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Robust and Accurate Automated Methods for Detection and Segmentation of Brain Tumor in MRI

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***Abstract:** In this proposed study, a novel Multimodal brain MR image segmentation method is presented to overcome the unattractive and undesirable over segmentation characteristics of conventional Watershed method. The proposed work, presents Optimal Region Amalgamation Technique (RAT) that merge the Watershed method (spatial domain) and Fuzzy C-means clustering (feature spaces) to reduce the unattractive and undesirable over segmentation in brain MR images. In the proposed work, to improve the quality of segmentation results of Watershed method, initially it construct a RAG(Region Merging Graph) for optimal RAT by applying the most popular MRF(Markov Random Field) method . Consequently, the inter-region comparison is presented by applying the watershed method in Spatial Domain and Fuzzy C-Means clustering method in Feature Space for image mapping to compute the Optimal Region Amalgamation. Further, to determine the Feature space and domain space illustration of the brain MR image segmentation, the SGD (Spatial Graph Depiction) is presented that is computed with FSD (Feature Space Depiction) which is obtained by watershed partitioning and FCM clustering method. The experimental results on multimodal brain MR image datasets presents that the proposed novel Optimal Region Amalgamation Technique (RAT) exhibits more promising MR images segmentation results with compared to the traditional watershed method. Finally, an assessment and evaluation of the state-of-the-art brain tumor segmentation methods are presented and future directions to improve and standardize the detection and segmentation of brain tumor into daily clinical treatment are addressed.*

***Keywords :** Fuzzy C-Means method, Watershed method, Markov Random Field, Optimal Region Amalgamation Technique (RAT), 3D Multimodal Brain MR Images, Bilateral Filter.*

I. INTRODUCTION

The brain tumor is the most dangerous disease, which origins disorder to human central nervous system. The MRI (Magnetic Resonance Image) is most popular imaging modality for the detection and analysis of brain abnormalities and tumor in brain. The detail analysis and characteristics of brain tumor can be captured in Brain MRI. The most powerful Neuroimaging protocols are widely used to represent the characteristics of the brain tumor for before and after clinical treatment.

The accurate detection and segmentation of brain tumor is challenging task for the analysis and diagnosis of the clinical treatment and to identify the clues about the tumor and its characteristics, the growth rate of tumor and its prediction and further treatment planning. Moreover, fully automated and efficient detection and segmentation of brain tumor in multimodal MR images is very difficult, complex and tedious task due to various characteristics and factor involved in Brain MR imaging. To capture in details biological properties of the brain, it's better to detect and segment each and every part of the brain tumor for accurate segmentation and detection of the tumor and its very necessary to study on 3D Multimodal Brain MR Images, e.g. Brain T1 MRI, Brain T1C MRI, Brain T2 MRI and Brain FLAIR MRI to trace a unique label to specific tumor and tissue type. It's very difficult and complicated process to scan and study 3D Multimodal Brain MR Images.

The proposed work is experimentally evaluated on four different multimodal brain MR imaging modalities e.g, T1, contrast enhanced T1 (T1c), T2 and FLAIR with brain tumor and each modalities represents the specific region of tumor as shown in [Figure-1].

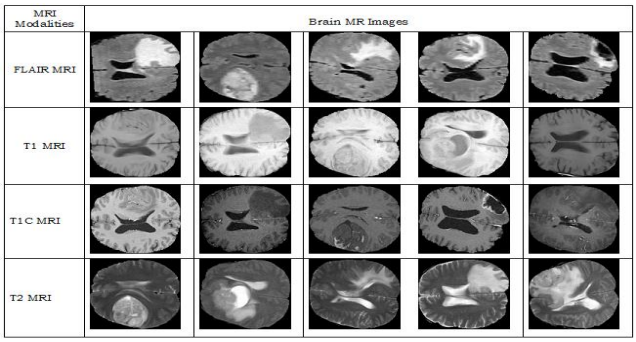

Fig.1. 3D Multimodal Brain MR Images

The Comparison of the various state-of-the-art automatic and semi automatic segmentation methods for brain MR Images are presented [1][4][13].

The major drawback of watershed method is it invariably presents over- segmentation problem due to noise or local irregularities in the segmentation of brain MR images.

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The proposed accurate segmentation method is addressing the issue of undesirable over segmentation problems occurred in conventional Watershed method. The rest of the research work is planned to develop the robust segmentation technique to overcome the over-segmentation problem of existing watershed method.

The proposed work presents the optimal amalgamation technique for merging of initial segmentation results of Watershed method and Fuzzy c-means method to optimize the over-segmentation issue of watershed method. The remainder of the proposed research paper is organized as follows. In Section II, the proposed method Novel Optimization Technique for Segmentation of 3D Multimodal Brain MR Images is described in detail. The implementation and results of Novel Optimization Technique for Segmentation of 3D Multimodal Brain MR Images are presented in Section III, and lastly, Section IV presents the conclusion research articles globally.

II. PROPOSED METHODOLOGY

The main objective behind this proposed research work is to the find the Optimal Region Amalgamation Technique (RAT) for the brain tumor detection and segmentation of brain 3D Multimodal Brain MR Images. The magnetic resonance techniques used to present the visual depiction of brain images result in four different 3D Multimodal Brain MR Images i.e T1, T1c, T2 and FLAIR image[1][2][3]. Hence, this research work is focused to analysis and accurate detection of brain tumor in 3D Multimodal Brain MR Images. The proposed research work is equipped with the bilateral filter to improve the quality of input MR images and used to smooth MR images though preserving edges. The proposed research work as shown in [Figure – 1].

The research work, proposed Optimal Region Amalgamation Technique (RAT) to overcome the over-segmentation problem occurred in watershed method, first it presents a Region Merging Method (RMM) based on applying the Markov random field(MRF) model on the RAG(Region Adjacency Graph) [14][15][16] to improve the quality of watershed method. The relationship of inter-region similarities presents in tumor regions is then performed by watershed method in involving the spatial domain and clustering technique in feature space into image mapping in order to determine Optimal RAT. The proposed research work as shown in [Figure – 1] and [Figure – 2]. To obtain the spatial domain of brain MR images and feature spaces representation of the brain MR image, the spatial graph representation is used that is derived from the watershed partitioning and feature space representation obtained from the Fuzzy c-means (FCM) clustering technique[2].

The major contributions of this proposed paper are three-fold.

- This work proposed an Optimal Region Amalgamation Technique (RAT) for accurate detection and segmentation of tumor in brain MR images.
- The proposed work improves the quality of segmentation results and outperforms present state-of-the-art methods used in the field of brain tumor detection and segmentation in MRI.
- Proposed work permits for the in details analysis and diagnosis of brain tumor in 3D Multimodal Brain MR Images.

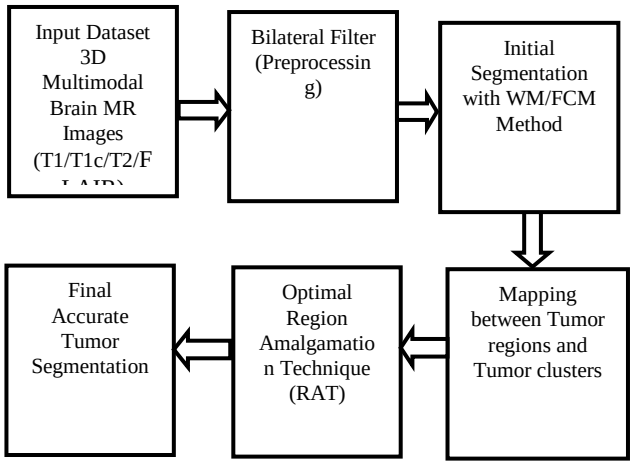

Fig.2. Proposed Methodology

A. The major components in proposed work:-

- The pre-processing of input 3D Multimodal Brain MR Images with Bilateral Filter to smooth regions and improve the quality of input MR images.
- Initial segmentation is done with Watershed method for detection and segmentation of tumor regions.
  Tumor regions= {TR1,TR2,TR3……TRn}
- Initial segmentation is done with Fuzzy C-means clustering method for detection and segmentation of tumor clusters.
  Tumor Clusters= {TC1,TC2,TC3……TCn}
- Proposed Optimal Region Amalgamation Technique (RAT) for merging of similar tumor regions to reduce the over-segmentation problem.
- Experimentally evaluated the performance of the proposed method on 3D Multimodal Brain MR Images.

The watershed method [3][4][5][11][12] is most popular brain MR image segmentation technique for brain tumor which is described as morphological gradient based segmentation, the present research work minimal watershed method is used as shown in [Figure – 2].The major drawback of watershed algorithm [3][4] [6][11] is undesirable over-segmentation. This research work overcomes the over-segmentation issue by merging spatial space i.e tumor regions with feature space i.e cluster regions.

FCMC method [2][8] [9] [10] [13] is most popular brain MR image segmentation technique for brain tumor. FCMC is unsupervised automatic brain tumor segmentation methods as shown in [Figure-2][Figure-3]. The major drawback of Fuzzy C-means clustering method is suffering with slight segmentation accuracy for the detection and segmentation of brain tumor in 3D Multimodal Brain MR Images.

The proposed research work focused to develop an optimal Region amalgamation Technique (RAT) of initial segmented regions with Watershed method and Fuzzy C-Means Clustering (FCMC) method as shown in [Figure-3].

Preprocessing of MR Images: This section is crucial for the pre-processing of input 3D Multimodal Brain MR Images to improve the quality of input MR images, smooth regions of MR images and remove the noise present in input MR image. The application of Bilateral filter as shown in [Figure-3] and Equation (1) and Equation (2).

The Bilateral filter is explained as

$$\mathrm{MRImg}'(SCo_1) = \frac{1}{I(SCo_1)} \sum_{SCo_1 \hat{I} Px} \mathrm{MRImg}(SCo_2).\mathrm{Gm}(SCo_1, SCo_2).\mathrm{Pm}(\mathrm{MRImg}(SCo_2), \mathrm{MRImg}(SCo_1)) \quad (1)$$

Where,

- MRImg and MRImg', denotes the original MR image and the filtered and noise removed MR image.
- SCo1 and SCo1 denote the spatial coordinates of the MR image.
- Px, denotes the collection of pixels around the noise in the MR image.
- I(SCo), denotes the normalization constant for each pixel to restrict the value after normalization within geometric and photonic range denoted by Px.
- Gm and Pm, denotes the geometric and photometric similarities of the MR image.

Consequently, the enhancement of the image is proposed to regularize the local signal amplitude of every pixel value:

$$\mathrm{MRImg}'(SCo_1) = \frac{1}{I(SCo_1)} \sum_{SCo_1 \in Px} \mathrm{MRImg}(SCo_2).\theta(SCo_1, SCo_2, t) \quad (2)$$

Where

$$\theta(SCo_1, SCo_2, t) = (1 - a(SCo_1)).Gm(SCo_1, SCo_2) + a(SCo_1).Gm(SCo_1, SCo_2).$$

$$Pm(\mathrm{MRImg}(SCo_1), \mathrm{MRImg}((SCo_2)).\sum_{n=1}^{D-1} d_i(SCo_1, SCo_2)$$

Where,

a(SCo1) and dn, denotes the regularized local signal amplitude of the pixel and denotes the MR image dimensions for during noise removal.

B. Representation of mapping to feature spaces clustering statistic probability with spatial domain of brain MR images:

The proposed work presents the association of inter-region similarities presents in tumor regions in initial segmented brain MR images with watershed method which involving the spatial domain and the feature space is generated by using most popular FCM clustering technique. The inter-region similarities presents in tumor regions in watershed method is mapped to tumor cluster in the feature space, which is generated by using most popular FCM clustering technique in order to compute the optimal region amalgamation and accurate segmentation results. The proposed Optimal Region Amalgamation Technique (RAT), initially it presents a Optimal Region Amalgamation (RMM) based on applying the Markov random field(MRF) model[2] [14][15][16] on the region Adjacency Graph to improve the quality of watershed method for segmentation and detection tumor in brain MR images. The spatial graph is mostly used to obtain the spatial domain and feature spaces on brain MR images. In initial segmentation of brain MR images is generated on the spatial domain and feature spaces, which is illustrated to the spatial graph presentation that is derived from the Fuzzy c-means (FCM) clustering technique of feature space representation and the watershed method partitioning.

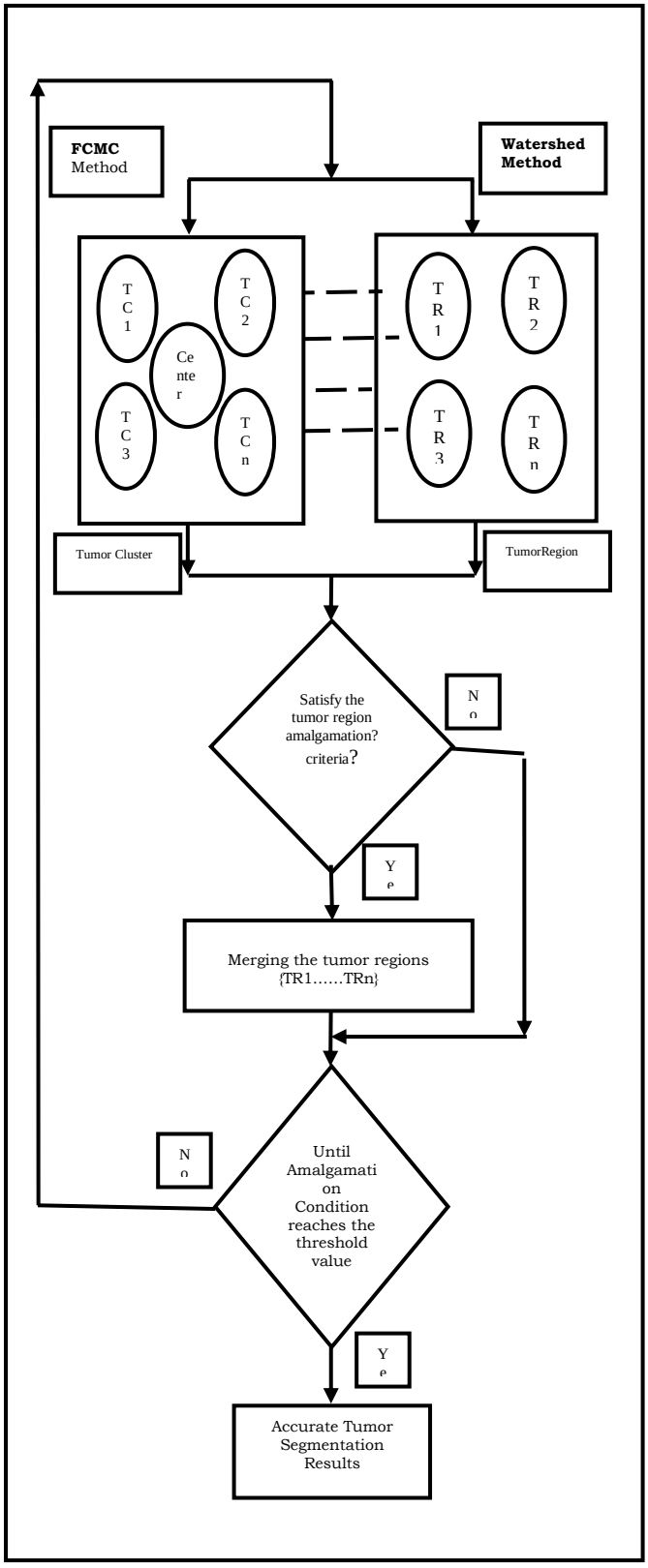

Fig.3. Framework for Proposed Methodology

- To define the pair-wise similarity measure between tumor regions. The membership values used i.e in a result of the FCMC method and allotted to μ_{xc}Ɛ[0,1].
- In a clustering system, cr is the clustering numbers and Cr is defined Equation (3).

$$Cr = \cup_{Cr=1}^{i} Cr1 \cup Cr2 \cup \ldots \cup Cri$$

i:clusteringnumbers. (3)

- The watershed-segmented tumor regions {TR1,TR2,TR3……TRn} are the results of the initial partitioning of the brain MRI image and map to the feature space in FCMC method.
- The FCMC method membership values are represented to

μ_{nCr} n=1,2,3,…k and Cr=1,2,3…,I ,

Here n and x are clustering number value and segmented tumor region.

- Incase Ri is initial results of watershed method, if it mapped to spatial spaces to a new domain which is developed by FCMC $\mu_{nCr} \in [0,1]$, of the nth region to the Crth cluster.
- The tumor region similarity is represented in the domain of membership values μ_{nCr} . Hence, the similarity of the regions in features is defined by cluster centers and cluster center defines the similarity tumor regions in feature space**.**
- Hence, the mapping function i is defined for cluster Cr as shown in Equation (4) and Equation (5).

$$i = \{\mu_{nCr} \mid n = 1,2,3,---\text{k and Cr} = 1,2,3,..,i\} \quad (4)$$

$$\mu_{nCr} = \frac{TRi \cap Crcr}{\sum_{n=1}^{i}(TRi \cap Crn)'}, n = 1,2,3,---\text{k and Cr} = 1,2,3,..,i \quad (5)$$

Where RiƐR, crƐCr. The initial segmented tumor regions with watershed method For tumor regions Ri, a set βi of the length n is acquired as shown in Equation (6) .

$$\beta_i = \{\mu_n, \mu_n, \ldots \mu_{nCr}\} \quad (6)$$

Where Ri belongs to watershed segmentation region.

Ri mapping from watershed region to the FCM cluster center, gives $\mu_{nCr}, Cr = 1,2,3\ldots i$ where n is the number of FCM clustering in feature space.

Every segmented tumor region of watershed method Ri, $\mu_{nCr} = \mu_{nCr} \in TRi, \mu_{nCr} \in \beta i$ Where Cr=1,2,…,i.

Her, βi in equation is exhibitive of the regions crucial area in the cluster center.

MAP estimate as shown in Equation (7).

$$\ell' = \arg\max_{\ell \in \theta}\{P(\ell \mid \omega\}. \quad (7)$$

The energy is the difference between the two regions E(Rx) and E(Rx'). The followings are the detailed description about the two regions energy.

$$En(Ri) = \sum_{cr=1}^{i} \mu_{nCr} \text{ and } En(Rj) = \sum_{Cr=1}^{i} \mu_{jCr} \quad (8)$$

ΔEn is shows actual value of the varies in membership value as shown in Equation (8) represents the value of ΔEn .

- If two tumor regions region TRi and TRj to be merged than segmented region En(TRi) and adjacent region En(TRj) to be determined. If it is satisfy energy function than tumor regions TRi and TRj can be merged.
- If ΔEn less than a defined threshold level, the tumor regions TRi and TRj are considered as similarity tumor regions.
- Two tumor regions merging of described spatial details and tumor cluster features to be integrated the benefit of the watershed method and FCMC method.
- In equation (9), the adjacent tumor regions are amalgamation as per the given condition in order to obtain a final segmentation.

$$\triangle En = En(Ri) - En(Rj) = \sum_{Cr=1}^{i} \mid \mu_{iCr} - \mu_{jCr} \mid \quad (9)$$

.

C. **Algorithm for Optimal Region Amalgamation Technique (RAT):**

Objective: RAG is developed based on initial over segmented MRI s for optimal amalgamation of tumor regions until an accurate and final segmentation results are obtained.

Input: Original MRI s and Initial segmented images are given as an input for merging algorithm**.**

Output: Accurate and best segmentation results**.**

Steps:

Step1. The RGA(Region Adjacency Graph) is initialized with the Initial segmented MRI s elements to maintain the RSA(Regional Statistical Relationship) and Determine the required energy i.e △E

Step2. The threshold value is fixed based on related critical value and level of significance.

Step3. The enhancement and improvement of the MRI segmentation results is done by applying the iterative process of determining the probability values of AR(adjacent regions) with respective to the △E values to calculate the best AR are to be merged.

Step4. Choose any one of node i.e Ri. Select it's any neighbor's node i.e Rj.

Step5. Determine the SOE (second-order energy) to maintain relationship in all initial segmented tumor region.

Step6. If the values of energy of regions Ri and $Rj \leq \triangle E$, amalgamation of the two regions and revise the current tumor region details and all adjacent tumor region relationships.

Step7. Repeat Steps 5 & 6 for tumor region Ri and its neighbors region Rj.

Step8. Repeat step 4-7 for all tumor regions until all adjacent tumor regions are distinct.

Step9. Set Flag false; the presented segmentation results are superior, which does not demonstrate more enhancements.

Step10. End.{Final segmentation Result has been obtained).

III. RESULTS AND DISCUSSION

A Brain MRI Dataset

The experimental evaluation of the proposed method is a very complex and tedious process for brain tumor detection and segmentation with the state-of-the-art methods. Though, with the development of a most accepted and benchmark MRI datasets for evaluation of brain tumor detection and segmentation is possible with widely used and common MRI dataset.

The proposed work is evaluated with most accepted BRATS MRI dataset contains 200 multimodal brain MRI scans of patients along with their ground truth images. The BRATS Brain MRI dataset is consisting of 200 3D Multimodal Brain MRI s of T1 MRI, T1c MRI, T2 MRI and FLAIR MRI and ground truth images as shown in [Figure-4].

The brain MRI dataset was represented to a common space, resolution resampled to isotropic 1mm ×1mm × 1mm. The dimensions of brain MRI s in dataset are 240 × 240 × 155 voxels. Ground truth image is manually segmented and annotated by label based brain tumor regions by trained expert in the field of brain MRI.

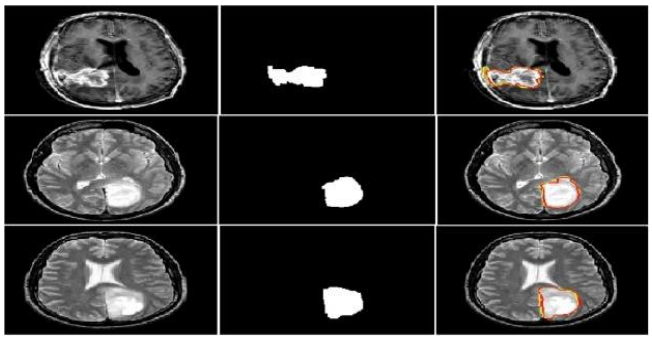

Fig.4. The BRATS Brain MRI dataset along with Ground truth

B Results of Bilateral Filter for preprocessing of Brain MRI s: In order to demonstrate the quality improvement of input MRI s are preprocessed with bilateral filter. The preprocessed MRI s are used for further better segmentation of brain tumor. The visual demonstration of bilateral filter on input 3D Multimodal Brain MRI s as shown in [Figure-5]. The numerical improvement subsequent to preprocessing of input 3D Multimodal Brain MRI s with bilateral filter is shown in [Table-I].The presented bilateral filter has been experimentally evaluated on BRATS MRI dataset's and furnishes better results.

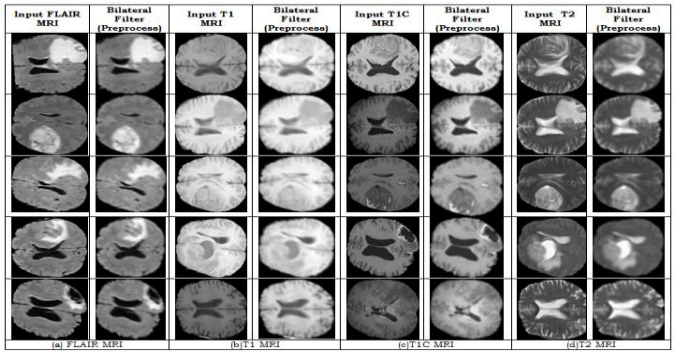

Fig.5. Processing and Enhancement of the input multimodal brain MRI

Table I. The Quantitative Bilateral filters results on the 3D Multimodal Brain MRI.

MRI Dataset	Actual MRI Variance	Filtered MRI Variance	Improvement In MRI	Actual MRI Std. Deviation	Filtered MRI Std. Deviation	Improvement In MRI
1	8616966.9	9325425.899	0.082217	73.134012	74.26609	0.01548
2	7298752.49	8231411.34	0.127783	71.921236	73.9413	0.028087
3	4355136.22	4923593.077	0.130526	68.444576	70.46317	0.029492
4	9554696.16	16036161.27	0.678354	77.144764	88.461	0.146688
5	2239552.24	8164522.795	2.645605	60.061124	84.23921	0.402558
6	5060902.71	4915045.117	0.02882	69.797568	69.5685	0.003282
7	21368886.1	18066531.68	0.15454	63.106152	60.30692	0.044357
8	2898009.13	5441952.068	0.877824	58.438954	68.75465	0.176521
9	3297844.71	3310126.799	0.003724	60.892958	61.29439	0.006593
10	7956455.46	9209704.089	0.157513	61.032613	63.33579	0.037737

C Evaluation of proposed methodology: This section presents the quantitative evaluation of the optimal RAT on multimodal BRATS Brain MRI s. The optimal RAT in this work is quantitatively evaluated with Segmentation accuracy as shown in Equation (10) on multimodal brain MRI and benchmark multimodal brain MRI datasets. The visual experimental results of brain tumor segmented with Watershed Method, FCMC method and proposed Optimal RAT method as demonstrated in [Figure-7] and [Figure-8]. The comparisons between the segmented results of Watershed Method, FCMC method and proposed Optimal RAT method are visually demonstrated.

Segmentation Accuracy (%) =

$$\frac{TP(True\_Positive)+TN(True\_Negative)}{TP(True\_Positive)+TN(True\_Negative)+FP(False\_Positive)+FN(False\_Negative)}*100 \quad (10)$$

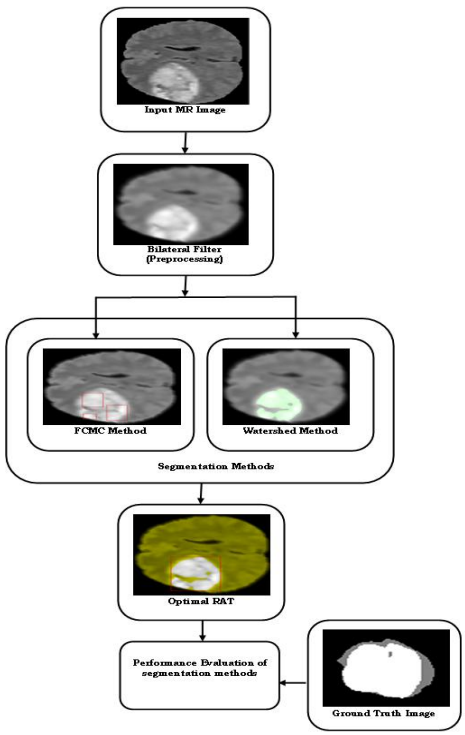

Fig.7. Demonstration of proposed Optimal Region Amalgamation Technique (RAT) for segmentation of brain MRI s.

The detection and segmentation of brain tumor in three patients MRI scans with Watershed Method, FCMC method and proposed Optimal RAT method as demonstrated in [Figure-8].

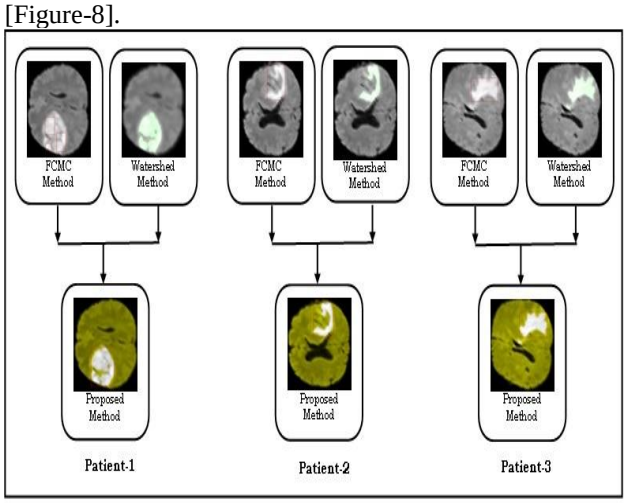

Fig.8. Demonstration of Optimal Region Amalgamation Technique (RAT) for initial segmented 3-patients MRI s with Watershed method and FCMC method.

According to the quantitative segmentation results on 3D Multimodal Brain MRI s as shown in [Table-2], the existing methods cannot achieve a superior segmentation results for brain tumor segmentation. However, the proposed optimal RAT has superior segmentation results on 3D Multimodal Brain MRI s as shown in [Table-II]. In this proposed work, we focused on the inter-similarity measure and the optimal region amalgamation process in the brain tumor segmentation technique.

Table II. The quantitative segmentation results and comparison evaluation of various State-Of-The-Art Method on 20 3D Multimodal Brain MRI s from BRATS Dataset.

Multimodal brain MRI	Patient MRI Scan	Truth File Name	Segmentation Accuracy (%)		
			Watershed Method	FCMC	Optimal RAT
T1 MRI	MRI01_T1	MRI01_truth_T1	95.87	96.13	96.19
	MRI02_T1	MRI02_truth_T1	97.12	97.02	98.72
	MRI03_T1	MRI03_truth_T1	92.53	94.2	95.25
	MRI04_T1	MRI04_truth_T1	95.67	96.07	96.12
	MRI05_T1	MRI05_truth_T1	96.63	95.36	96.89
		Average Accuracy (%)	95.56	95.75	96.63
T1c MRI	MRI01_T1c	MRI01_truth_T1c	96.58	96.23	96.98
	MRI02_T1c	MRI02_truth_T1c	98.01	98.92	99.01
	MRI03_T1c	MRI03_truth_T1c	94.76	95.1	95.63
	MRI04_T1c	MRI04_truth_T1c	94.41	94.01	94.87
	MRI05_T1c	MRI05_truth_T1c	97.18	97.91	98.17
		Average Accuracy (%)	96.18	96.43	96.93
T2 MRI	MRI01_T2	MRI01_truth_T2	96.71	97.01	97.65
	MRI02_T2	MRI02_truth_T2	97.74	97.69	98.23
	MRI03_T2	MRI03_truth_T2	95.53	96.27	96.94
	MRI04_T2	MRI04_truth_T2	93.23	93.13	94.03
	MRI05_T2	MRI05_truth_T2	98.28	98.17	98.92
		Average Accuracy (%)	96.29	96.45	97.15
FLAIR MRI	MRI01_FLAIR	MRI01_truth_FLAIR	97.24	97.62	98.41
	MRI02_FLAIR	MRI02_truth_FLAIR	98.13	97.87	98.29
	MRI03_FLAIR	MRI03_truth_FLAIR	95.31	96.27	97.31
	MRI04_FLAIR	MRI04_truth_FLAIR	94.52	94.79	95.38
	MRI05_FLAIR	MRI05_truth_FLAIR	98.27	98.86	99.01
		Average Accuracy (%)	96.69	97.08	97.68

In this section, the experimental results are quantitatively compared the proposed to most popular existing two conventional methods which includes watershed method and FCMC methods. The evaluation methods for each presented method are fixed to common BRATS dataset with ground

truth image segmented by expert. Analysis of average segmentation accuracy on 200 3D Multimodal Brain MRI from BRATS dataset with Watershed method, FCMC Method and proposed Optimal RAT method as shown in [Table-III].

The average segmentation accuracy of Watershed method-95.68%, FCMC Mtehod-95.71% and proposed optimal RAT- 96.67% on T1 MRI s. The average segmentation accuracy of Watershed method-96.47%, FCMC Mtehod-96.41% and proposed optimal RAT- 96.98% on contrast enhanced T1C MRI s. The average segmentation accuracy of Watershed method-98.71%, FCMC Mtehod-98.93% and proposed optimal RAT- 98.97% on contrast enhanced T1C MRI s. The average segmentation accuracy of Watershed method-97.71%, FCMC Mtehod-97.93% and proposed optimal RAT- 97.97% on T2 MRI s. The average segmentation accuracy of Watershed method-96.73%, FCMC Mtehod-97.21% and proposed optimal RAT- 97.93% on FLAIR MRI s.

Table III. Analysis of Average Segmentation Accuracy on 200 3D Multimodal Brain MRI s from BRATS dataset with Watershed method, FCMC Method and proposed Optimal RAT method.

Input MRI Modalities	Dataset Size(Patients MRI Scans)	Average Segmentation Accuracy (%)		
		Watershed Method	FCMC Method	Optimal RAT
T1 MRI	50	95.68	95.71	96.67
T1c MRI	50	96.47	96.41	96.98
T2 MRI	50	97.71	97.93	97.97
FLAIR MRI	50	96.73	97.21	97.93

In [Figure10], the average segmentation accuracy on 200 3D Multimodal Brain MRI s from BRATS dataset for three methods i.e, Watershed method, FCMC method and optimal RAT methods are presented. Each one of the Watershed method, FCMC method and optimal RAT segmentation results are evaluated on four different multimodal MRI modalities. The average segmentation results of proposed method is compared against Watershed method and FCMC method, the proposed method provides enhanced average segmentation accuracy as shown in [Figure-9].

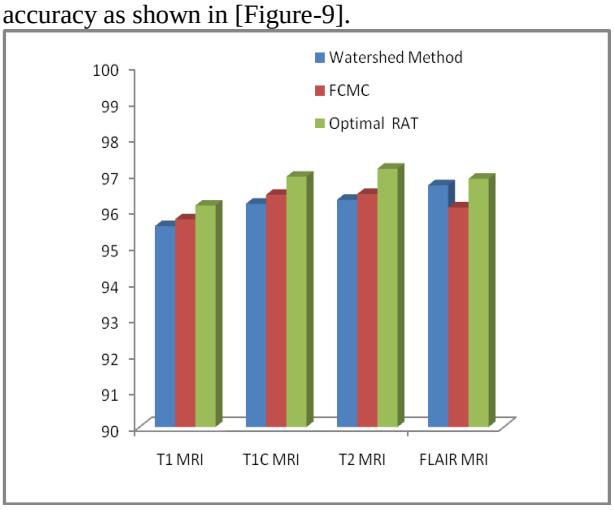

Fig.9. Comparison evaluation of average segmentation accuracy of proposed method with Watershed Method and FCMA method on 200 3D-Multimodal Brain MRI s from BRATS dataset.

IV. CONCLUSION

The major focus of this paper was accurate detection and segmentation of brain tumor in 3D Multimodal Brain MRI s was presented. The quality of segmentation results were enhanced with proposed Optimal Region Amalgamation Technique (RAT), which is presented on improved Markov Random Field model to build the RAG. RAG was constructed from the initial brain MRI divided into tumor regions. The initial segmented tumor regions were amalgamation with respect to cost function condition to acquire an accurate detection and segmentation results. Two major benefits of the proposed work: first, the over-segmentation problem was optimized, the presented superior segmentation results were achieved with Optimal Region Amalgamation Technique (RAT), and second, the optimal energy cost solution for every edge for brain MRI s in the RAG presents the inter-similarities between two neighbor tumor regions. The analogous neighbor tumor regions were merged after satisfying the optimal energy cost. In this proposed work, the amalgamation of watershed method and FCMC method with respect to the optimal cost criteria. The major benefit of proposed work was to enhance the quality of detection and segmentation of tumor in brain MRI s. The proposed work in this paper was experimentally evaluated on 200 3D-Multimodal Brain MRI s from BRATS dataset with the existing methods and Proposed Method and it was shown the improvement in segmentation results for 3D Multimodal Brain MRI s. The presented optimal RAT in this work may lead to the improvement of diagnosis of brain tumor in daily clinical routine and treatment planning.

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