

Spatial Regularization and Adaptive Distance Metric Methods through DST for Tumor Segmentation



M.Jasmine, P.Satyanarayana, M.N.Giri Prasad

Abstract: The process of segmentation in MRI pictures is turning into a significant assignment to be considered in clinical oncology applications, in view of the noise and blur that is available normally in MRI images. To minimize this natural disadvantages in the MRI images an imaging tool called belief theory is taken as the base alongside the proposed evidential clustering algorithm (ECM-MS). This proposed technique joins the adaptive distance metric in so as to limit the clustering distortions and the comparability that happen between the voxels. The local homogeneity is measured by the spatial regularization dependent on the belief theory called Dempster Shafer Theory (DST). To get definite division the surface highlights are extricated from the data picture and is incorporated with the force of the voxels in the proposed strategy, thusly giving a decent presentation contrasted with different strategies.

Keywords: Dempster-Shafer theory, MRI images, spatial regularization, Adaptive distance metric, ECM-MS, voxels.

I. INTRODUCTION

To improve the radioactive therapy treatment and for diagnosis purpose the image system accuracy is very important. As the MRI acquisition system has the natural disadvantages of noise and blurs the process of segmentation of tumour volumes becomes more important in clinical applications. There are many segmentation algorithm available either automatic or semi automatic methods. The very simple method is the thresholding method because of its simplicity but very sensitive to noise. The other method is the region growing method that depends entirely on the process of initialization of segmentation and also includes the spatial context in images. The statistical method has various statistical distributions of intensities in any case, they are touchy to heterogeneous take-up of positive tissues. The chart cut technique gives preferable precision over different strategies as it depends up on the impact of the nature of the

seeds. Compared to all the methods discussed above the clustering methods are more applicable for unsupervised segmentation because of their diversity nature. The FCM [2], [8] method has more stable segmentation compared to other clustering methods. there many version of FCM came into existence including the spatial information ,here in this paper the method called Evidential c-Means (ECM) [3], is proposed considering the spatial information directly modeled through DST[4],[6], to get appropriate and further enhancement in the performance for low quality MRI images. Most of the clustering methods only intensity values that are assigned to the voxels are considered but in the proposed method the texture information [13], [14],[15], is also added with the intensity values to get accurate delineation of tumour volumes. Here the texture features extracted may have unreliable texture information also but they can be removed to improve segmentation. To obtain this an adaptive distance metric is used to remove this distortions occurring in the clusters and spatial regularization for improving local homogeneity in the clusters.

II. EXISTING METHOD

In existing method positive tissues are in homogeneous for different patients with varying shapes. The supervised method used in this existing method does not give enough output with this type of imperfect information. Thus the proposed unsupervised method[11],[12], through DST[7], [9], [10],with the MRF as the energy function and combining the adaptive distance metric will provide more accurate delineation of tumours .The remaining section of the paper is the explanation of proposed method and evaluation of 2D image along with the result analysis and conclusion..

III. PROPOSED METHOD

The size of the image is 128x128 in the proposed method .The weight of the patient is 50 and the dosage applied to the patient is 275. The standard uptake value is calculated as

$$\text{SUV (i)} = \text{weight/dose}$$

Where $i=1$: pixel value

The pixel value is taken as 128 for the input image considered. In the proposed ECM-MS [18], method the size of the image is 3x3 to extract the features of the image. By utilizing this window the SUV (max), SUV (min), scope of SUV ((max)- (min)), Avg of SUV and Std Deviation of SUV are determined as highlights for focusing the voxels.

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The Gray level size zone matrix (GLSZM) is calculated as
 $GLSZM = glszm(img, 10, 6)$

In order to extract 6 texture features from the input image. The (GLCM) Gray-level co-occurrence matrix is measured as

$$Glcms = graycomatrix(img, numlevels, 15)$$

To extract fifteen highlights from the picture. When the highlights are extricated the versatile separation metric is determined. The positive definite matrix called low transform matrix having the jaccard indexes as their elements is given as

$$Jac(1 \ 0 \ 0.5, 0 \ 1 \ 0.5, 0.5 \ 0.5 \ 1)$$

Using this matrix the dissimilarity matrix is calculated to reduce the distortions that occur in the clusters by removing the unreliable features extracted. The parameter η which controls the local homogeneity is a predefined parameter taken as $\eta > 0$ for the target tumour in the proposed method based on its size. The local homogeneity is quantified by the mass function m_1 and m_2 as the specific MRF through DST [19], [20], This specific MRF [1], [5] is the spatial regularization to reduce the local homogeneity that occurs between the selected clusters. Thus the accurate segmentation of the target tumour can be achieved by the proposed ECM-MS [16],[17], method compared to other clustering segmentation methods. For clinical reason the general parameters to be determined from fragmented picture is Dice coefficient (DSC), the Hausdorff separation (HD) and the mean supreme surface separation (MSD). These parameter including region of the tumor are determined in the proposed ECM-MS technique for breaking down the size of the tumor from the sectioned picture and for further treatment.

IV. SIMULATION RESULT

The proposed ECM-MS method is applied on the input image and the obtained output segmented image is given below with simulation result and the tabular column of the parameters calculated for the output image. Figure.1 shows the output images obtained from the proposed method and Table I shows the Results are presented as Mean ± Standard Deviation

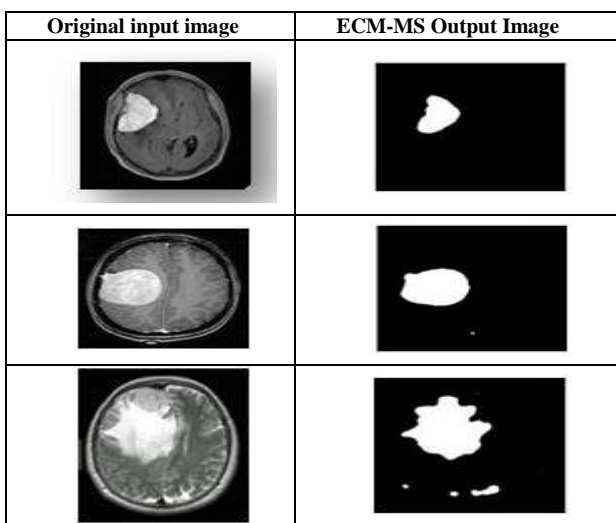


Fig. 1. Segmented image output obtained by the proposed method

Table- II: The Results are presented as Mean ± Standard Deviation

ECM-MS for 2D Brain Image	DSC	HD	MSD	AREA
Image 1	2.3029 ± 11.0164	126.7455 ± 38.3522	0.0413 ± 0.0486	6.9138
Image 2	4.6057 ± 15.2353	144.7517 ± 33.4719	0.0494 ± 0.0561	13.7725
Image 3	7.4591 ± 18.8317	144.7568 ± 43.0276	0.0498 ± 0.0565	22.3513

V. CONCLUSION

Through DST the proposed ECM-MS strategy with the blend of versatile separation metric and spatial regularization contrasted with different techniques gives quite certain division of the tumor.

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