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RELEVANT ALGORITHMS AND TECHNIQUES FOR BRAIN TUMOR SEGMENTATION USING MAGNETIC RESONACE IMAGING

[1]Dr.Pradeep Gurunathan, [2]Preethi Saroj S

ABSTRACT--*Due to faster technological evolution, medical field too requires algorithms and techniques for carrying out diagnosis and treatment with better accuracy. Tumour segmentation plays a prominent role in medical image processes sing field. It aims to separate diseased tumour tissue from normal one with least error. Among various imaging modalities, Magnetic Resonance Imaging(MRI) is most predominantly used. MRI contains multiple noises, affecting the segmentation process. Hence the image has to be pre-processed to remove noises and improve data quality. This paper describes various segmentation techniques. Finally, evaluation metrics for analysing the segmentation techniques and some standard datasets are discussed.*

Keywords--*Brain Tumour, Magnetic Resonance Imaging, Segmentation techniques*

I. INTRODUCTION

Brain tumour is a deadly disease affecting many humans in recent years. Research is extensively carried out for revising the existing techniques and innovating new ones. Many risk factors contributes brain tumour including prolonged usage of cell phones, inherited conditions, a weak immune system, head injuries and others. The tumour affected cell once become malignant and starts spreading the tumour to neighbourhood cells also. Major symptoms of brain tumour covers headache, memory problems, sleep problems, drowsiness, fatigue, etc. They are majorly classified into two categories: 1. Primary/Benign and 2. Secondary/Malignant. World Health Organization (WHO) orders brain tumour from Grade I to Grade IV. Grade I and II are of primary type that can be removed when detected at an early stage. While other grades are malignant and have higher chances of re-growing back even after removing.

Some major brain tumours are Glimos, CVS lymphoma, epeldymomas, medulloblastoma, craniopharyngioma, chordoma, oligodendrogloma. They require appropriate diagnosis and treatment. For diagnosis, multiple images of the brain taken at various angles are studied. Some scans use dyes such as gadolinium to distinguish abnormal and healthy tissue. Abnormal or diseased tissue absorbs more *dye* and reflects in the scan image[1]. Numerous scans are available to diagnose tumour. These modalities comprises Computer Tomography (CT) scan, ultrasound, Magnetic Resonance Imaging(MRI), Magneto Encepholo Graphy(MRE), Positron Emission Tomography(PET), Single Photon Emission Tomography(SPET). However, CT-scan and MRI are widely preferred at first stage of diagnosis. CT scan aids in locating and detecting tumour. In malignant stage, recurrent tumour growth is identified

[1] *Supervisor, A.V.C College of Engineering, pradeep.g8@gmail.com..*
[2] *Research Scholar,A.V.C College of Engineering,preethisaroj@gmail.com*.

through CT-Scan. MRI acts as a benchmark for brain tumour diagnosis. It gives images from multiple angles without any radiation. Through this three dimensional image can be constructed making this effective than other scans. Contrast agent(Dyes) are applied to vein for better visualization of abnormalities.

There are several types of MRI assisting doctors in recent years such as Functional MRI, Magnetic Resonance Angiography(MRA), Contrast-Enhance MRA(CE-MRA), Flow Sensitive(FS-MRI), Magnetic Resonance Venography(MRV). These MRI estimates the size, location and severity of tumour for better diagnosis and treatment. MRI as a whole is not required for diagnosis as it covers numerous angles. Segmentation is done to extract the required tumour affected part from the normal tissue for further analysis. Research work is proceeding for over three decades in the field of medical imaging segmentation. Numerous segmentation approach exists each having its own pros and cons.

II. RELATED WORKS

Evangelia et al[17] puts forward a novel semi-supervised scheme that detects and segments abnormalities encountered in brain images. In case of larger data dimensions, it is not feasible to estimate probability density function. To overcome this, the method treats images as overlapping blocks. Image partitioning along with distributed estimation can handle this high dimension problem. Concave likelihood function is maximized to detect abnormality in each block. Local estimates are grouped to form global estimates to satisfy consistency constraints. Abnormality is detected by objective function formalization and optimization. Experiments were carried out on both simulated and real MRI data sets that covers i. White matter ii. Infarcts and iii. Dysplasia. Real data set contains FLAIR scans. Anomalous regions of spatially normalized brain images are segmented using anomaly detection and decomposition. Here statistical model is framed from normal brain image and it is used to segment the test data. SPM8 is used to analyse the MRI of patients. Results show that the method performs well over others.

Dzung et al[18] proposes a fuzzy segmentation technique to segment two-dimensional and three-dimensional multispectral MRI that suffers shading artefacts problem. Intensity in homogeneities are modelled as Gain Field such that image intensities can be varied smoothly across image space. For a large three-dimensional image multi-grid based algorithm is described. FCM is unsupervised and robust to initial conditions. General FCM techniques involves centroid initialization, membership function computation and assignment of closer values to the centroid. It gets iteratively repeated till the points get converged. But to tackle intensity homogeneities, Gain Field is incorporated in the objective function. This can be scalar or vector quality. Experiments were done in C on Silicon Graphics OS system. It also tests both simulated and real data set. Experiments show that this technique is more robust to intensity inhomogeneities. One disadvantage is that it takes only clusters which are of same shape and size.

Nicolaos et al[19] presents a brain MRI segmentation technique based on Fuzzy algorithm for Learning Vector Quantization(FALVQ). It is modelled as unsupervised vector quantization process. Here feature vectors are build from local values of relaxation parameter represented by small set of prototypes. It splits set of feature vectors from brain MRI into small number of clusters called prototypes and are represented by vectors containing T1, T2 and SD parameters for certain imaging location. Through LVQ brain MRI can be segmented and feature vector is expressed by its closest prototypes. Experiments were done over T1-Weighted, T2-weighted and SD-MR images of Meningioma (intracracical tumour) affected patients. This method is simple and does not require any prior knowledge about the tumour. Results show that the algorithm successfully differentiated abnormal tissue from normal tissues.

III. EMPIRICAL STUDY

Sr. No.	Author Name	Year	Methodology	Highlights
1	Adam R	1994	Region growing by automatic seed selection	-Regions with similar criterion such as intensity gets grouped - correctly segments the region
2	Clark, M. et al	1998	Knowledge based segmentation	-Segments gliblastoma multiform tumors based on multispectral histogram analysis
3	Sato M. et al	2000	Modified Region Growing Method	-eliminates partial volume effects which is more common in region growing methods -accurately detects the boundary
4	Kaus, M. et al	2001	Region growing by statistical classification	-splits the MRI across multiple classes based on their signal intensity -uses local segmentation process
5	Dam E. et al	2004	Multi-scale watershed transformation	-Iterative method that builds blocks at various scales and the required portion can be segmented
6	Schmidt et al	2005	Support Vector Machine	-alignment features are extracted, compared and combined -due to less features, soft-margin support vector machine along with SVM light optimization strategy yields accurate results
7	Dou W. et al	2007	Fuzzy information fusion framework	-forms fuzzy models from features collected from numerous image sequence
8	El-Dahshan et al	2010	Artificial Neural Network	-applies discrete wavelet transform and principle component analysis for feature extraction and dimensionality reduction respectively

				-robust since it uses both feed forward neural network and k-means clustering
9	Angel Viji	2011	Watershed segmentation	-Supervised tumour detection in 2D and 3D brain MRI based on shape, texture and content -high degree of locality with faster computation
10	Phem et al	2011	Adaptive fuzzy C-means clustering	-Intensity inhomogenity addresses through automatic iteration -handles shading artifacts problem -looks only for clusters of same size and shape
11	Abhishek et al	2014	Pixel based probabilistic segmentation method	-segments the cervical cancer based on probability value of different shape parameters
12	Deepthi M et al	2014	Morphological segmentation	-applies binary erosion and dilation including binary closing and opening operation -clusters high intensity pixels as tumors
13	Hesamian et al	2014	Deep Learning	-separates critical homogeneous tumour part for diagnosis -lesser training time and faster convergence time -larger data size can eliminate over-fitting problem
14	Nameirakpam et al	2014	K-means clustering algoritm	-unsupervised method for segmenting tumour from background -subtraction cluster chooses initial cluster centeroids -achieves smaller RMSE and larger PSNR values
15	Wassim et al	2018	Gamma distribution	-Gaussian distribution address only symmetric distribution while Gamma addresses both

				symmetric and asymmetric distributions -enhances Li's method for image segmentation
16	Dan Liu et al	2019	Multi-weight Probability map	-Handles outliers and non-Gaussian noise -Parzen window method estimates probability distribution of all local models and fuses to a global model

IV. EVALUATION AND VALIDATION

Validation of brain tumour segmentation is a crucial issue in medical imaging as it paves way for diagnosis and treatment. For accessing segmentation techniques, udupa et al[2.3] primarily considered three metrics, i. Precision describes how exactly the tumour is segmented from MRI, ii. Accuracy represents the degree of correctness, iii. Efficiency deals with computational time and speed. For validation, ground-truth is framed by combining manually segmented tumour regions from various experts. Overlapping of segmented image with ground truth is taken into account for evaluation. Dice Similarity Coefficient(DSC) and Jaccard Coefficient are widely adopted evaluation metrics[128]. DSC is calculated as 2(TP)/2(TP)+FP+FN where TP, FP and FN are True Positive, False Positive and False Negative respectively. Jaccard coefficient is obtained by dividing the number of shared tumour cells between ground truth and segmented image to total number of tumour cells in both. Other metrics such as sensitivity, specificity have certain disadvantages and hence not preferred as prime metrics in validation.

Receiver Operating Characteristic(ROC) also helps in tumour diagnosis. It provides the relationship of ground truth and segmented image by plotting true positives and false positive on y and x-axis respectively. Area Under Curve(AUC) shows how well positives and negatives are separated. For analysing brain tumour segmentation methods, VALMET tool can be adopted. For validating segmentation algorithm, numerous databases are available such as multimodal Brain Tumor Segmentation(BRATS), NSG Brain Tumour DataBase, IBSR, BrainWeb and many more. Among this BRATS is widely preferred by researchers. Some of the open tools for carrying segmentation process are TumorSim, GLISTR, MITK, FSL, Python.

V. CONCLUSION

This paper surveys various segmentation techniques that are widely used for brain tumour identification. At first, currently proposed methods in medical imaging are discussed briefly. Further some the standard methods are analysed. Based on the survey, threshold based techniques are not affected by noise. Accuracy greatly depends on the chosen threshold intensity value. Among the various threshold algorithms, adaptive thresholding method handle the uneven illumination problem effectively. Edge-based techniques aids in primary stage to extract the required portion like region of interest. But it is not effective in segmenting the tumour affected part accurately when compared with others. Between the edge-based techniques, pattern fitting approach performs well over the derivate approach.

Region-based methods work by partitioning the image into multiple regions. Region growing approach relies upon the seed value and pixel grouping. It is simple and correctly segments the image with same properties. Watershed segmentation is also an effective region-based techniques but it encounters over-segmentation problem. Present of noise may lead them to segment wrongly. Hence pre-processing is mandatory for region-based approach. Pixel-based methods is most predominantly used in brain medical images due to its efficiency to handle large datasets either in semi-supervised or unsupervised way. Non-homogenous tumour can be segmented easily with the help of Fuzzy C-Means algorithm. While K-Means segments the image accurately even in the presence of noise and outliers.

Through this survey several conclusions can be proposed to enhance brain tumour segmentation process. Incorporating some machine learning concepts to these methods can speed up the process and better values in performance metrics can be achieved. Each approach contains future scope of building them to segment the image in an unsupervised way.

REFERENCES

1. Murthy T. S. D and Sadashivappa G, “Brain tumor segmentation using thresholding, morphological operations and extraction of features of tumor,” , 2014 International Conference on Advances in Electronics Computers and Communications, pp. 1–6, 2014.
2. W. El Hajj Chehade, R. A. Kader, and A. El-Zaart, “Segmentation of MRI images for brain cancer detection,” in 2018 International Conference on Information and Communications Technology (ICOIACT), 2018, pp. 929–934.
3. Adams, R. And Bischof, L. “Seeded region growing”, IEEE Transactions on Patter Analysis and Machine Intelligence, Vol. 16, pp. 641-647, 1994.
4. Kaus, M., Warfield, S., Nabavi, A., Black, P., Jolesz, F. And Kikinis, R. “Automated segmentation of MRI of brain tumors”, Radiology, Vol.218, pp. 586-591, 2001.
5. Sato, M., Lakare, S., Wan, M. and Kaufman, A. “A gradient magnitude based region growing algorithm for accurate segmentation”, IEEE Proceedings of the International Conference on Image Processing, Vol.3, pp. 448-451, 2000.
6. Dou, W., Ruan, S., Chen, Y., Bloyet, D. And Constants, J.M. “A frame work of fuzzy information fusion for the segmentation of brain tumor tissues on MR images”, Image and Vision Computing, Vol. 25, pp. 164-171,2007.
7. D. Liu, X. Yu, Q. Feng, W. Chen, and G. Manogaran, “Brain Image Segmentation Based on Multi-Weight Probability Map,” IEEE Access, vol. 7, pp. 14736–14746, 2019.
8. E. Dam, M. Loog, and M. Letteboer, “Integrating automatic and interactive brain tumor segmentation,” in Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004., 2004, vol. 3, pp. 790-793 Vol.3.

9. K. S. Angel Viji and J. Jayakumari, “Automatic detection of brain tumor based on magnetic resonance image using CAD System with watershed segmentation,” in 2011 International Conference on Signal Processing, Communication, Computing and Networking Technologies, 2011, pp. 145–150.
10. Clark, M., Hall, L., Goldgof, D., Velthuizen, R., Murtagh, R. and Silbiger, M. “Automatic tumor segmentation using knowledge based techniques”, IEEE Transactions on Medical Imaging, Vol. 17, No.2, pp. 187-201, 1998.
11. M. H. Hesamian, W. Jia, X. He, and P. Kennedy, “Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges,” J. Digit. Imaging, vol. 32, no. 4, pp. 582–596, Aug. 2019.
12. E.-S. A. El-Dahshan, T. Hosny, and A.-B. M. Salem, “Hybrid intelligent techniques for MRI brain images classification,” Digit. Signal Process., vol. 20, no. 2, pp. 433–441, Mar. 2010.
13. M. Schmidt, I. Levner, R. Greiner, A. Murtha, and A. Bistritz, “Segmenting brain tumors using alignment-based features,” in Fourth International Conference on Machine Learning and Applications (ICMLA’05), 2005, pp. 6-11.
14. D. L. Pham and J. L. Prince, “Adaptive fuzzy segmentation of magnetic resonance images,” IEEE Trans. Med. Imaging, vol. 18, no. 9, pp. 737–752, Sep. 1999.
15. Abhishek, Avijit Kar & Debasis Bhattacharyya 2014, “Early Detection of Cervical Cancer using novel segmentation algorithms”, Invertis Journal of Science & Technology, vol. 7, no.2, pp.91-95
16. N. Dhanachandra, K. Manglem, and Y. J. Chanu, “Image Segmentation Using K -means Clustering Algorithm and Subtractive Clustering Algorithm,” Procedia Comput. Sci., vol. 54, pp. 764–771, Jan. 2015.
17. Evangelia I. Zacharaki and Anastasios Bezerianos, “Abnormality Segmentation in Brain Images via Distributed estimation”, IEEE Transaction on Information Technology in Biomedicine, vol.16, no. 3, pp. 330-338, 2012.
18. Dzung L.Pham and Jerry L. Prince, “Adaptive Fuzzy Segmentation of Magnetic Resonance Images”, IEEE Transactions on Medical Imaging, Vol.18, no. 9, pp. 737-752, 1999.
19. B. Karayiannis and Pin I.Pai, “Segmentation of Magnetic Resonance Images using Fuzzy algorithm for Learning Vector Quantization”, IEEE Transactions on Medical Imaging, Vol. 10, no. 2, 1999, pp. 172-180