International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-2S2, January 2019

A Survey on Detection, Recognition, Segmentation and Classification of Brain Tumor

P.Harish, S.Baskar

***Abstract:** In the human body the brain is the most significant organ as it controls all the functions of human. Due to few abnormal conditions, unhealthy and unrestrained growth of tissue occurs which is referred as an uncommon action. This sort of action which occurs in the brain is called as brain tumor. It is significant to detect this tumor in order to minimize the death of humans affected by tumor. Cancerous cells detection is the most complex and long term process in medical image processing. Magnetic Resonance Imaging (MRI) is a methodology widely utilized owing to its significant features. MRI provides plenty of information in the tumor detection. MRI image is segmented with high rate of accuracy then tumor is classified whether it is malignant or benign. Because of the complexity and changes in the characteristics of tumor like its shape and size. This paper elaborates the numerous researches for tumor recognition, segmentation and classification of previously proposed methods highlighting its strength and limitations. There is a scope for further to recognize tumor and good image quality. Processing medical images to find solution to different issues by a computer with new algorithms has been drawing a very significant focus of the researchers over last few decades. A literature survey about diagnosis of brain tumor presented in this paper provides critical evaluation of the survey which inhibits new research.*

***Key words:** MRI, image enhancement image segmentation, image registration, multi -resolution.*

I. INDRODUCTION

Brain is the major organ of the human body. Every section of brain has a unique function hence due to some critical situations few cells grow unnaturally. This unnatural growth in brain is called tumor. A set of unnatural cells developed in or surrounding the brain. Benign and malignant are the two classifications of tumor. Benign are not harmful whereas malignant are deadly harmful.

The MRI of brain can give superior detection of tumor but the radiologist has to calculate the area quantification. Brain MRI provides proper detection of tumor hence MRI is used widely. But for segmentation it is complex. To overcome the limitation computer aided

Segmentation and detection is needed. A number of methodologies have been proposed. To overcome this, an automated system has to be found by considering accuracy and robustness. Hence artificial intelligence mechanisms are used with pattern recognition, fuzzy logic and machine learning.

The work presented in this paper elaborates brain tumor survey with MRI enhancement, segmentation and classification techniques of the recent works.

II. MATERIALS AND METHODS

Evangelia I.Zacharaki et al [2008] made a comparative study of biomechanical simulator in deformable registration of brain tumor images. The exactness of deformable enrollment will change for various biomechanical test system. In this paper two test systems were utilized. The non direct lagrangian test system (NL Approach) utilizes Finite Element Module of nonlinear versatility and unstructured cross sections. In Piecewise Linear Eulerian test system (PLE Approach) incremental direct flexibility and standard frameworks were utilized. These test systems offers more affordable biomechanical test system for tumor enlistment.

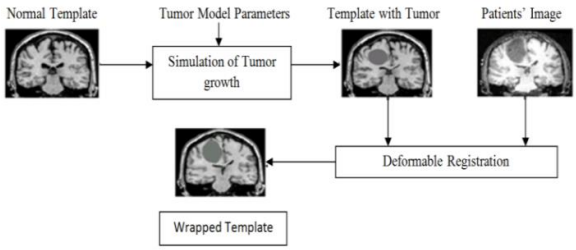

Fig.1. Flowchart summarizing the basic steps for registration of a normal template (brain atlas) with a tumor patient's image.

This process involves:

- Insertion of a little tumor seed in the layout and recreation of tumor development and
- Registration of the layout that is twisted by tumor development with the patient's picture.

The underlying tumor seed is extended by the biomechanical test systems until the extent of the recreated tumor in the map book turns out to be near the measure of the tumor in the patient's image.

The enrollment strategy is based upon the possibility of the HAMMER enlistment calculation. The downside of the framework is that an immediate correlation isn't made between the two methodologies due to various demonstrating approaches and numerical techniques. With respect to, the NL approach is computationally slower and can cause huge work bends and reenactment disappointment on account of expansive tumors.

Manuscript published on 30 January 2019.
***** Correspondence Author (s)
Mr.P.Harish, Research Scholar (PT), Department of EEE, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai. Assistant Professor, Department of ECE, AITS, Tirupati. (E-mail: harishpasupulati@gmail.com)
Dr S.Baskar, Professor, Department of Electrical & Electronics Engineering,School of Electrical and Communication, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai – 600 062. (E-mail: drbaskar@veltech.edu.in)

The PLE biomechanical reenactments are in normal around multiple times quicker than the relating NL reproductions, which is an imperative gain towards quick picture enrollment.

Evangelia I. Zacharaki et al [2008] proposed a deformable enrollment technique for enlisting ordinary brain with tumor persistent. The region of tumor seed and tumor advancement demonstrate is updated in a multi objectives and different leveled plot. The streamlining is revived by focal section examination. The structure is called Optimization of tumor and Registration of Brain Images with Tumors (ORBIT). The essential great position of this system is the breaker of likeness model and progression of deformation strategy of tumor images.

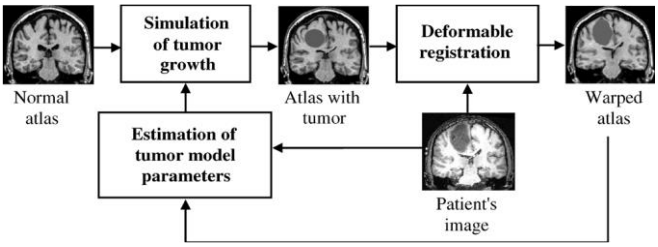

Fig. 2. Flowchart summarizing the basic steps of ORBIT Algorithm

The essential parts of ORBIT include:

- a simulation model for tumor development and mass impact,
- a deformable enlistment strategy for tumor-bearing images, and
- an advancement strategy for assessing the parameters of the tumor development and mass impact demonstrate.
- For examination, pictures are enrolled utilizing ORBIT, the Image Registration Toolkit (ITK) and HAMMER, individually.

The drawback of the system is that ORBIT has been differentiated and two unique enlistments methods, HAMMER and Image Registration Toolkit (ITK), using the best decisions for these two techniques. The suitability of the three enrollment methods is nothing yet hard to consider in cerebrum regions far from the tumor as a result of the vulnerability in describing correspondence between different personalities. The achievement bungle is apparently exceptionally tremendous for all enlistment systems and did not show a basic upgrade for abstract appraisal.

Yu Guoet al [2010] introduces a sparse representation method for magnetic resonance spectroscopy. It is a recurrence area ghastly examination procedure. Attractive reverberation range comprises of metastatic spectra, a gauge and commotion. To isolate distinctive spectra (inadequate portrayal) interest calculation is utilized. A wavelet channel is utilized to channel the smooth and expansive part of watched spectra. An earlier learning about pinnacle frequencies is utilized to lessen the computational multifaceted nature and enhance the evaluation performances. The drawback of the system is that it is hard to acquire precise metabolic profiles of MR pictures.

Shang-Ling Jui et al [2016] presented an improved feature extraction to increase to increase the segmentation accuracy. Utilizing three dimensional misshapening demonstrating procedure, the parallel ventricular distortion is estimated in MR pictures. With the utilization of ANN and SVM order calculations, the exactness of tumor division is made strides. The highlights like picture forces, surfaces, edges and arrangement are not related with real anatomical importance of cerebrum tumor.

V. Anitha et al [2016] proposes two-level classifier with versatile division strategy to arrange cerebrum tumor. The proposed framework utilizes versatile column k-implies calculation for division. This two-level order approach is the grouping technique. One self sorting out guide neural system prepares the highlights extricated from DWT. The proposed two-level order system group cerebrum tumor in twofold preparing procedure with ideal performances.

Most of the programmed and self-loader picture characterization bombs because of obscure commotion, poor picture differentiate, in homogeneity and frail limits. This mechanized examination system could be reached out for the order of pictures with various neurotic condition, types and sickness status.

Proposed system utilize versatile column K-implies for MRI division and a two-level classifier to order tumors. At first, pre-preparing the cerebrum MRI to evacuate clamor and stripping skull shape the picture, at that point the division procedure is done on the upgraded picture by versatile column k implies. Urgent highlights are removed from the portioned picture utilizing DWT mix. At long last the extricated highlights are prepared and characterized by two-level classifier system. Consider ΔD is the brain MRI database, ΔD ∈ {D1, D2, D3, … Dn} where 'n' is the number of images and the vector function of each image in the MRI database is given as i × j.

III. RESULTS AND DISCUSSIONS

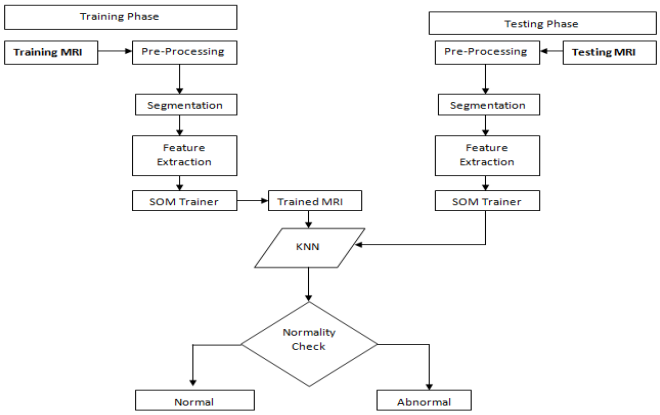

Fig.3: System Design flow of two-tier classifier with adaptive segmentation technique

Meiyan Huang et al [2014] presented exhibited segmentation dependent on nearby autonomous projection grouping. This LIPC orchestrate each voxel into different classes. Differentiated and other coding approaches, this system was progressively sensible in disentangling straight redoing loads. Furthermore this method requires no regularization in light of the fact that the fix feature contains important information of a vovex in the image.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

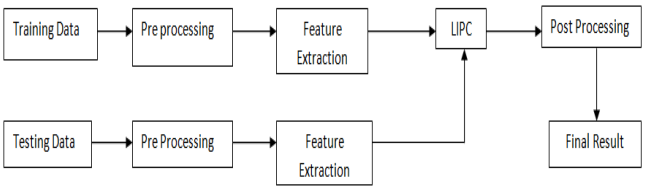

Fig.4: Flow chart of Brain Tumor Segmentation Based on Local Independent Projection-based Classification

The proposed technique comprises of four noteworthy advances, i.e., preprocessing, include extraction, tumor division utilizing the LIPC strategy, and post handling. To decrease computational costs, we inserted the proposed technique in a multi-goals structure.

Albeit various division techniques proposed, improving tumor division is as yet difficult on the grounds that MRI pictures show complex characteristics. The fix highlight might be lacking to separate the cerebrum tumor division assignment in light of the mind boggling attributes of mind MRI pictures.

Sergio Pereira et al [2016] proposed an automatic division dependent on convolutional neural systems (CNN). The precise division of gliomas and its intratumoral structures is conceivable with this technique. The preparing stages comprise of inclination field remedy, force and fix standardization. The quantity of preparing patches was misleadingly expanded. The proposed technique is assessed in BRATS 2013 and considered as best methodology.

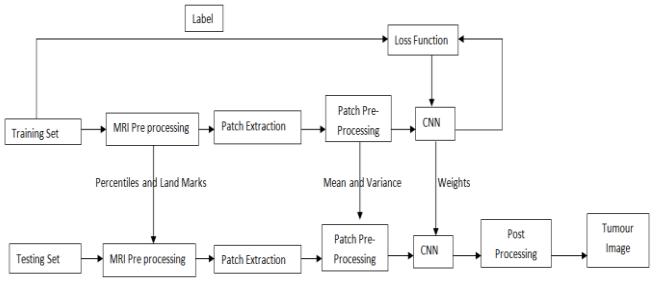

Fig. 5 presents an overview of an automatic segmentation based on convolutional neural networks (CNN).

There are three main stages are Pre-processing, classification via CNN and post-processing.

Guang Yang et al [2015] presented Discrete Wavelet Transform of whole spectral or sub spectral information of key metabolites combined with unsupervised learning. The combination of DWT and unsupervised clustering achieve an overall clustering accuracy of 94.8% and error rate of 7.8%. It is the first study using DWT and unsupervised clustering to separate SV MR data from different tumor images. A sub-spectral analysis is sufficient to distinguish different grades of brain tumor. DWT based feature extraction produces brain tumor classification.

ShaheenAhamed et al [2011] look into reasonability of using various features, for instance, control, fractal surface and level set shape in division of back fossa tumor. A story PCA based procedure is proposed for dimensionality decline of features. Lift feature subset and decision system is proposed to pick and rank characteristics in microarray data for decision of best component, PCA, boosting, KLD and to take a gander at entropy estimations. The organized KLD-EM tumor division offers best execution among various systems.

The proposed system may not be sufficient to discriminate among the brain tissues such as WM, GM, and CSF from tumor.

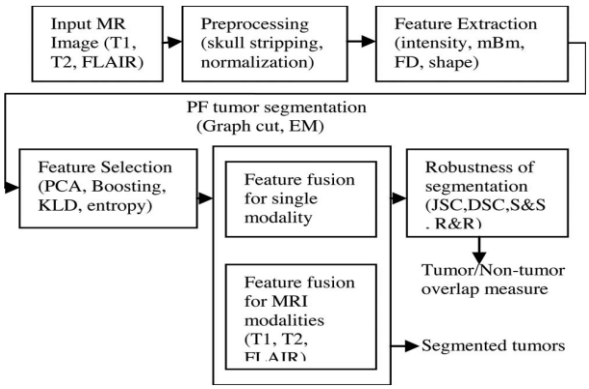

Fig. 6 Block diagram of PCA based method of image segmentation.

The initial step incorporates the pre handling stage that limits power predisposition utilizing a standardization calculation. After pre preparing step, we separate four highlights, for example, power and FD utilizing PTPSA calculation, mBm utilizing fractal-wavelet calculation, and shape utilizing level-set strategy in multimodality MR pictures. We utilize both KLD and the entropy esteems for highlight positioning and choice. The highlights chosen are then utilized for the division of the tumor district in MRI utilizing EM.

Jason J. Corso et al [2008] displayed a programmed division of heterogeneous tumor pictures that crosses over any barrier between the partiality based and generative model based division approaches. The delicate model task estimation of affinities was joined by Bayesian detailing. The division by weighted accumulation calculation is utilized identify and section tumor in multichannel attractive reverberation. SWA calculation is utilized to coordinate model based terms into affinities. This calculation runs quicker than different systems and gives enhanced outcome.

Jiaen Lie et al [2017] focused on the electrical properties tomography procedure on mind tissue by abusing the deliberate B1 information of MRI. These electrical properties can be utilized as biomarker for diagnosing and observing sicknesses, for example, tumor, stroke, liver, and so on. They likewise utilized in understanding the association of tissues with electromagnetic field for enhancing the productivity and precision of accounts. The high spatial goals and straightforward activity makes EPT an enhanced technique for clinical applications. The disadvantage of this technique is more exact warmth exchange show should be created. Smitha Pradhan et al [2016] displayed a novel closeness measure for registering the improved common data utilizing joint histogram of two pictures. Common data has been utilized as an effective likeness measure for multimodal picture enlistment. Punished spine addition is utilized to gauge closeness.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

The documentation of the weighted relative data boosts entropy. The smoothness of EMI is more as contrasted and other likeness estimation. It is not suitable for critical analysis of deformed medical images.

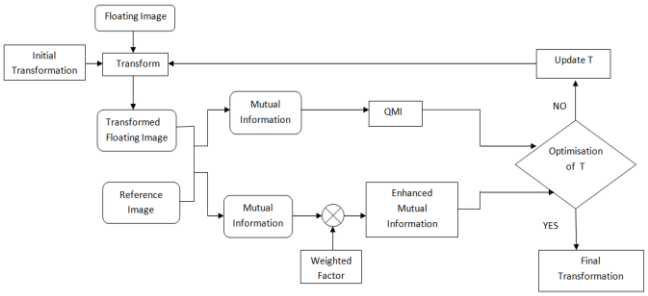

Fig. 7 Block diagram of intensity-based image registration.

Jao Wang et al [2009] proposed another methodology called fluid vector stream dynamic shape model to address issues of deficient catch range and poor assembly concavities. This strategy demonstrates enhancement over different methods like inclination vector stream, limit vector stream and magneto static dynamic form. Examination on cerebrum tumor picture demonstrates that liquid vector stream has mean of 0.61 and middle 0.60 with littlest standard deviation of 0.005. This methodology can be reached out to dissect 3D medicinal images.

Xiatong et al [2014] introduced electrical properties tomography come nearer from its fundamental to investigate result. Recurrence subordinate electrical properties of organic tissues give critical symptomatic data called tumor qualities. Electrical properties will be properties of latent tissues. This EPT constructed approach did not depend in light of exact 3D displaying and did not give summed up estimation of total B1 stage and EP map.

Matthieu Le et al [2016] proposed a scientific model of investigating the particular parameters of tumor development show. The estimation of back likelihood depends on Lattice Boltzmann technique and Gaussian process Hamiltonian montecarlo. It doesn't require complex calculation. The estimation of back likelihood requires multiple times a greater number of assessments than direct enhancement and gives more data about the state of the back.

The uncertainty of segmentation limits Bayesian personalization. Estimating the parameters of reaction diffusion model is also difficult because of uncertainty, model approximation and complex dynamics of tumor evolution.

Zhenyu Tang et al [2018] grew new multi chart book division for MR tumor pictures. The fundamental thought is enlist and breaker name data from various typical mind chart books to new cerebrum picture for division. Multi map book division utilizes picture enlistment to exchange name data. By presenting another spatial limitation SCOLAR+MAS is equipped for recouping typical cerebrum appearance from tumor area. This enhances chart book enrollment and division precision.

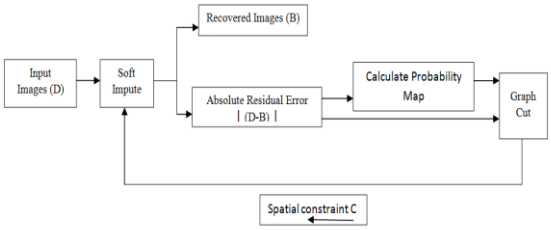

Fig. 8 Block diagram of multi atlas segmentation for MR tumor images.

The limitation of this method is that tumor region should have relatively discriminate appearance from normal brain region in MR tumor images. Tumor mass effect affects the performance of segmentation.

Atiq Islam et al [2013] proposed a stochastic model for tumor surface element extraction and tumor division. To figure adequacy, division execution utilizing multi fractal include is contrasted and Gabor surface component. A notable AdaBoost calculation is utilized for tumor division. This division approach requires deformable picture enrollment with no predefined chart book. The computational multifaceted nature is straight and increments with goals. In future enrolled chart book data joined with division will be more helpful for complex tumors.

Stefan Bauer et al [2012] introduced a novel methodology for breaking down tumor picture with multiscale displaying. The tumor is developed in chart book based multiscale multiphysics demonstrate for cell expansion and tissue twisting. Eulerian approach is utilized for taking care of extensive scale twisting and limited component calculation. This methodology can be connected for strong tumors and gliomas with particular limits to catch tumor mass impact.

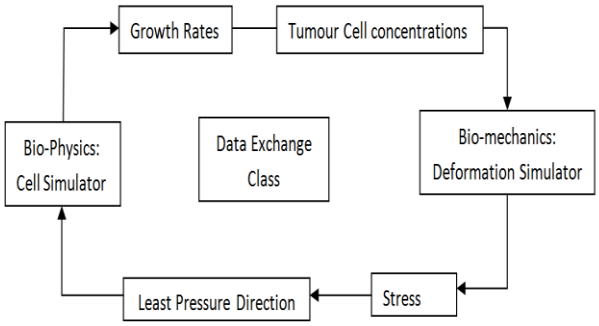

Fig. 9 Block diagram tumor image analysis with multiscale modeling.

The coupling of the two previously mentioned models is delineated in the accompanying: On the one hand, the cell test system requires data on the heading to which new tumor cells will spread, which can be chosen dependent on the weight of the encompassing tissue. Then again, the mechanical reproduction needs data on the sum by which individual geometrical cells will grow, which thus can be extricated from the cell fixations computed by the cell test system.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

When using full image resolution for tumor growth model, this method does not provide good result

AntacHamanci et al [2012] developed a fast and practical tool for segmentation of solid tumors with minimum user interaction. Cell automata based seeded tumor division technique is utilized. The principle preferred standpoint of CA calculation is its capacity to acquire a multi mark arrangement in a synchronous emphasis. The nearby progress rules are easy to decipher and force earlier learning in division calculation. It is hard to look at the changed methodologies as it requires same datasets by various gatherings. Thus the outcome alone was given rather than point by point correlation.

Lama Sallemi et al [2015] proposed a progressed and jovial calculation for mind glioblastomas tumor development estimation. Quick conveyance coordinating information driven calculation dependent on worldwide pixel data is utilized to remove tumor district. Cell automata and quick coordinating strategy are utilized to appraise tumor advancement. Bayesian incorporation display is utilized to limit the expense of the framework. The hole between the scientific and natural model was considered as test in medicinal picture examination.

IV. CONCLUSION

In this work a moderate survey of numerous techniques for classification of MR image. By analyzing a number of techniques a comparative study is done. Evaluation of traditional techniques is neatly explained for detection of tumor and the results are with accuracy. By utilizing modified algorithms for detection of brain tumor more effective results can be provided than the existing methods. For comparison of the techniques computational time is the major criterion.

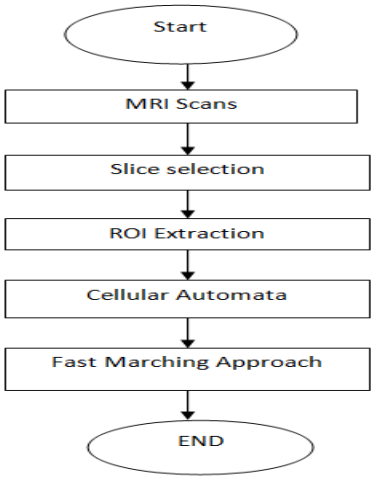

Fig. 10 Flow chart showing advanced and convivial algorithm for brain glioblastomas tumor growth estimation.

As detection of tumor is the challenging task, sensitivity, accuracy and reliability have gained major significant. So detailed techniques which highlight the important criteria like sensitivity, accuracy and reliability for the enhancement of image segmentation methodology is much needed.

REFERENCES

1. Evangelia I. Zacharaki, Cosmina S. Hogea, George Biros and Christos Davatzikos, "A Comparative Study of Biomechanical Simulators in Deformable Registration of Brain Tumor Images", IEEE Transaction on BiomedicalEngineering, vol. 55, no. 3, march 2008,PP.1233-1236.
2. Evangelia I. Zacharaki, Dinggang Shen, Seung-Koo Lee and Christos Davatzikos, "ORBIT: A Multiresolution Framework for Deformable Registration of Brain Tumor Images", IEEE transactions on medical imaging, vol. 27, no. 8, august 2008,PP.1003-1017.
3. Yu Guo, Su Ruan∗, J´erˆomeLandr´e, and Jean-Marc Constans, "A Sparse Representation Method for Magnetic Resonance Spectroscopy Quantification", IEEE transactions on biomedical engineering, vol. 57, no. 7, july 2010,PP.1620-1627.
4. Jin Liu, Min Li, Jianxin Wang_, Fangxiang Wu, Tianming Liu, and Yi Pan "A Survey of MRI-Based Brain Tumor Segmentation Methods", Tsinghua Science And Technology ISSNll1007-0214ll04/10llpp578-595 Volume 19, Number 6, December 2014.
5. Anitha, S. Murugavalli, "Brain tumour classification using two-tier classifier with adaptive segmentation technique", The Institution of Engineering and Technology, doi: 10.1049/iet-cvi.2014.0193, 2015 PP.1-9.
6. Meiyan Huang, Wei Yang, Yao Wu, Jun Jiang, Wufan Chen, and Qianjin Feng, "Brain Tumor Segmentation Based on Local Independent Projection-based Classification", IEEE Transactions on Biomedical Engineering vol. 61, no. 10, OCT 2014,PP. 2633 - 2645.
7. Sergio Pereira, Adriano Pinto, Victor Alves and Carlos A. Silva, "Brain Tumor Segmentation using Convolutional Neural Networks in MRI Images", IEEE Transactions on Medical Imaging, Volume: 35, Issue: 5 , May 2016, PP-1240 – 1251.
8. Guang Yang , Tahir Nawaz, Thomas R. Barrick, Franklyn A. Howe, and Greg Slabaugh,"DWT Based Whole-Spectral and Sub-Spectral Analysis for Improved Brain Tumor Clustering using Single Voxel MR Spectroscopy", IEEE Transactions on Biomedical Engineering, Volume: 62 , Issue: 12 , Dec. 2015 ,PP. 2860 – 2866.
9. Shaheen Ahmed, Khan M. Iftekharuddin, and ArastooVossough, "Efficacy of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI", IEEE Transactions on Information Technology in Biomedicine, vol. 15, no. 2, March 2011
10. Jason J. Corso, Eitan Sharon, ShishirDube, Suzie El-Saden, Usha Sinha, and Alan Yuille, "Efficient Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification", IEEE Transactions on Medical Imaging, vol. 27, no. 5, May 2008
11. Jiaen Liu, Yicun Wang, Ulrich Katscher, and Bin He, "Electrical properties Tomography Based on B1 Maps in MRI: Principles, Applications, and Challenges", IEEE Transactions on Biomedical Engineering, vol. 64, no. 11, November 2017
12. Smita Pradhan, DiptiPatra, "Enhanced mutual information based medical image registration", DOI: 10.1049/iet-ipr.2015.0346, The Institution of Engineering and Technology 2016, PP.1-10
13. Tao Wang, Irene Cheng, Member, IEEE, and AnupBasu, "Fluid Vector Flow and Applications in Brain Tumor Segmentation", IEEE Transactions on Biomedical Engineering, vol. 56, no. 3, March 2009

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

14. Xiaotong Zhang, Jiaen Liu, and Bin He, "Magnetic Resonance Based Electrical Properties Tomography: A Review", IEEE Reviews in Biomedical Engineering, vol. 7, 2014
15. Matthieu Le, HerveDelingette, JayashreeKalpathy-Cramer, Elizabeth R. Gerstner,TracyBatchelor, Jan Unkelbach, Nicholas Ayache, "MRI Based Bayesian Personalizaton of a Tumor Growth Model", IEEETransactions on Medical Imaging, Volume: 35 , Issue: 10 , Oct. 2016,PP. 2329 - 2339
16. Zhenyu Tang, Sahar Ahmad, Pew-Thian Yap, Senior Member, IEEE, andDinggang Shen, "Multi-Atlas Segmentation of MR Tumor Brain Images Using Low-Rank Based Image Recovery", IEEE Transactions on Medical Imaging Volume: 37, Issue: 10 , Oct. 2018,PP. 2224 - 2235
17. Atiq Islam, Syed M. S. Reza and Khan M. Iftekharuddin, "Multi fractal texture estimation for detection and segmentation of brain tumors", IEEE Transactions on Medical Imaging Volume: 60, Issue: 11 , NOV. 2018,PP. 3204-3215.
18. Stefan Bauer, Christian May, DimitraDionysiou, GeorgiosStamatakos, Philippe B¨uchler, and Mauricio Reyes, "Multiscale Modeling for Image Analysis of Brain Tumor Studies IEEE Transactions on Biomedical Engineering, vol. 59, no. 1, January 2012
19. AndacHamamci*, Nadir Kucuk, KutlayKaraman, KayihanEngin, and GozdeUnal "Tumor-Cut: Segmentation of Brain Tumorson Contrast Enhanced MR Images for Radiosurgery Applications", IEEE Transactions on Medical Imaging, vol. 31, no. 3, March 2012
20. Lamia Sallemi Ines NjehandStephaneLehericy, "Towards a Computer Aided Prognosis for BrainGlioblastomas Tumor Growth Estimation", IEEE Transactions on Nanobioscience, vol. 14, no. 7, October 2015

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)