash, Department of Electronics and Communication Engineering, Sri Indu College of Engineering and Technology, Hyderabad, 501510, T.S, India
S.Jaya Pratha, Research Scholar, Department of CSE,Annamalai University, Chidambaram-608002, T.N, India
N. Tamilarasan, Department of Electronics and Communication Engineering, Sri Indu College of Engineering and Technology, Hyderabad, 501510, T.S, India

There are three types of tissue in a normal healthy brain, such as cerebral-spinal fluid, white matter andgray matter In a good quality image, these three regions can be classified manually by a simple selection of image pixel intensity values. But the choice of threshold for this intensity value selection is highly complex.
There are several non-invasivemethods like MRI, computed tomography (CT), x-ray techniqueetc. are used in imaging the inner anatomy for screening the breasts for tumors, and the anatomy of the organs under examination provides an effective means for noninvasive mapping by using the other imaging modalities. By the development of these techniques the diagnosis and treatment for several deadly diseases can be done easily. There are several image segmentation algorithms which help in quantity tissue volume and features.

III. RELATEDWORKS

Radiologist's diagnostic withComputer-Aided Diagnosis (CAD) enhance the recognition of basic disease [1]. In order to locate a bounding box around the brain abnormality in an MR image, this paper proposes a clear-cut, real-time method. This algorithm utilizes left-to-right dimension of the head structure. Pre- processing, labelled image data and training image registration are non-indispensable. It uses only two user- defined elements and can be acted as a real-time. The proposed systems can play a major part in indexing and storage of massive MRI data and provide the primary step to help algorithms designed to locate precise tumor boundaries.

All the same, the setback of the suggested algorithm is that it supposes the irregularity to be confined to the left or right side of the head and does not cross the LOS. So, the algorithm is likely to identify only the significant part of the irregularity if the tumor is split into several factions [2]. Classification of MRI brain images with the help of an automated system having diverse pathological disorders is shown in another report [3].

The method discussed in this work shows that the irregularity is categorized into malignant and benignin an unmanned method. An uncomplicated categorizationprocess using feed forward neural network is employed in this system and the rough set theory is applied to estimate the texture features.

Thus, the regularity of brain tumors is efficiently categorized by the proposed system.Another paper [4] proposes a variation method based on the propagation of intensity possibility distribution and region appearance. Thishelps to concentrate along the object regardless of the complexity of theuninterestedbackground.

Adistinctconfined contouring algorithm is combined with the modified K-means segmentation method for segmentation and during this processon the computerized tomography image frames;five different neighbourhoods are differentiatedto split the image. This method gives quick and precise segmentation and 3 –D rendering define tumor parts with least user interaction.

Both anatomical and pathological information are provided by MRI images for pathological and clinical ratings. Images are segmented based on certain anatomic features by the process called division [5]. These segmented regions are assigned certain unique labels to identify each class of segmented objects.

Segments provide categorical classification results like volume size, distance between region surface and so on [6].

Binary segmentation algorithm with hybrid feature of using multiple intensity distributions to segment various images with normal and abnormal tissue came into existence [7].

Similarly, theprobabilisticsegmentation method is depending uponthe voxels.

The contrasting features among soft tissues and diseased tissues are alsodiscussed. Comparison of several image segmentation methods is also analyses. [8]

IV. SEGMENTATION OF IMAGE:

The splitting of an image into a set of non-overlapping region based upon certain common features is called an image segmentation[9].Typically the image is converted into two regions, namely background and foreground.The combination of foreground and background region should give the entire image.

For an automated segmentation of image using a computer, it is a complex task to program the computer. The program is coded in such a way that the region is split under distinct boundary. Also, the pixels inside the segmentation and outside the segmentation should be distinct with certain varying features. They are

1. Animage segmentation should be uniform and analogous withrespect to some characteristics, e.g. grey level or texture.
2. Theinteriorregionshould be simple and without many holes.
3. Itshould have significantly varying valueswith respect to the characteristic or adjacent regions.
4. Each boundary segment should be simple, not ragged, and must be spatially accurate.

In the present work,two DCS metric is employed,i.e.,(A) repeated binary segmentation of intraoperative 0.5T and preoperative 1.5T MRIs of the prostate's PZ composed during the segmentationand before brachytherapy for prostate cancer [10] and (B)composite voxel-wise gold standard uses three various types of brain tumors resulting from repeatingimages from expert manual segmentations [11].Segmentations were performed for both the prostate and brain data sets and reported previously [12]. Here, themethodology is elaborated and a statistical validation reviewis shown using these existing databases DSC (A, B) = 2(A∩B)/ (A+B)

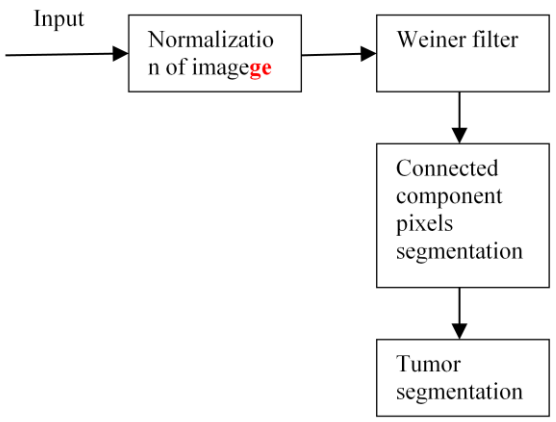
V. PROBLEM DEFINITION

Normalized image under goes for the process of noiseremoved by means of Weiner filter. [13]After that the noise removed image undergoes the process of image segmentation. Here we used two types segmentation. The first oneis Region-based edge detection segmentation and the second one is Connected Component Pixels Segmentation. The first one gives the initial suspicion about the brain tumor, and the second give the extraction of tumor cell from the given image with suitable color variation[14].

In the non-existence of better ground truth,processing of image segmentation methods is quite difficult. The results of so many users are obtainable and there is lack of better ground truth inter-observer variability is critical.

So, we planned to move to accurate segmentation of cancer cells with connected component pixel algorithm.

A The Proposed architecture



B.Connected Component

Basics Pixel-Connectivity.

A pixel p consists of four direct neighbors, at coordinate (x, y), four diagonal neighbors and N4 (p), eightneighbors and
ND (p), N8 (p) of pixel p consist of the union of N4 (p) and ND (P) see [i]for a basic description[15]

The pixels p and q comprises three types of connectivity:

i) If q lies in N4 (P) it is termed as 4-connectivity;

ii) If q lies in N8 (p) it is termed as 8-connectivity;

iii) If qlies in N4 (P), or if q is in ND (P) and

N4 (p) ∩ N4 (q) = Ø it is termed as m-connectivity;

Table.I

A	1	2	3	4	5	6
1		1				1
2	1					
3				1		
4			1		1	
5				1		
6	1					

Table.II

b	1	2	3	4	5	6
1	1	1				1
2	1	1				1
3			1	1	1	
4			1	1	1	
5			1	1	1	
6	1	1				1

In this work novel computation is carried out using various dimensions of N the and the conclusion of the processing time is prepared and listed in Table1[16] for the picture with dimension of 2008K (e.g.,512*512 pixels). Fig 1 shows the different sizes of N as a function for CPU time. When N=1 division in the image do not occur andthe algorithm is similar as theactual one evolvedby Pfaults and Rosenfeld [17].

Table.III Original Image Divisions into 3*3Regions.

region[1]	region[2]	region[3]
region[4]	region[5]	region[6]
region[7]	region[8]	region[9]

With an I3 processor 4 GB RAM PC, it is not plausible to figure the associated segment progressively when N=1, 2 or 3. Our new calculation figures associated segment inside of 2 seconds for a picture size of 2008K with N=25. Table 4 demonstrates the examinations with different calculation with diverse size picture. As indicated by Zungia [18] a picture size of 973K can be figured in 78 second with their technique. With the quick associated part marking calculation, the picture size of 973K can be ascertained inside 0.82 seconds[19].

Fig.1showsthe next level segmentation and detection of cancer from the brain images.

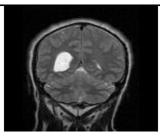
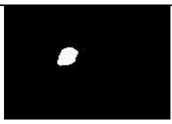
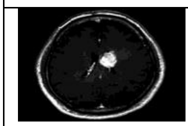
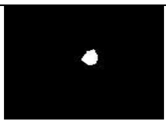
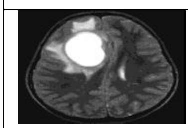
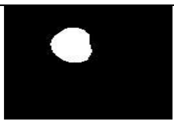
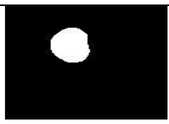
Input image	Ground truth	Output
		
		
		

Table.IV Comparison

Algorithm	Computation time (Seconds)	DSC values
Canny	0.35	0.92
Sobel	0.30	0.90
Prewit	0.33	0.89
CCPS	0.27	0.88

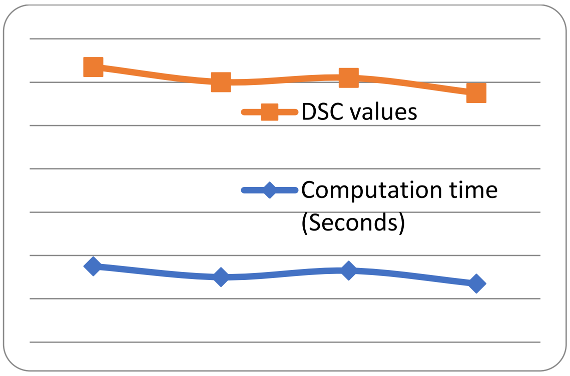


Fig.2Computation Vs DSC

VI. CONCLUSION

This segmentation is based on the connected component pixel .So the image clarity directly interacts with the output. The DSC valuesshow that the segmentation algorithm reflects only minimum deviation from Ground Truth images. So this algorithm is acceptable one. Also this method is very fast. The early methods were designed to scan a maximum of 3 or 4 MRI images. But the proposed algorithm is designed to scan more than 100 MRI images for the detection of tumors. This tumor detection can be accomplished within 2 seconds .Sothe future work will move towards the classification of brain tumor affected images and normal images using suitable machine learning algorithm or neural network algorithms.

REFERENCES

1. Chaddad, A., Zinn, P.O. and Colen, R.R., "Brain tumour identification using Gaussian Mixture Model features and Decision Trees classifier.,"Information Sciences and Systems (CISS), 2014 48th Annual Conference on, vol., no., pp.1,4, 19-21 March 2014.
2. Ray, N., Saha, B.N. and Brown, M.R.G., "Locating Brain Tumours from MR Imagery Using Symmetry,"Signals, Systems and Computers, 2007. ACSSC 2007. Conference Record of the Forty-First Asilomar Conference on, vol., no., pp.224, 228, 4-7 Nov. 2007.
3. Rajesh, T. and Malar, R.S.M., "Rough set theory and feed forward neural network based brain tumour detection in magnetic resonance images,"Advanced Nano materials and Emerging Engineering Technologies (ICANMEET), 2013 International Conference on , vol., no., pp.240,244, 24-26 July 2013.
4. Sangewar, S., Peshattiwar, A.A., Alagdeve, V. and Balpande, R., "Liver segmentation of CT scan images using K means algorithm,"Advanced Electronic Systems (ICAES), 2013 International Conference on , vol., no., pp.6,9, 21-23 Sept. 2013.
5. Rajikha Raja, Neelam Sinha and Jitender Saini, "Characterization of White and Gray Matters in healthy brain: An in-vivo Diffusion Kurtosis Imaging study",IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, Jan.2014.

6. Zou, K.H., Wells, W.M., Kaus, M.R., Kikinis, R., Jolesz, F.A. and Warfield, S.K., Statistical validation of automated probabilistic fractional segmentation against composite latent expert gold standard in MR imaging of brain tumours. In: Proceedings of 5th International Conference on Medical Imaging Computing and Computer Assisted Interventions, Sept 25–28, 2002, Tokyo, Japan. Berlin: Springer-Verilog, 315–322.
7. Zou, K.H., Wells, W.M., Kaus, M.R., Kikinis, R., Jolesz, F.A. and Warfield, S.K., Validation of partial tissue segmentation of single-channel magnetic resonance images of the brain Nero image. 2000;12:640 –656.
8. Tao Song, Mo M. Jamshidi, Roland R. Lee and Mingxiong Huang, "A Modified Probabilistic Neural Network for Partial Volume Segmentation in Brain MR Image"IEEE Transactions on Neural Networks,vol.18, no.5, pp.1424-1432, Sept.2007
9. Kao, Y.H., Sorenson, J.A., Bahn, M.M. and Winkler, S.S., Dual-echo MRI segmentation using vector decomposition and probability technique: a two-tissue model. Magnetic resonance in medicine 1994; 32:342–357.
10. Wenchao Lv, Yahui PengChao Yang and Xinchun Li, Reconstruction of brain tissue surface based on three-dimensional Tl-weighted MRI images", 8th International Congress on Image and Signal Processing (CISP), Feb.2016.
11. Smitha Sunil Kumaran Nair and K. Revathy, "Quantitative Analysis of Brain Tissues from Magnetic Resonance Images", IEEE international Conference on Digital Image Processing, Bangkok, Thailand, Mar.2009.
12. Warfield, S.K., Zou, K.H., Kaus, M.R. and Wells, W.M.,Simultaneous validation of image segmentation and assessment of expert quality. International Symposium on Biomedical Imaging, July 7–10, 2002 IEEE.2002; 1494:1–4.
13. Bharatha, A., Hirose, M., Hata, N., Warfield, S.K., Ferrant, M., Zou, K.H., Suarez-Santana, E., Ruiz-Alzola, J., D'amico, A., Cormack, R.A. and Kikinis, R., Evaluation of three-dimensional finite element-based deformable registration of pre- and intraoperative prostate imaging. Med Phys. 2001; 28:2551–2560. [PubMed]
14. Jaccard, P., The distribution of the flora in the alpine zone. 1. New physiologist, 11(2), pp.37-50.
15. Russo, D., Merolla, F., Mascolo, M., Ilardi, G., Romano, S., Varricchio, S., Napolitano, V., Celetti, A., Postiglione, L., Di Lorenzo, P. and Califano, L., 2017. A new prognostic biomarker for OSCC.International journal of molecular sciences, 18(2), p.443.
16. Zou, K.H., Warfield, S.K., Fielding, J.R., Tempany, C.M., Wells III, W.M., Kaus, M.R., Jolesz, F.A. and Kikinis, R., 2003. Statistical validation based on parametric receiver operating characteristic analysis of continuous classification data1. Academic radiology, 10(12), pp.1359-1368.
17. Zou, K.H., Wells III, W.M., Kikinis, R. and Warfield, S.K., 2004. Three validation metrics for automated probabilistic image segmentation of brain tumours. Statistics in medicine, 23(8), pp.1259-1282.
18. Gerig, G., Jomier, M. and Chakos, M., 2001, October. Valmet: A new validation tool for assessing and improving 3D objects segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 516-523). Springer, Berlin, Heidelberg.
19. Huttenlocher, D.P., Rucklidge, W.J. and Klanderman, G.A., 1992, June. Comparing images using the Hausdorff distance under translation. In Proceedings 1992 IEEE Computer Society Conference on Computer Vision and PatternRecognition (pp. 654-656).

AUTHORS PROFILE

Dr.J.Martin Sahayaraj is working as a **Professor** in the Department of Electronics and Communication Engineering in **Sri Indu College of Engineering and Technology, Sheriguda, R.R (Dt),Hyderabad,T.S.** He is having **10 years** of experience in teaching and research. He has published around 14 papers in various International Journal & Conferences. He has authored two books which includes Computer Networks.

N.Subash is currently working as a Professor in the Department of Electronics and Communication Engineering in Sri indu College of Engineering and Technology,Hyderabad. He is having **15 years** of experience in teaching and research. He has published around 16 papers in various International Journal & Conferences. His areas of interest are cloud computing and Image processing.

S.Jaya pratha as a Research Scholar in the Department of Computer Science and Engineering in Annamalai University, Chidambaram-608002, T.N, India.She is worked as lecturer in the Department of Computer Science and Technology in DMI-St John the Baptist university,Malawi.She is having **02 years** of experience in teaching and research. She has published around 06 papers in various International Journal & Conferences.Her area of interest are image processing and Ad-hoc networks.

N. Tamilarasan was born in Puducherry, India in 1980. He received his B.Tech M.Tech, and Doctorate degree in Electronics and Communication Engineering from Pondicherry University, Puducherry, India in the year of 2004, 2006 and 2016 respectively. Presently he is working as a Professor in the Department of Electronics and Communication Engineering, Sri Indu College of Engineering and Technology, Hyderabad, Telangana, India. He has published 12 papers in International conference proceedings and journals. His area of interest includes Wireless Communication and Computer Networking.