Segmentation and Classification for Brain MRI Image Based on Modified FCM with Zernike Moment Classifier

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Abstract— *Automatic segmentation of brain tissues from MRI is of great importance for clinical application and scientific research. We propose a robust discriminative enhancement and segmentation methods from the view of information theoretic learning. Adaptive Histogram Equalization(AHE) is used to enhance the image which has a tendency to over-amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called Contrast Limited Adaptive Histogram Equalization (CLAHE) prevents this by limiting the amplification. So we use CLAHE method to improve the contrast of the image.*

Fuzzy clustering using fuzzy C-means (FCM) algorithm proved to be superior over the other clustering approaches in terms of segmentation efficiency. But the major drawback of the FCM algorithm is the huge computational time required for convergence. The effectiveness of the FCM algorithm in terms of computational rate is improved by modifying the cluster center and membership value updating criterion. In this paper, the application of modified FCM algorithm for MR brain tumor detection is explored. Experimental results show superior results for the Modified FCM algorithm in terms of the performance measures. Along with this we have used Gray Level Co-Occurrence Matrix which is used for feature extraction and a classifier called Zernike Moment Classifier is used to classify the image whether it is normal or abnormal.

IndexTerms*—discriminative segmentation, fuzzy C-means(FCM) algorithm, modifiedFCM algorithm, zernike moment classfier.*

I.INTRODUCTION

The advantages of magnetic resonance imaging (MRI) over other diagnostic imaging modalities are its high spatial resolution and exceptional discrimination of squashy tissues. MRI provides affluent information about anatomical structure, enabling quantitative pathological or clinical studies [1]; the descent of computerized anatomical atlases [2]; as well as pre and intra-operative supervision for therapeutic intervention. Such information is also important as an anatomical reference for functional modalities, such as PET, SPECT, and functional MRI [6]. Advanced applications that employ the morphologic contents of MRI frequently entail segmentation of the imaged volume into tissue types. Such tissue segmentation is frequently achieved by applying statistical classification methods to the signal intensities [8,9], in juxtaposition with morphological image processing operations.

Conventional intensity-based classification of MR images has proven problematic, however, even when advanced techniques such as non-parametric, multi-channel methods are used. Intra-scan intensity inhomogeneities due to RF coils or acquisition sequences (e.g. susceptibility artifacts in gradient echo images) are a common source of difficulty. Although MRI images may appear visually identical, such intra-scan inhomogeneities often perturb intensity-based segmentation methods.

In the ideal case, differentiation between white matter(WM), gray matter(GM) and cerebro-spinal fliud(CSF) in the brain should be simple since these tissue types reveal diverse signal intensities. In practice, spatial intensity inhomogeneities are often of ample magnitude to cause the distributions of signal intensities related with these tissue classes to overlap significantly. In addition, the operating conditions and status of the MR equipment recurrently affect the observed intensities, causing significant inter-scan intensity inhomogeneities that often necessitate manual training on a per-scan basis.

The rest of this paper is organized as follows. Section II first reviews existing method. Our proposed method is described in Section III. Then experimental results are reported in Section IV to demonstrate the superior performance of our framework. Finally, conclusions are presented in Section V.

II.EXISTING METHOD

The existing method is Intensity based Region-growing segmentation.

1. Intensity based Region-growing segmentation:
The principle of segmentation is to separate one or more regions of interest in an image from regions that do not contain appropriate information. Region growing is a easy region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the assortment of initial seed points. This approach to segmentation examines neighboring pixels of initial "seed points" and determines whether the pixel neighbors should be added to the region. The process is iterated on, in the same manner as general data clustering algorithms. The basic drawback of histogram-based region detection is that histograms offer no spatial information.

Regions that do not contain related information are called background. Depending on the image, segmentation can be a very intricate process. The underlying assumption is that pixels belonging to the features of interest occupy a diverse value range than that of background pixels.

If the assumption is further that the distribution of feature pixels and background pixels is approximately Gaussian, a characteristic intensity distribution with two peaks in the histogram emerges. Such a distribution is called bimodal because there are two mode values: one for the background and one for the feature. Intensities are normally spread around the modal values because of the additive noise and intensity inhomogeneities of the features. The simplest approach for segmentation would be the selection of a suitable intensity threshold, as indicated. All pixels with a value higher than the threshold value are classified as feature pixels, and all pixels with a lower value are classified as background pixels. Most commonly, a new image is created by using

$$I_T(X,Y) = \{ \begin{matrix} 1\ for\ I(X,Y) \geq T \\ 0\ for\ \ I(X,Y) \geq T \end{matrix}$$

In many cases, some feature pixels will have intensity values below the threshold value, and some background pixels will lie above the threshold value because of image inhomogeneities and additive noise. With pure intensity-based thresholding, these pixels cannot be classified correctly.

2. Disadvantages of Existing Algorithm

i. The region growing segmentation is not preferred for its limited range of applications and automatic features are not having accurate values.

ii. Preprocessing experiments are needed to find which type of filtering will be more beneficial. This increases the effect of the speckle noise and Gaussian noise the ultrasound, mammogram Images and MRI Images.

iii. The desired cancer area is selected from the segmented image to calculate the volume. The volume of the desired cancer area is greater than the original cancer area. The region growing algorithm will segment not only the tumor area but also the non tumor area which has high intensity ratio.

iv. This algorithm fully depends on the intensity of the image not the shape and texture. So the accuracy and sensitivity is low.

III. PROPOSED METHOD

Clustering approach is widely used in biomedical applications particularly for brain tumor detection in abnormal magnetic resonance (MRI) images. Fuzzy clustering using modified fuzzy C-means (FCM) algorithm proved to be superior over the other clustering approaches in terms of segmentation efficiency.

Features are said to be properties that describes the whole image. It can also refer as an important piece of information which is relevant for solving the computational task related to specific application. The Zernike moment classifier is proposed to classify the image into normal or abnormal.

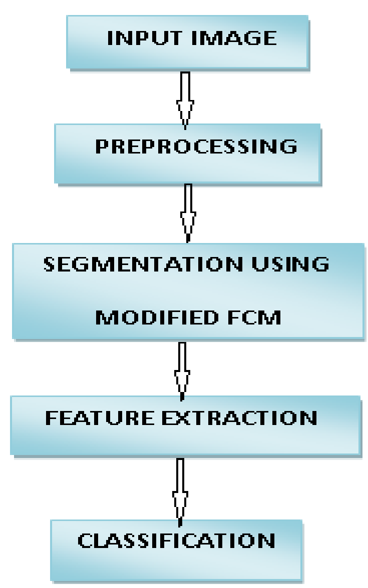


Fig.1: Block Diagram of Proposed Method

A. Pre-Processing

Pre-processing steps include geometric correction, destripping, subsetting of the images according to region of interest, noise and dimensionality reduction and finally atmospheric correction. Here for the denoising of image we used the Anisotropic Diffusion fusion Filter.

Anisotropic Diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. This can be used to remove noise from digital images without blurring edges.

After applying the filter image enhancement is done by using Contrast Limited Adaptive Histogram Equalization (CLAHE algorithm)to improve the contrast of the image so that the visibility of image will be very clear. It differs from the ordinary histogram equalization .However, AHE has a tendency to over-amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization prevents this by limiting the amplification. Histogram equalization is applied to enhance the image's contrast by transforming the intensity values of the image (the values in the color map of an indexed image), which are given by the following equation:

$$s_k = T(r_k) = \sum_{j=1}^{k} p_r\,(r_j) = \sum_{j=1}^{k} \frac{n_j}{n}$$

Where sk is the intensity value in the processed image corresponding to r_k in the input image, and $p(r$) =1, 2, 3... L is the input fingerprint image intensity level. In other words, the values in a normalized histogram approximate the probability of occurrence of each intensity level in the image.

In contrast limited histogram equalization (CLHE), the histogram is cut at some threshold and then equalization is applied. Contrast limited adaptive histogram equalization (CLAHE) is an adaptive contrast histogram equalization method [7-10], where the contrast of an image is enhanced by applying CLHE on small data regions called tiles rather than the entire image. The resulting neighboring tiles are then stitched back seamlessly using bilinear interpolation. The contrast in the homogeneous region can be limited so that noise amplification can be avoided.

B. Segmentation using Modified-FCM

The most medical images always present overlapping gray-scale intensities for different tissues. Therefore, Modified fuzzy clustering methods are particularly suitable for the segmentation of medical images. Let X={x1, x2, …, xn} denoted a set of n objects to be partitioned into C clusters, where each x_j has d features. The FCM algorithm minimizes the objective function defined as follows:

$$J = \sum_{i=1}^{C} \sum_{j=1}^{n} (u_{ij})^m \, D(x_j, v_i)$$

There are several Modified FCM clustering applications in the MRI segmentation of the brain. The Modified Fuzzy c-means (FCM) can be seen as the fuzzified version of the k-means algorithm. It is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function.

1.Advantages of Modified-FCM

A) It is good for convergence of gradients of the image pixels.

B) It is the fastest algorithm when compared to the k means algorithm and Fuzzy C Means algorithm.

C) The MFCM algorithm can have linear convergence and the speed is based on how many information is lost.

D) MFCM algorithm is applicable for RGB color space images.

E) The convergence rate of MFCM algorithm is the convergence rate of the E-step. That is to say, if the maximum value in M-step can be easily obtained, the convergence rate will be very fast to converge.

F) The exact segmentation of the tumor of MRI is possible.

C. Feature Extraction

In our paper, statistical features based on image intensity and features from gray level co-occurrence matrix are used to distinguish between normal and abnormal patient.

Angular Second Moment is high when image has very good homogeneity or when pixels are very similar

$$ASM = \sum_{i=0}^{n_g-1} \sum_{j=0}^{n_g-1} p_{ij}^2$$

Where i, j are the spatial coordinates of the function p (i, j), Ng is gray tone. The GLCM is a well-established statistical device for extracting second order texture information from images. A GLCM is a matrix where the number of rows and columns is equal to the number of distinct gray levels or pixel values in the image of that surface. GLCM is a matrix that describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation. Given an image, each with an intensity, the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section.

Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest. Typically, the co-occurrence matrix is computed based on two parameters, which are the relative distance between the pixel pair d measured in pixel number and their relative orientation. Normally, is quantized in four directions (e.g., 0º, 45 º, 90 º and 135 º), even though various other combinations could be possible.

GLCM has fourteen features but between them most useful features are: angular second moment (ASM), contrast, correlation, inverse difference moment, sum entropy and information measures of correlation. These features are thoroughly promising.

D. Classification

This proposed classification proposes an intelligent classification technique to identify normal and abnormal slices of brain MRI data. The manual interpretation of tumor slices based on visual examination by radiologist/physician may lead to missing diagnosis when a large number of MRIs are analyzed. To avoid the human error, an automated intelligent classification system is proposed which caters the need for classification of image slices after identifying abnormal MRI volume, for tumor identification. Simply the projection of the image function onto these orthogonal basis functions.

$$A_{mn} = \frac{m+1}{\pi} \iint f(x,y)[V_{mn}(x,y)]^* dxdy$$

$$where\ x^2 + y^2 \leq 1$$

An advanced kernel based techniques such as Zernike moment for the classification of volume of MRI data as normal and abnormal will be deployed. ZM's are orthogonal that they will be made easy to use for reconstructions. However, the fact that they are orthogonal is not their most important features. Any orthogonal polynomial could be used as a basis function from which easy reconstructions could be made. What makes ZM's valuable for the task of image classification is that they are rotationally invariant.

First, let's define the ZP's as V_{nm} where:

$$V_{nm}(\rho,\theta) = R_{nm} \exp(jm\theta)$$

The polynomial is split into two parts the real part, $R_{n,m}$and the complex part exp(jmθ).

The transform has the same characteristics as the moments, minimum information redundancy and robustness to image noise and invariant to rotation. It classifies the images between normal and abnormal along with type of disease depending upon features.

IV.RESULTS

To test the performance of the proposed algorithm we have taken the widely used brain MRI dataset from Internet Brain Segmentation Repository(IBSR) as the input and processed as follows. We apply Anisotropic Diffusion Filter in order to remove noise and then the contrast enhanced image is generated by applying CLAHE. Then the generated output image is segmented by using Modified Fuzzy C Means Segmentation to get the accurate segmented part in the image. Finally by applying Zernike Moment Classifier we classify the stage of the tumor.

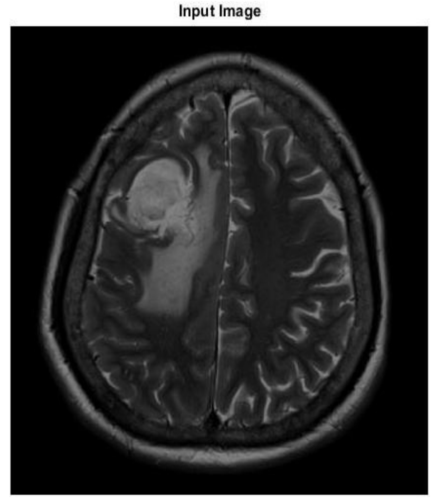


Fig1:Original image

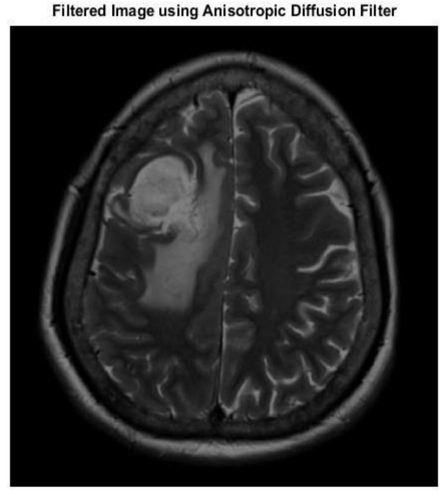


Fig2: Filtered Image using Anisotropic Diffusion Filter

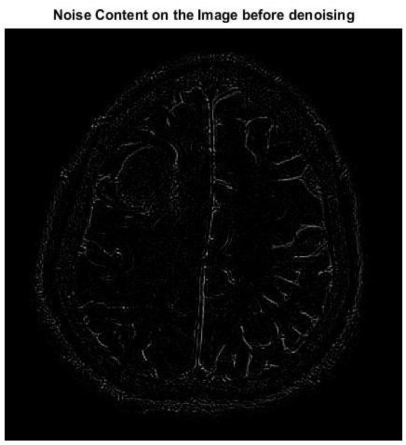


Fig3: Noise Content on the Image before Denoising

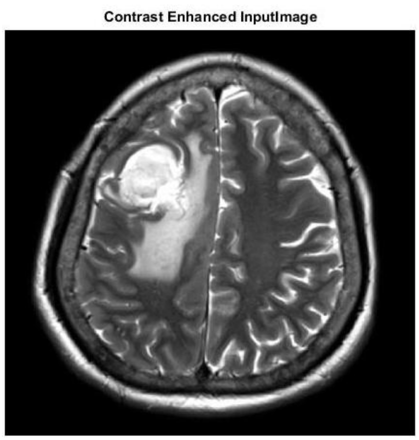


Fig4: Contrast Enhanced Input Image

Fig5:Modified Fuzzy C Means Segmentation

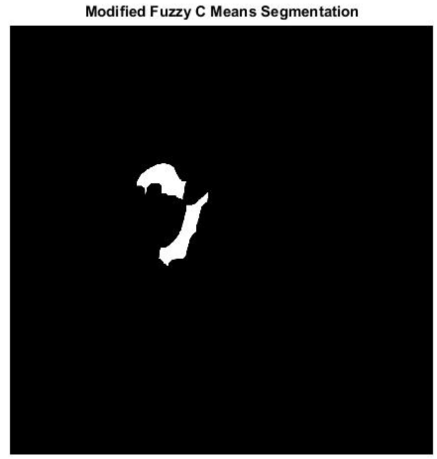
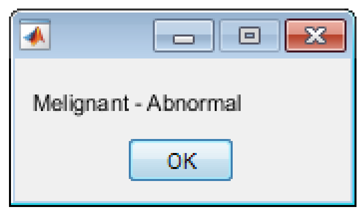
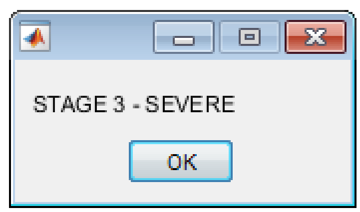


Fig6: Modified Fuzzy C Means Segmentation





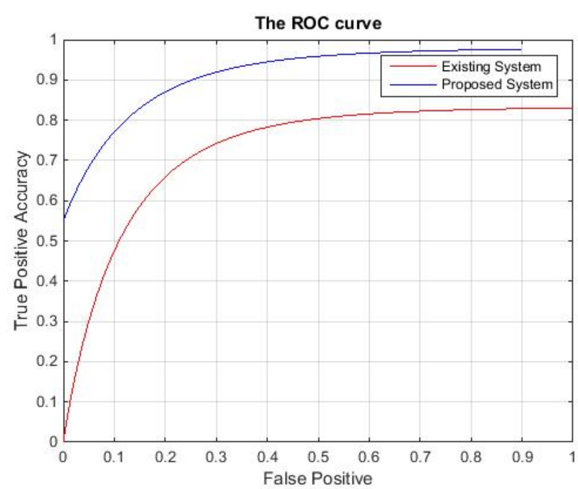


Fig7:Comparison of Existing and Proposed Method

I. Comparison Table

IBSR	Existing method	Proposed method
CSF	0.51	0.44536
GM	0.75	0.335
WM	0.78	0.355
Time(sec)	8	6

V.CONCLUSIONS

In this paper, we proposed a new technique to in the original space and then derived the alternative MFCM. Then for classification we used the Zernike moment classifier to classify the normal and abnormal conditions. This new algorithm provides the stages of tumor. The results of this paper confirmed that the methods we proposed could be used for the segmentation of medical images. The method has the advantages of calculating various parameters and reducing the time consumption. The validity of new algorithm was verified in the process of exacting details of images. . In the future research, some better GUI design could be implemented and some new technique could also be offered.

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