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A Comparative Study of Region-Based Segmentation Algorithms on Brain MRI Images

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***Abstract*— Image Segmentation is the one of the principle component of image processing. In medical image processing the segmentation play an important role for classification, image analysis, and extraction of brain tumour, Different image segmentation methods are used for examination of medical images but efficient segmentation methods lead to accurate diagnosis. In this paper, we review the different segmentation algorithm on MRI Brain Images has been presented in order to obtain the accurate algorithm. The segmentation algorithms has been divided into four categories K-means, Fuzzy c means, Special constrained Fuzzy-c-means and Expectation Maximization. Efficient algorithm is obtained by computing the evaluation criteria such as Martin Criteria, Probability rand index and Variation of information**.

***Index Term:* K-means, Fuzzy c means, Special Constrained fuzzy c means and Expectation Maximization. Evaluation criteria such as martin criteria, Probability rand index and Variation of information**

I. INTRODUCTION

Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame; the output of image processing may be either an images, attributes, set of characteristics or parameters related to the image components of image processing. Medical image segmentation is a challenging task due to the various characteristics of the images which lead to the complexity of segmentation. Brain has a particularly complicated structure. Segmenting brain precisely is very important for detecting brain tumors, edema, and necrotic tissues etc. The goal of Image segmentation is to simply the representation of an original image into meaningful portions which makes it easier to analysis. The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application.

Magnetic resonance imaging (MRT) is currently a crucial diagnostic imaging technique for the early detection of abnormal changes in tissues and organs. It possesses fairly good contrast resolution for different tissues. The major advantage of MRI over computerized tomography (CT) for brain studies, is its superior contrast properties. Many image processing techniques have been proposed for brain MRI segmentation, most notably thresholding, region growing, and clustering.

The Region-based segmentation methods are powerful tools for objet detection and recognition. These methods aim at differentiating regions of interest (objects / background). Their objective is to divide the image into homogeneous zones to separate the different entities in the image. The quality of imagery and the requirement of accurate segmentation are the crucial aspect in characterizing the performance of segmentation algorithms in brain images.

Segmentation technique is related to the texture which is one of the important characteristics of an image. The purpose for based-region segmentation is to identify coherent regions of an image.

Region based segmentation methods can be grouped into two famous families such as deterministic based methods and probabilistic based classification methods. By the same way, each of these families can be subdivided into two groups. Deterministic classification family is composed of unsupervised and supervised methods. Whereas, probabilistic classification family contains parametric and non-parametric methods. In this paper, we present a comparative study of clustering based segmentation methods on synthetic and MR images are k-means, fuzzy c means, special constrained fuzzy c means and expectation maximization. k-means, fuzzy c means, special constrained fuzzy c means are come under deterministic classification they are the unsupervised clustering algorithm and Expectation Maximization come under probabilistic classification. This paper is mainly devoted to study

situations in which using different methods for the image segmentation. Its principal purpose is used four criteria and time requirement to execute the each algorithm. The performance of each technique is evaluated using the Martin's (GCE, LCE), Probabilistic Rand Index, and Variation of Information. These measures compute the consistency degree between the regions produced by two segmentations.

The remainder of the paper is organized as follows: Section 2 presents the different region-based segmentation methods used for MR image analysis. Section 3 presents the evaluation criteria. Section 4 describes the materiel and data used in this study. Experimental results on synthetic and real images are presented in section 5. Finally, a discussion concludes this paper in section 6.

II. METHODOLOGY

Given a brain MRI image, the first step enhances the image, the second step segments the brain tumor image shown in Fig1

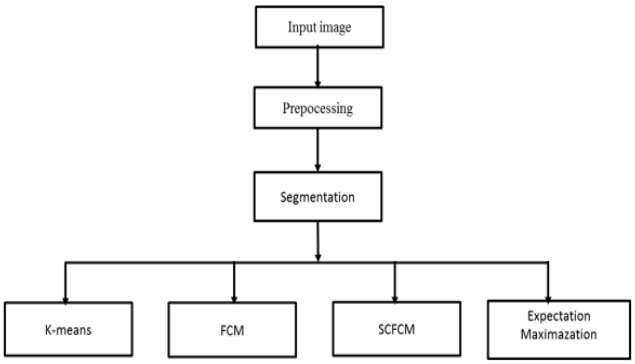

Fig1.Segmentation algorithm

A. Preprocessing Step:

Preprocessing of brain MR image is the first step in our proposed technique. Preprocessing of an image is done to reduce the noise and to enhance the brain MR image for further processing. Steps for preprocessing

- Image is converted to gray scale image.
- A 3x3 median filter is applied on brain MR image in order to remove the noise.

B. Segmentation:

After enhancing the brain MR image, the next step of our proposed technique is to segment the brain tumor MR image. Segmentation is done to separate the image foreground from its background. Segmenting an image also saves the processing time for further operations. Here considering the different Region based segmentation techniques namely

1. K-means

K-means clustering algorithm is the simplest unsupervised learning algorithm that can solve clustering problem. The procedure followed to classify a given set of data through a certain number of clusters is very simple. In K-means 'K' centres are defined, one for each cluster. These clusters must be placed far away from each other. The next step is to take a point belonging to a given data set and associate it to the nearest centre. When no point is pending, the first step is completed and early grouping is done. The second step is to recalculate 'k' new centroids as bary centre of the clusters resulting from the previous step. After having 'K' new centroids a new binding has to be done between the same data set points and the nearest new centre. A loop has been generated. As a result of this loop, the k centres change their location step by step until centres do not move any more.

Advantage of k means and disadvantage

2. Fuzzy C-means (FCM)

FCM clustering is an unsupervised method for the data analysis. This algorithm assigns membership to each data point corresponding to each cluster centre on the basis of distance between the cluster centre and the data point. Membership grades are assigned to each of the data points. These membership grades indicate the degree to which data points belong to each cluster, thus points on the edge of a cluster with lower membership grades may be in the cluster to a lesser degree than points in the center of cluster. The data point near to the cluster centre has more membership towards the particular centre. Generally, the summation of membership of each data point should be equal to one. After each iteration, the membership and cluster centres are updated accordingly. Advantage of FCM are Unsupervised and Always converges. Disadvantages are Long computational time, Sensitivity to the initial guess (speed, local minima), Sensitivity to noise One expects low (or even no) membership degree for outliers (noisy points).

3. Spatial Constrained FCM

Fuzzy C-Means algorithm with Spatial Constraint (SCFCM) is based on the clustering algorithm FCM described above, two kinds of information in image are used, the gray value, and space distributed structure. Based on the relevance of nearly pixels, the neighbors in the set should be similar in feature value. Its effectiveness contributes not only to introduction of fuzziness for belongingness of each pixel but also to exploitation of spatial contextual information. SCFCM clustering algorithm preserves the homogeneity of the regions better than existing FCM techniques, which often have difficulties when tissues have overlapping intensity. In order to reduce the noise effect during segmentation, the

proposed method incorporates both the local spatial context and the non-local information into the standard FCM cluster algorithm using a novel dissimilarity index in place of the usual metric distance. This algorithm is efficient in handling data with outlier points. In comparison with FCM algorithm it gives
very low membership for outlier points.

4. Expectation maximization (EM)
Expectation Maximization is one of the most common algorithms used for density estimation of data points in an unsupervised setting. EM algorithm iteratively fills in the missing data and updates the parameters accordingly. The resulting pixel-cluster memberships provide a segmentation of the image. Estimates the probabilities of the elements (pixels) to be in a certain class. It works iteratively by applying two steps are E-steps (expectation) and M-steps (maximization).
Each of the E and M steps is straight forward assuming the other is solved. In E steps by knowing the label of each pixel, we can estimate the parameters. M steps we can assign a label to each pixel by knowing the parameters of the distribution.
EM steps are demonstrated in the following steps are

Step1: Initialize mean and Covariance matrix using K-means.
Step2: Calculate membership probability of each training data.
Step3: Compute the mean and variance of each Gaussian component using membership function obtained in step 2.
The step 2 and 3 are repeated until convergence.

The EM algorithm has demonstrated greater sensitivity to initialization than the K-Means or FCM algorithms. A common disadvantage of EM algorithm is that the intensity distribution of brain images is modeled as a normal distribution.

III. EVALUATION CRITERIA

The goal of this study is to perform a quantitative comparison between automatic segmentation of one algorithm with respect to other algorithm. The criteria are

1. The Probabilistic Rand Index (PRI)
This criteria counting pairs of pixels that have compatible label relationships between the two segmentations to be compared. We consider two images reference and segmented respectively S1 and S2. The Rand Index can be computed as the ratio of the number of pairs of vertices or faces having the compatible label relationship in S1 and S2. Can be defined as:

$$R(S_1, S_2) = \frac{1}{(2^N)} \sum_{\substack{i,j \\ i \neq j}} [I(l_i = l_j \wedge l_i' = l_j') + I(l_i \neq l_j \wedge l_i' \neq l_j')]$$

Where I is the identity function, and the denominator is the number of possible unique pairs among N data points.

2. Martin Evaluation Criteria
Martin proposed two error measures to quantify the consistency between image segmentations of differing granularities,
The Martin error measure is sensitive to qualitatively different segmentations. A segmentation error measure takes two segmentations S1 and S2 as input, and produces a real valued output. For a given pixel pi consider the segments in S1 and S2 that contain that pixel. The segments are sets of pixels. If one segment is a proper subset of the other, then the pixel lies in area of refinement and the local error should be zero. If there is no subset relationship, then the two regions overlap in an inconsistent manner. In this case, the local error should be non-zero. If R(S, pi) is the set of pixels corresponding to the region in segmentation S which is the region that contains pixels pi, the local refinement error, E, is defined as:

$$E(S_1, S_2, p_i) = \frac{\left| R(S_1, p_i) / R(S_2, p_i) \right|}{|R(S_1, p_i)|}$$

GCE and LCE are the global consistency error, the local consistency error are defined as

$$GCE(S_1, S_2) = \frac{1}{n} \min\{ \sum_i E(S_1, S_2, p_i), \sum_i E(S_2, S_1, p_i)\}$$

$$LCE(S_1, S_2) = \frac{1}{n} \sum_i \min\{E(S_1, S_2, p_i), E(S_2, S_1, p_i)\}$$

Although these error metrics are calculated by grouping pixels into objects first, they unfortunately tolerate over-segmentation and under-segmentation, as a consequence of their intended purpose for comparing human segmentations. As LCE greater than GCE, it is clear that GCE is a tougher measure than LCE.

3. Variation of Information
The proposed metric measure is termed the variation of information (VI) and is related to the conditional entropies between the class label distributions of the segmentations. Due to the lack of spatial knowledge in the measure, the label assignments to pixels may be permuted in a combinatorial number of ways to maintain the same proportion of labels and keep the score unchanged.

IV. DATA SYNTHETIC MR IMAGE

The database is composed of three-dimensional coronal brain Magnetic Resonance Images. MRI image data sets were provided by the center of morphometric analysis at JSS general hospital, Medall diagnosis center and are also available at IBSR. For the project work 25 test T1 series images were collected from Medall diagnostic center.
The images collected were in dicom format. The images are converted to jpg using microdicom viewer.

V. RESULT

The different region based segmentation methods are applied on images and the Martin's criteria are used to evaluate the performance of each algorithm. In Fig2 shows the output of each algorithms.
The EM performs significantly better in segmentation than the FCM, K-Means, SCFCM. The GCE, LCE, and RI values of the EM method in Table1, for 25 brain images, which demonstrate the robustness of the method EM.

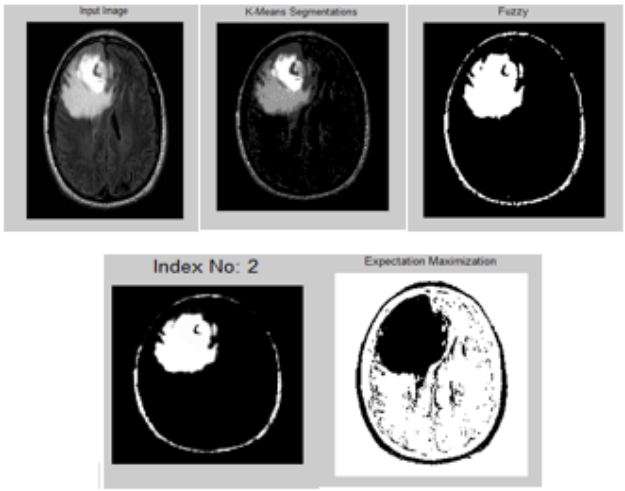

Fig2. Output of each segmentation algorithm a) input image,
b) k-means, c) FCM, d) SCFCM, e) EM

Table1. Performance Evaluation using Probabilistic rand index, global consistency error, the local consistency error and Variation of Information.

	k-means	FCM	SFCM	EM
PRI	0.667	0.534	0.782	0.878
GCE	0.041	0.169	0.042	0.087
LCE	0.041	0.169	0.092	0.126
VI	1.200	1.240	0.647	0.514
Time (s)	0.04324	0.06	0.03	0.434
STD	1.2580	1.2680	2.278	1.2652

The processing time for segmenting images is presented in Table1. We list the CPU time in segmenting images in Fig1. It can be seen from Table1 that shows the processing time for EM are higher than the other algorithms.

V I. CONCLUSION

Many image segmentation methods have been developed in the past several decades for segmenting MRI brain images, but still it remains a challenging task. A segmentation method may perform well for one MRI brain image but not for the other images of same type. Thus it is very hard to achieve a generic segmentation method that can be commonly used for all MRI brain images. In this work, we consider the merits, demerits, performance evaluation values of various segmentation techniques for brain tumour identification is analyzed in detail by the way we justify the best segmentation algorithm. Several algorithm are k-means, FCM, SCFCM and EM are computed in that we justify Expectation Maximization is the best method by considering results of performance evaluation. But the disadvantage of this algorithm is computational time is high.

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