

Automated brain tumor segmentation and classification for MRI analysis system

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ABSTRACT

This paper proposed a new analysis technique of brain tumor segmentation and classification for Fluid Attenuated Inversion Recovery (FLAIR) Magnetic Resonance Images (MRI). 25 FLAIR MRI images were collected from online database of Multimodal Brain Tumor Segmentation Challenge 2015 (BRaTS'15). The analysis comprised four stages which are preprocessing, segmentation, feature extraction and classification. Fuzzy C-Means (FCM) was proposed for brain tumor segmentation. Mean, median, mode, standard deviation, area and perimeter were calculated and utilized as the features to be fed into a rule-based classifier. The segmentation performances were assessed based on Jaccard, Dice, False Positive and False Negative Rates (FPR and FNR). The results indicate that FCM offered high similarity indices which were 0.74 and 0.83 for Jaccard and Dice indices, respectively. The technique can possibly provide high accuracy and has the potential to detect and classify brain tumor from FLAIR MRI database.

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1. INTRODUCTION

Brain tumor is one of the main leading diseases which causes human death. It has become the second most important cause of death related to children and young adults [1]. Central Brain Tumor Registry of the United States (CBTRUS) reported 64,530 cases of primary brain and central nervous system tumors at the end of 2011 [1]. This brain tumor is known as a mass that is formed by the accumulation of abnormal cells [2] that grow out of control. Magnetic Resonance Imaging (MRI) is primarily applied in clinical practice in scanning and examining brain tumor. Various types of modalities use MRI to diagnose the brain tumor. The function of these modalities is to produce high level of contrast for the brain image. Furthermore, it also enhances the image quality and data gained. Fluid Attenuated Inversion Recovery (FLAIR) is the modality used for brain tumor examination. It provides better visualization in edema and tumor as it can detect contrastive elements and enhance the effect of the particularly high contrast between background tissue [3].

Although MRI is widely used for diagnosis of the brain tumor, the MRI image also provides large variance and very complex information to the size, location and the intensity of the brain tumor [1]. Due to that, the process of analyzing brain tumor is very difficult. It can only be performed by professional radiologists for the examination, analyses and final conclusion. It is time consuming and may leads to errors.

Computer aided diagnosis (CAD) can be used as a second opinion that helps radiologists to detect any suspicious lesion in the brain scan imaging. Radiologists can finally find the conclusion based on the findings. Manual segmentation is very tedious and takes longer time [4]. Segmentation software such as ITK-SNAP, 3D-Slicer and MRIcron is commonly used to help radiologist in extracting the ROI of the brain image [5-7]. These soft wares which also known as semi-automatic segmentation help the experts to analyze and evaluate the brain images [8]. Although semi-automatic segmentation techniques can give faster result, but it also comes into being different results from different experts or the same user at different times [9]. Therefore, automated segmentation integrated with the sophisticated graphical user interface (GUI) is helpful to delineate the tumor lesion.

Abdel-maksoud et al. (2015) stated that image segmentation is considered as the most essential and crucial process for facilitating the delineation, characterization, and visualization of ROI in any medical image [10]. A hybrid clustering technique was proposed by the researchers using k-Means and FCM algorithm using T1, T2 and proton density images. The objective of doing hybridization is to reduce the number of iterations resulted with less execution time. Thresholding and level set method were integrated to provide an accurate brain tumor detection. The results show that the k-Means obtained 92.49% and FCM obtain 95.23% accuracy.

Telrandhe et al (2016) proposed k-Means clustering and Support Vector Machine (SVM) for classification of brain tumor from benign and malignant using MRI images [11]. The image was preprocessed with median filter, morphological operation and wavelet transform before segmentation of the brain tumor using k-Means clustering. Histogram Oriented Gradient (HOG) was applied to extract the ROI as the classifier input of SVM. The percentage accuracy obtained from the proposed technique is 80%. Kiranmayee et al. (2017) proposed an effective analysis for MRI brain tumor using hybrid data mining techniques [12]. In the proposed approach, segmentation and classification techniques were applied using Nearest Neighbor with Generalization (NNge), Best-First Decision Tree (BFTree), LADTree, and Random Forest classifiers. These techniques were able to classify the type of abnormal and normal region include tumor region from the brain dataset. The accuracy for NNge, BFTree, decision tree, LADtree and Random Forest is 96.3%, 66.7%, 66.7%, 85.2% and 96.3%, respectively.

Havaei et al. (2016) proposed Convolutional Neural Network (CNN) that was able to segment 75 patients with brain tumor using T1, T2 and FLAIR images [13]. The results gain from the proposed CNN technique were able to distinguish the boundaries between tumor sub-class and improve the Dice index on all tumor regions. However, the drawback of this technique is it consumed high processing time. Therefore, high performance GPU was mandatory. Based on the proposed technique, the dice coefficient, sensitivity and specificity obtain is 0.84, 0.88 and 0.84, respectively.

El-Melegy et al. (2018) proposed an automatic brain tumor segmentation from machine learning classifier including Random Forest, Linear Discriminant Analysis (LDA) and SVM using MRI modality from T1, T2 and FLAIR images [14]. The researcher segments the whole tumor, tumor core and active core by involving the processing, feature extraction training and classification stage. The proposed technique shows that the Dice score obtained was in the range 0.8 with the highest score is from the Random Forest Classifier with 0.89. Batra and Kaushik (2017) proposed an automatic segmentation and classification technique to detect the Gliomas in the MRI brain tumor [15]. The segmentation technique proposed involved the FCM technique and the classification technique involve the SVM technique. The MRI brain tumor was segmented and the lesion was categorized into two types which are malignant and benign. SVM classifier was chosen to classify the tumor. Based on the proposed technique, the results for the automatic segmentation and classification were 98.18%, 97.5% and 100% for the accuracy, sensitivity and specificity, respectively.

Gurusamy (2017) proposed MRI brain tumor classification using four types of machine learning classifiers which were analyzed using Neural Network, k-NN, Naïve Bayes and SVM [17]. The segmentation technique proposed was the k-Means clustering technique. The results obtained for the Neural Network, k-NN, Naïve Bayes and SVM was 97, 96,93.7 and 98, respectively. Gupta and Khanna (2019) developed a fast and efficient CAD system to detect tumor from brain MRI data [16]. Block based segmentation was applied to segment tumorous region. Then, mean, homogeneity, contrast, directionality and moments were extracted to be fed into classification stage. The extracted features were then classified as tumor or non-tumor using thresholding of block wise matching. Accuracy and precision values obtained through the experiments were 97.93 % and 97.76 % respectively.

Fuzzy C-Means (FCM) segmentation have been proposed by many researchers for wide variety of applications [18]. It has the ability in retaining more information from the original image compared to other segmentation methods [19]. FCM is an unsupervised machine learning technique by clustering that does not rely on various sorts of clusters but rely upon the predefined classes and training cases while arranging the data objects [20]. It specifies membership function from the data point that belongs to every cluster.

This study proposes an automatic segmentation method that detects and diagnoses brain tumor lesions using FLAIR images. The analysis began by collecting the images of brain lesion from Multimodal Brain Tumor Segmentation Challenge 2015 (BRaTS'15) online database followed by preprocessing of the images. The proposed framework of analysis was based on the FCM segmentation technique. The results were evaluated using Jaccard, Dice, False Positive and False Negative Rates (FPR and FNR). The accuracy of the automatic segmentation method was evaluated according to the feature extraction and classification method to classify between brain tumor and normal brain.

2. RESEARCH METHODOLOGY

2.1. Proposed Analysis Framework

As depicted in Figure 1, the analysis framework began by collecting FLAIR MRI images of brain tumor lesion using online database provided in [21]-[23], followed by preprocessing stage. Segmentation technique was obtained to accurately delineate the region of interest (ROI) of the brain tumor lesion. Then, features extraction and classification were applied and the performance of the proposed technique was evaluated.

2.2. Imaging Parameter

FLAIR MRI images were gained from the Multimodal Brain Tumor Segmentation Challenge by Multimodal BRaTS'15 database online [21]. These data comprised MRI modality with MHA format in 16 bits and were converted into Neuroimaging Informatics Technology Initiative (NIFTI) format using ITK-SNAP software. The format of the dataset was then changed to Digital Imaging and Communications in Medicine (DICOM) format using (X) MedCon applications. The dataset was encoded in 8-bit DICOM to standardize each image for the proposed segmentation method. The parameter of the dataset was 240 x 240 of pixel resolution with 25 slices of each patient. Each dataset was provided with reference image to compare with the proposed segmentation method of the ROI for brain tumor lesion.

2.3. Preprocessing

The preprocessing stage was performed to improve the brain tumor images. Normalization intensity was applied to normalize the pixel intensity value. The actual MRI image that contained 16-bit depth pixel intensity was normalized and was down-sampling into 8-bit depth pixel intensity value to standardize the input image with the MRI dataset. The image normalization with its histogram is as shown in Figure 2.

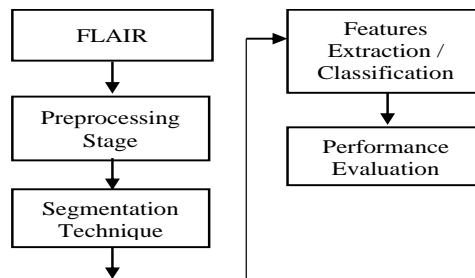


Figure 1. Flowchart of the Analysis

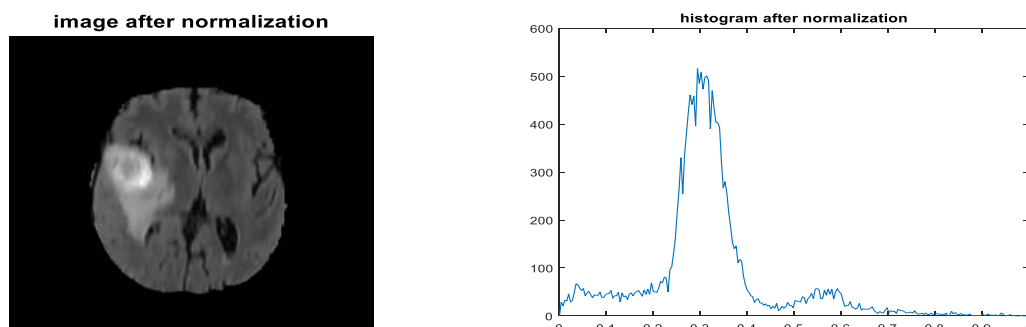


Figure 2. Image after normalization with its histogram

2.4. Segmentation

FCM was the clustering method performed by grouping or portioning the information pattern with respect to the desired information pattern group [24]. Each data point in the data clustering belonged to the degree of certain cluster by a membership value. FCM method consisted of n vectors collection which was classified through the fuzzy group of c to find the cluster center in every group. The fuzzy portioning was applied to a data point given in the membership values which could specify the values between zero and from the cluster degree of belonging. The summarized step of FCM framework is as follows [25]:

- Step 1: Select the image after the preprocessing process
- Step 2: Convert the image format to double to enhance the range of the pixel
- Step 3: Identify the number of the iteration
- Step 4: Obtain the size of the image
- Step 5: Repeat the structure by calculating the possible distance
- Step 6: Calculate the possible distance by repeating the matrix for generating the large item
- Step 7: Identify large component of data of the pixel by starting the iteration
- Step 8: Stop the iteration if the possible identification elapses
- Step 9: Segmentation is generated

The membership matrix U is initialized with intensity cluster values from 0 to 1. The algorithm is based on the minimization of the objective function, as shown in (1) [25].

$$J_m = \sum_{i=1}^N \sum_{j=1}^c u_{ij}^m \|x_i - c_j\|^2, 1 \leq m < \infty \quad (1)$$

where:

m = real number ≥ 1 ,

u_{ij} = membership degree of x_i in the cluster j ,

$x_i = i$ of d -dimensional measured data,

c_j = d -dimension center of the cluster,

$\|*\|$ = any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning of the objective function was carried out through an iterative optimization shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}, c_j = \frac{\sum_{i=1}^N u_{ij}^m x_i}{\sum_{i=1}^N u_{ij}^m} \quad (2)$$

When $\max_{ij} \{|u_{ij}^{(k+1)} - u_{ij}^{(k)}|\} < \varepsilon$, the iteration will stop, where ε is the termination criterion between 0 and 1, and k is the iteration steps.

This procedure converged to a local minimum or a saddle point of J_m . The algorithm of the following steps is described below:

1. $U = [u_{ij}]$ matrix, $u^{(0)}$ is initialized with the random values between zero and one.
2. Calculate the cluster of center, using (3).

$$c_j = \frac{\sum_{i=1}^N u_{ij}^m x_i}{\sum_{i=1}^N u_{ij}^m} \quad (3)$$

3. $U^{(k)}, U^{(k+1)}$ is updated.
4. Calculate the table of the fuzzy membership function, using (4).

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (4)$$

5. Stop when $\|U^{(k+1)} - U^{(k)}\| < \varepsilon$; otherwise return to step 2.

The binary image and threshold level were obtained from FCM method by the matlab command *fcmtree* for FCM. The change for the cut-off position was 0 until 1 to indicate the cut between the small and middle classes and the middle and large classes.

2.5. Feature Extraction

Feature extraction was applied to represent the characteristics of the ROI which were obtained from the segmentation results using statistical data. The statistical data were calculated using the formulas of mean, median, mode, standard deviation, area and perimeter of the ROI. Each value of the statistical data was to determine the location, shape and other elements in the lesions [26].

$$\mu = \frac{1}{N} \sum_{i=1}^{N-1} P(i) \tag{5}$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N-1} (P(i) - \mu)^2} \tag{6}$$

$$Median = \frac{1}{2}(n + 1)value \tag{7}$$

$$Perimeter = Length (boundary) \tag{8}$$

$$Compactness = \frac{Perimeter^2}{Area} \tag{9}$$

3. RESULTS AND ANALYSIS

3.1. Segmentation Results

Table 1 shows the results of brain tumor with FCM segmentation compared with the manual reference image given in the dataset. The obtained segment is compared with the extracted manual segment in terms of its similarity and the tumor area. As presented in Table 1, the obtained FCM segmentation results have been quite satisfactory. However, due to the existence of noise, FCM does not consider the spatial information which makes it sensitive to the noise. The table portrays the FLAIR, manual reference and FCM results for tumor segmentation.

Table 1. The Segmentation Results of the Brain Tumor Lesions

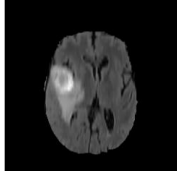

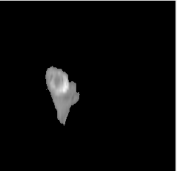
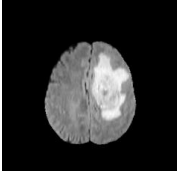
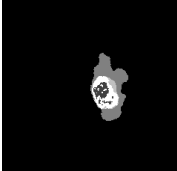
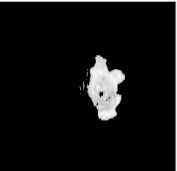
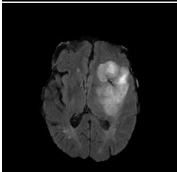
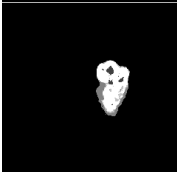
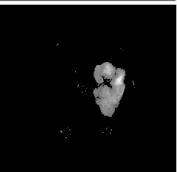
FLAIR	Manual Reference	FCM Result
		
		
		

Figure 3 shows the performance results of Jaccard index for the brain tumor lesions. Only patient 10 showed samples of Jaccard index below 0.5 with the index of 0.43. The highest index of the Jaccard index was in patient 5 with the reading of 0.93. Figure 4 shows the results of the Dice index. All of the patients obtained Dice index above 0.5 with the lowest value of 0.6 in patient 10. The highest sample of the Dice index was 0.96 in patient 5. Figure 5 shows the result of the FPR performance, that measures the index of oversegmentation error. Only patient 10 failed to obtain error rate below 0.5 with the value of 0.56. The lowest error was obtained in patient 4, 13, 14, 17 and 20 with the FPR reading of 0. Figure 6 shows the readings of the FNR performance for undersegmentation error. All of the patient samples obtained

best results which were below 0.5 with the highest reading at 0.41 and the lowest reading at 0.001 from patient 10.

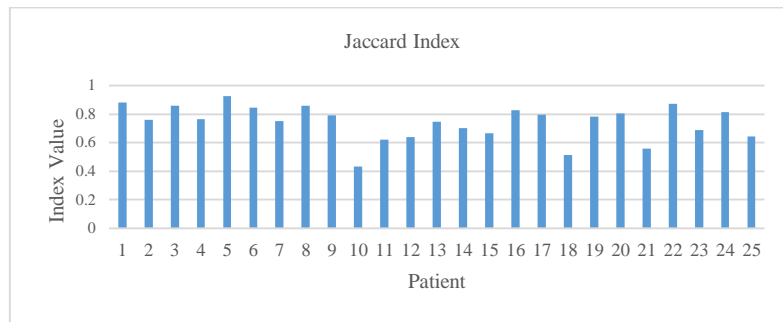


Figure 3. Jaccard Index Results for FCM Segmentation

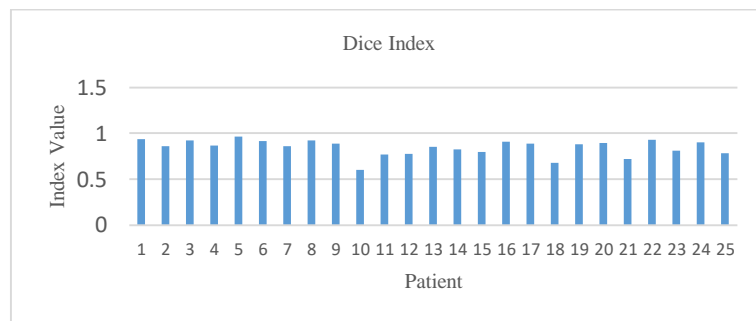


Figure 4. Dice Index Results for FCM Segmentation

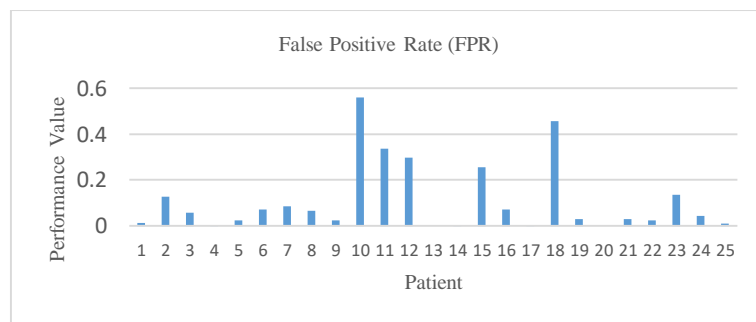


Figure 5. FPR Results for FCM Segmentation

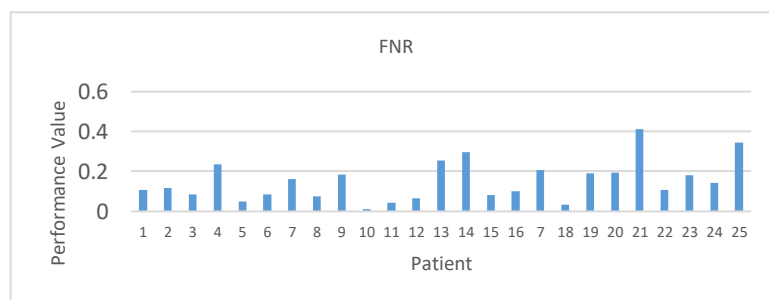


Figure 6. FNR Results for FCM Segmentation

3.2. Feature Extraction and Classification Results

Table 2 shows the feature extraction using mean, compactness, median and boundary, explained in Section 2. For each feature, minimum and maximum values corresponding to all features were identified for tumor and normal images. The range obtained for each feature produced a threshold value respective to it. The classification of the brain is tumor if the feature values lie in the threshold range of brain tumor MRI, else the MRI is normal.

Table 2. The Feature Extracted from the Brain Area

Symbol	Brain Tumor		Normal Brain	
	Min	Max	Min	Max
Range				
Mean	0.34	0.87	0.12	0.39
Compactness	13	433	14.5	18.9
Median	0.33	0.95	0.13	0.56
Boundary	0.2	0.75	0.09	0.37

The accuracy of the brain tumor segmentation was 96% over 25 samples of image. This is due to the Patient 25 has obtained below than 0.5 in the mean value. Supposedly the ROI brain tumor lesions must provide higher intensity value while normal brain must provide lower intensity value.

4. CONCLUSION

In this study, the FCM segmentation method is implemented for the segmentation of brain tumor using FLAIR images. The segmentation technique with the manual reference from the same database is compared to verify the accuracy. The results for the Jaccard index, Dice index, FPR and FNR are 0.74, 0.83, 0.11 and 0.14, respectively. Based on these results, FCM gives better segmentation result for the brain tumor based on the high values of Jaccard index and Dice index and low values of FPR and FNR. The segmentation method proposed can segment the brain tumor lesions in 25 samples of patients and it is also suitable for the analysis and classification.

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