AN EFFICIENT AUTOMATED MULTIMODAL CONTOUR SEGMENTATION OF MULTIMODAL BRAIN TUMOR IMAGE USING DYNAMIC SPARSE FIELD

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ABSTRACT

Segmentation of tumor cells from Magnetic Resonance Imaging (MRI) has witnessed significant popularity in recent years, bringing new challenges to advanced medical imaging. The performance of today's image segmentation on multimodal brain images heavily depends on the consumption of processing time. In this work, we propose Automated Multimodal Contour Segmentation (AMCS), an efficient technique to achieve robustness under different scanning region points on multimodal brain images. Here, effective segmentation is performed by evaluating the tumor volume, curvature, global and local regions. The proposed MBIS algorithm result shows that the multimodal brain images with higher true positive rate compared with certain benchmark techniques in the literature while being efficient in terms of processing time, true positive rate and robustness in terms of segmentation accuracy.

Keywords: automated multimodal contour segmentation, contour constrained multiple threshold, image segmentation, dynamic sparse field, local regions.

1. INTRODUCTION

For effective assessment of tumor and providing the treatment according to the nature and stage, automatic segmentation of brain tumor images are considered to be highly significant but at the same time, it is considered to be very difficult task. Region-based fuzzy clustering and deformable model on MRI images [1] was presented to improve the rate of segmentation. Initial segmentation was performed on the basis of regions obtained using fuzzy clustering and was provided as input to deformable model for extraction of final contour. An algorithm for gradient differential analysis was included in [2] that were used as the main metric for detection and identification of tumor cells. In the past few decades, representation of active contour is significantly and invariably applied in the area of image segmentation as it provides convincingly good results. To provide solutions for intensity related homogeneities, a novel type of active contour model was introduced in [3] using Laplace information. However the active contour model results in over segmentation with the increase in the number of images.

To provide solutions, a new segmentation algorithm was introduced in [4]. The new algorithm preserved the edge of the image, followed by it morphological gradient was applied for edge merging. Contrast enhancement and morphological gradient was provided using bottom Hat transformation and regional minima respectively improving the overall algorithm in terms of execution time. A Mixture of Dirichlet Process (MDP) [5] was designed for efficient segmentation of brain tumor images, which were being performed without the initialization of clusters using Markov Random Field which resulted in the improvement of accuracy being achieved and time with which the accuracy being achieved. However, certain MR model features were not used. Hybrid Algorithm using Symmetry and Active contour [6] was introduced to provide MR model using hybrid algorithm by mapping original image to active contour image. Though tumor abnormality was identified, but was not robust in identifying the abnormality.

To deal with these limitations, in the following sections, we propose a novel multimodal contour segmentation technique on brain tumor medical images to improve the robustness involved during segmentation. Instead of considering only single modal, we now consider multimodal brain images, based on the contour constrained multiple threshold and dynamic sparse technique. Followed with the introduction, the AMCS on brain tumor medical images are described with neat flow chart in section II. The experimental results and discuss of the proposed method are illustrated in section III and finally consolidated the results in section IV.

2. AMC SEGMENTATION ON BRAIN TUMOR MEDICAL IMAGES

The complete solution of automated multimodal contour segmentation on brain tumor medical images is split into two steps which are Contour Constrained Multiple Threshold Technique and Dynamic Sparse Field (DSF) mechanism. First one describes the usage of Automated Multimodal Contour Segmentation to achieve robustness under different scanning region points on multimodal brain images.

The main objective of designing Automated Multimodal Contour Segmentation (AMCS) technique is to segment the brain images on the 2D radial slices for monitoring the tumor volume progression on the brain [7]. In AMCS technique, for each brain images, a central axis is selected manually, followed by this, each tumor slicing operation is carried out at regular intervals. Segmenting

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brain image using AMCS technique extracts tumor information and offers reliable segmentation resulting with high precision rate.

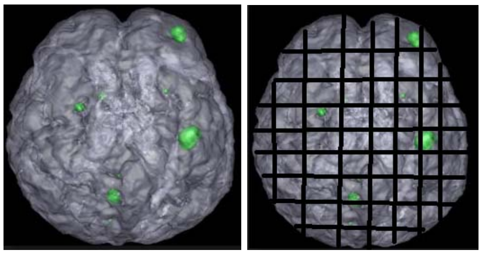

Figure-1. Brain image with Tumor and its 2D radial slicing.

The brain image with tumor point is illustrated in Figure-1 (a) whereas Figure-1 (b) illustrates the radial slicing based segmented brain image to identify the tumor volume using AMCS technique. Automated multimodal segmentation is a process of separating the brain image tumor space into certain non-overlapping varying boundary regions [8].

2.1 Brain image detection in AMCS

The contour based segmentation is carried out on multimodal brain images and the flow diagram of Automated Multimodal Contour Segmentation (AMCS) is depicted in Figure-2.

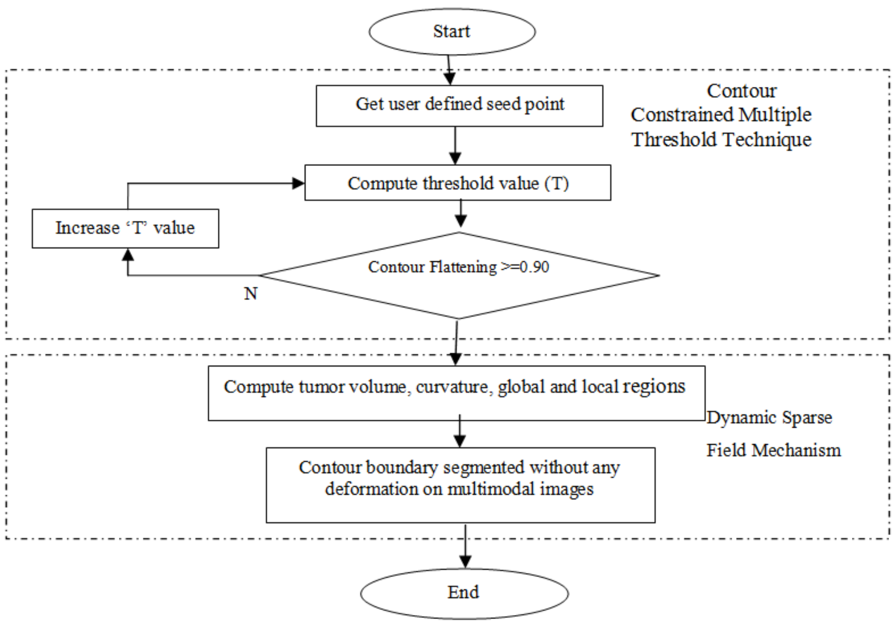

Figure-2. Flow diagram of AMCS technique.

The first step in AMCS technique is to obtain the user defined seed point and measure the threshold value. The value of threshold 'T' is obtained using Contour Constrained Multiple Threshold (CCMT) technique. To measure the 'T' value, CCMT measures the contour flattening value. If the contour flattening value of the brain image is greater than the specified value, then the processing loop enter into the second step of AMCS technique. Otherwise, the threshold value of 'T' is increased. The second step involved in AMCS technique is to perform the Dynamic Sparse field mechanism on the brain images. The brain images with respect to the tumor volume, curvature, global and local regions are evaluated. With this, the regions on the multimodal images are segmented without any deformation of contour points.

3. EXPERIMENTAL RESULT AND DISCUSSION

Automated Multimodal Contour Segmentation (AMCS) experimentation is implemented on MATLAB platform. The Multimodal Brain Image segmentation (MBIS) algorithm uses the Brain Images of Tumors for Evaluation (BITE) database with multimodal images. Pre and post operative MRI and intra-operative ultrasound brain images have been acquired from 14 patients. All patients on multimodal images (i.e.,) Pre and post resection ultrasound images, Pre-operative MR and pre-resection ultrasound image and Pre-and post-resection MR images are taken for this experimental work. In order to analyze the characteristics and functionality of the AMCS technique, has compared against the existing Patch-based Sparse Representation (PSR) [9] technique and Multi-resolution Stochastic Level Set (MSLS) [10] technique. To support transient performance, in Table-1 apply an efficient Multimodal Brain Image segmentation (MBIS)

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algorithm to obtain the sensitivity ratio and comparison is made with two other existing techniques, PSR and MSLS.

3.1 Comparison and measurement of sensitivity

Table-1. Tabulation for sensitivity.

No. of images	Sensitivity (%)		
	AMCS technique	PSR technique	MSLS technique
4	43.45	32.40	27.30
8	48.75	37.70	32.60
12	52.45	41.40	36.30
16	57.85	46.81	41.71
20	62.55	51.52	46.42
24	72.35	62.30	57.20

Figure-3. Measure of sensitivity.

Figure-3 shows that the proposed Automated Multimodal Contour Segmentation (AMCS) provides higher sensitivity ratio when compared to PSR and MSLS. The application of automated multimodal segmentation that eventually separates the brain image tumor space into non-overlapping varying boundary regions and improves the sensitivity by 13-25% when compared to PSR technique and it have the improved sensitivity by 20-35% than the MSLS technique.

Table-2. Tabulation for segmentation processing time.

No. of images	Segmentation processing time (ms)		
	AMCS technique	PSR technique	MSLS technique
4	0.134	0.185	0.205
8	0.147	0.195	0.225
12	0.185	0.205	0.265
16	0.215	0.225	0.285
20	0.225	0.245	0.315
24	0.285	0.315	0.325

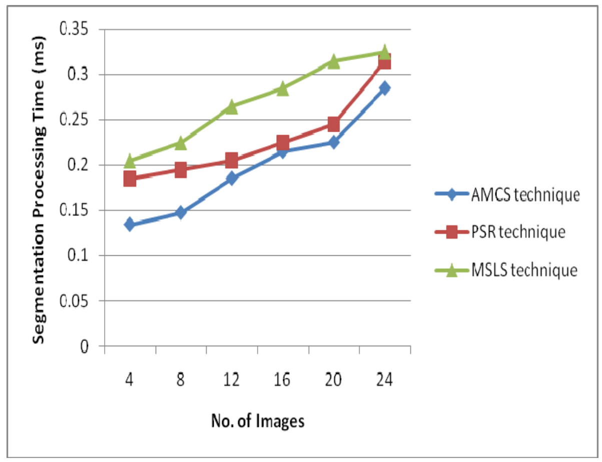

Figure-4. Measure of segmentation processing time.

This is because with the application of the pixel derivate function uses the curvature constrains in Dynamic Sparse Field (DSF) efficiently measures the brain tumor at different position improving the segmentation processing time by 4-38% when compared to PSR. Furthermore, by providing optimal Threshold value 'T' and sparse field 'S' combines the two processes for effective segmentation of tumor with minimum segmentation time by 14-53 % than compared to MSLS.

3.2 Comparison and measurement of true positive rate

The true positive value for AMCS technique is elaborated in Table-3 and its true positive rate in Figure-5 attained using varying images collected from 14 different patients for experimental purpose and applied in MATLAB. From that, the value of true positive rate achieved using the proposed AMCS method is higher than the other two existing. By increasing the number of images, the true positive rate is increased using all the methods. But comparatively, it is higher in AMCS technique because the AMCS technique segment brain images on 2D radial slices for monitoring the tumor volume progression on the basis of a central axis. Segmenting brain image using AMCS technique extracts tumor information and offers reliable segmentation resulting with high precision rate improving the true positive rate by 14-30 % when compared to PSR. The segmentation precision rate gets improved using central axis points by 26-53 % than when compared to MSLS.

Table-3. Tabulation for true positive rate.

No. of images	True positive rate (%)		
	AMCS technique	PSR technique	MSLS technique
4	32.35	22.40	15.20
8	37.65	27.70	20.50
12	41.35	31.40	24.20
16	46.75	36.81	29.61
20	51.45	41.52	34.32
24	61.25	52.30	45.10

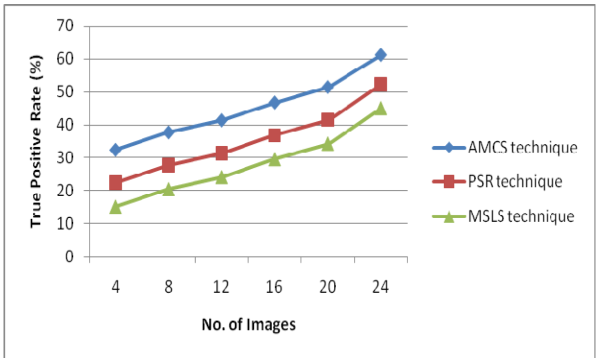

Figure-5. Measure of true positive rate.

Table-4 and Figure-6 illustrate the segmentation accuracy and it has illustrative that the segmentation accuracy is higher using the AMCS technique than the other two existing techniques. Because of the integration of two methods Contour Constrained Multiple Threshold and Dynamic Sparse Field Mechanism for different patient's brain images that efficiently segment the tumor images and therefore increases the robustness of the technique involved by 9.95 % and 10.65 % improvement when compared to the existing techniques, PSR and MSLS respectively.

Table-4. Tabulation for segmentation accuracy.

Techniques	Segmentation accuracy (%)
AMCS technique	82.35
PSR technique	74.15
MSLS technique	66.25

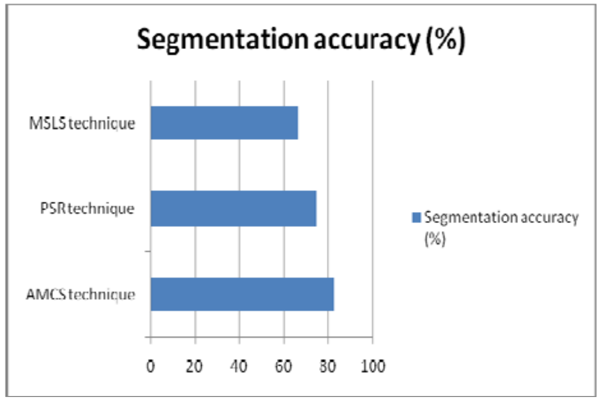

Figure-6. Measure of segmentation accuracy.

4. CONCLUSIONS

The proposed Automated Multimodal Contour Segmentation (AMCS) is adaptive because it has different scanning region points with the help of tumor volume, curvature, global and local regions. Segmentation accuracy on multimodal brain tumor images and measured the performance in terms of sensitivity, segmentation processing time, true positive rate and segmentation accuracy. The proposed AMCS technique provides higher level of precision and accuracy and also increases the robustness by consuming less processing time on multimodal brain images.

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