Efficient Fuzzy Clustering Based Approach to Brain Tumor Segmentation on MR Images

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Abstract. Image segmentation is one of the most vital and significant step in medical applications. The conventional fuzzy c-means (FCM) clustering is the most widely used unsupervised clustering method for brain tumor segmentation on magnetic resonance (MR) images. However, the major limitation of the conventional FCM is its huge computational time and it is sensitive to initial cluster centers. In this paper, we present a novel efficient FCM algorithm to eliminate the drawback of conventional FCM. The proposed algorithm is formulated by incorporating distribution of the gray level information in the image and a new objective function which ensures better stability and compactness of clusters. Experiments are conducted on brain MR images to investigate the effectiveness of the proposed method in segmenting brain tumor. The conventional FCM and the proposed method are compared to explore the efficiency and accuracy of the proposed method.

Keywords: Segmentation, Magnetic resonance image, Fuzzy c-means clustering, Brain tumor, Efficiency.

1 Introduction

Brain tumor is one of the major causes of death among adults and children [1]. Magnetic resonance imaging is the commonly used method for brain imaging. It gives the cross sectional images of the brain in several slices by using magnetic field and radiofrequency waves [2]. Image segmentation techniques can aid the radiologist in tumor volume analysis, surgical planning and in knowing the severity of the cancer. The unsupervised FCM clustering is the most extensively used method for segmenting brain tumor on MR images. The main characteristic of FCM clustering is to allow pixels to belong to multiple classes with certain degree. This can effectively process MR images where uncertainty, limited resolution and noise are present. But the conventional FCM algorithm consumes lot of time to partition the image into desired number of clusters and is sensitive to initial cluster centres values leading to local minima results [3]. There exist several improvements to conventional FCM in the literature. Kannan [4] improves the segmentation efficiency of the FCM algorithm by silhouette method based on cluster center initialization instead of random initialization. The FCM algorithm has been also improved using parallel processing [5]. Even though it provides high speed processing, the hardware implementation is

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not effective. Weiling et al [6] presents generalized framework for FCM clustering which guarantees robustness to noise and preserves edge details. Mohammed et al. [7] improved FCM clustering by eliminating those points with membership value smaller than a threshold value. The choice of appropriate threshold was not automatic but based on experiments. Rogerio et al. [8] reduced the number of iterations of FCM algorithm required for convergence by presenting a new equation to calculate cluster centres. Though the method could reduce total iterations, there was not much improvement in the efficiency of the algorithm. Bin et al. [9] presents improved model to FCM algorithm using membership smoothing constraint. The algorithm uses the spatial information of image and improves accuracy of segmentation. But the main drawback is that it computes neighbourhood term in each iteration, which is very time consuming. Snehashis et al. [10] proposed semi automatic fuzzy clustering method to classify tissues in brain MRI by incorporating the compactness term into traditional FCM. Most of the methods in the literature attempt to speed up the fuzzy clustering process but not concentrating on the compactness and well separation of clusters. Computed aided diagnosis in medicine expects the algorithms to be automatic, efficient and accurate to provide the better diagnosis of diseases [11][12]. Accordingly this paper proposes a novel efficient FCM based approach to brain tumor segmentation which partitions the image into well separated clusters and gives global optimal solutions.

3 Proposed Methodology

The proposed approach provides efficient segmentation of brain tumor on MR images by using wavelet and modified FCM clustering. In the first step, image is decomposed by applying wavelet transform and in the next step modified FCM algorithm is applied to segment the approximate image in the highest wavelet level. Operating on a low resolution image helps in reducing the computational complexity of the process and in restraining noise. Then the low resolution segmented image is projected on to the full resolution image by inverse wavelet transform.

3.1 Wavelet Decomposition

The discrete wavelet transform (DWT) is a linear transformation which operates on a data vector transforming it into numerically different vector of same length. DWT can be expressed as [13]:

$$DWT_{x(n)} = \begin{cases} d_{j,k} = \sum x(n) h_j * (n - 2jk), \\ a_{j,k} = \sum x(n) g_j * (n - 2jk). \end{cases} \tag{1}$$

The coefficient $d_{j,k}$ refer to the detail components in signal $x(n)$, where as $a_{j,k}$ refer to the approximation components in the signal. The functions $h(n)$ and $g(n)$ represent the coefficients of high-pass and low-pass filters respectively. The parameters j and k refer to the wavelet scale and translation factors. By using wavelets, the given image can be analysed at various levels with resolution matched to its scale [14].

3.2 Modified FCM

In traditional FCM clustering, time of segmenting the image is dependent on the image size. Hence, it takes more time to converge [15]. The proposed modified FCM considers image gray levels (*g)* instead of pixel intensities as number of gray levels is less than number of pixels in the image. This leads to improved complexity of *O(gcI).* Accordingly, the new cluster centres and membership function are calculated as:

$$u_{ig} = \frac{\left(g - v_i\right)^{-\frac{2}{m-1}}}{\sum_{j=1}^{c} \left(g - v_i\right)^{-\frac{2}{m-1}}}. \tag{2}$$

$$c_i = \frac{\sum_{g=0}^{L-1} h(g) u_{ig}^{m} g}{\sum_{g=0}^{L-1} h(g) u_{ig}^{m}}. \tag{3}$$

Where L is the maximum gray level in the image and $h(g)$ is the probability that the pixels have gray level g. The clustering should partition the given data into desired number of clusters such that the distance between the data points and the cluster centre should be minimized within the cluster and also the distance between the clusters should be maximized. Accordingly the objective function is defined as:

$$J = \sum_{i=1}^{c} \sum_{g=1}^{L-1} u_{ij}^{m} h(g) \left\| g - v_i \right\|^2 - \frac{1}{c(c-1)} \sum_{i=1}^{c} \sum_{k=1}^{c} \left\| v_i - v_k \right\|^2 . \tag{4}$$

The modified FCM algorithm effectively reduces the computation time and also ensures compact and well separated clusters.

4 Experimental Results

The proposed method is simulated using MATLAB. All the experiments were simulated on a personal computer with 1.5MHz Pentium processor and 2GB of memory running under Windows XP operating system.. The effectiveness of the proposed method was tested by experimenting on several MR images of the brain tumor. The MR images used in this study were acquired from Shirdi Sai Cancer Hospital, Maniapal. Each image was digitized to 512×512 size with each pixel representing 0.624mm×0.624mm of the actual size. All the images were in gray color with intensity ranging from 0 to 255. Fig.1 shows the original MR image of brain.

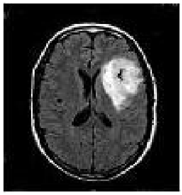

Fig. 1. Original MR brain image

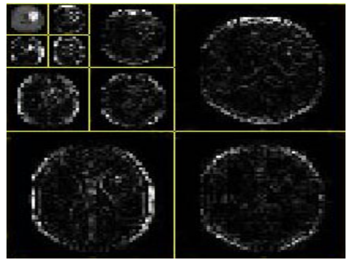

Fig. 2. Wavelet decomposition

Fig.2 shows the brain MR image decomposition using discrete wavelet transform. After creating the pyramid representation of the image by wavelet transform, the wavelet decomposed LL sub band image at the third level is segmented through application of modified FCM clustering algorithm on the image. The brain image is partitioned into four clusters such as white matter, gray matter, cerebrospinal fluid and fourth cluster represents brain tumor and skull region as shown in Fig.3, Fig.4, Fig.5 and Fig.6 respectively.

Fig. 3. White matter

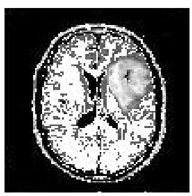

Fig. 4. Gray matter

Fig. 5. Cerebrospinal fluid

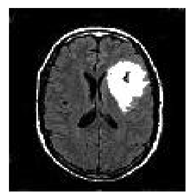

Fig. 6. Tumor and skull

During the initial stages of the experiments, the FCM produced considerably varied results on each run. Due to this finding, we used 10^{-7} as the minimal amount of improvement for the experiments. It was found that the performance of FCM improved and always achieved stable clustering results. As shown in Fig.6 tumor and skull are in same cluster. Thus skull is removed from the image by applying morphological operators on the binary image in Fig.7. The result of morphological processing is shown in Fig.8 and the boundary of the segmented tumor is marked on the original image by using 4-connected neighbours as shown in Fig.9.

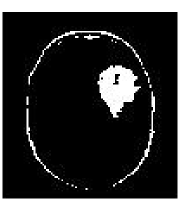

Fig.7. Tumor cluster in binary

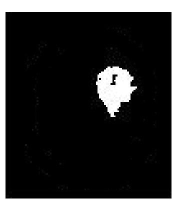

Fig.8. Morphology processing

Fig.9. Segmented brain tumor

To validate the clustering and test its quality, we have used Davies-Bouldin index and Xie-Beni index [16] which are defined in (5) and (6) respectively.

$$DB = \frac{1}{c}\sum \max_{i \neq l}\left\{\frac{d_w(v_i)+d_w(v_l)}{d_b(v_i,v_l)}\right\}. \tag{5}$$

$$XB = \frac{\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{2}\left\|v_i - x_k\right\|^{2}}{N\min_{i,k}\left\|v_i - v_k\right\|^{2}} . \tag{6}$$

Where d_w indicates within cluster distance and d_b indicated between cluster distance.The valid clustering procedure should make DB and XB value as low as possible. Table.1 presents the comparative analysis of conventional FCM and the proposed modified FCM based on execution time and cluster validity indexes.

Table 1. Performance comparision of fuzzy clustering algorithms

Method	DB index	XB index	Execution time (sec)
FCM	0.6513	0.46	1.320
Modified FCM	0.6301	0.41	0.521

5 Conclusion

The proposed method overcomes the drawback of conventional fuzzy clustering algorithm by improving its efficiency. The wavelet transform gives the low resolution images for analysis in the subsequent stages. The modified FCM has a good efficiency and also gives compact and well separated clusters by introducing a new objective function. The proposed method effectively segments the brain tumor from magnetic resonance images and thus can play a vital role in computer aided diagnosis of brain tumors enabling the radiologists to provide more accurate and faster diagnosis.

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