

Brain MR Image Segmentation using Enriched FCM

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Abstract— Medical image segmentation has been an area of interest to researchers for quite a long time. Segmentation of brain MRI is very complex. Standard Fuzzy C Means (FCM) algorithm has been widely used for brain image segmentation. But this standard FCM doesn't take into account the spatial information. An improved version of standard FCM is presented which takes into account information about neighboring pixels also. This new method has many advantages both in terms of computational efficiency and computational time.

Index Terms— Image processing, Medical imaging, Brain image, Segmentation, FCM, Enriched FCM, Spatial FCM, Validity functions.

1 INTRODUCTION

THE delineation of anatomical structures is a main parameter in assisting and automating radiological tasks. These algorithms are called image segmentation algorithms [1]. Image segmentation is defined as partitioning of an image into non overlapping constituent regions which are homogeneous with respect to some features. Methods for performing image segmentation vary widely depending on specific applications, imaging modalities and other factors. Image segmentation is very important in medical image processing with variety of applications such as detection and measuring tumor volume, detection of micro calcifications in mammograms, studying brain development, detection of stones in gall bladder etc..

Segmentation of magnetic resonance image (MRI) of brain is very complex. Many neurological conditions alter the shape, volume and distribution of brain tissue. The basic goal of segmentation is to divide the whole image into sub regions such as cerebrospinal fluid, white matter, gray matter and background and thereby detect the presence of tumor if present. The intensity values of cerebrospinal fluid (CSF) and background is almost same. MR images of brain show superb tissue contrast which makes segmentation easier. MR images are of two types T1 weighted or T2 weighted which basically differ in the order of contrast given to different regions [2]. Many clustering algorithms have been used for segmentation. In hard clustering a feature vector is assigned to one and only one cluster whereas fuzzy clustering allows each feature vector to belong to more than one cluster. Fuzzy clustering is an unsupervised clustering method and the most popular fuzzy clustering technique is fuzzy c means (FCM). Since FCM allow partial membership in different tissue classes, it can be used to model partial volume averaging artifacts. Even though stand-

ard FCM algorithm work very efficiently on normal brains, it's not that efficient on abnormal brains with tumor. FCM take care of only the pixel intensities but doesn't take care of the neighboring pixel intensities. The pixels on an image are highly correlated which means pixels in the neighborhood possess nearly the same feature data.

The MR images always contain significant amount of noise. In standard FCM a noisy pixel may be wrongly classified [10]. This can be avoided by considering spatial information of the pixels. The proposed methods differ from standard FCM in the way membership function is calculated. The membership function is evaluated by considering the cluster distribution of the neighborhood pixels. Thus segmentation is based on not only by pixel intensities but also by considering the neighborhood pixel's intensities.

2 METHOD

The method used here is a modified form of standard FCM. This method tries to eliminate the drawbacks of the standard FCM by taking into account the spatial properties also.

2.1 Fuzzy C Means Clustering

The Standard FCM algorithm was introduced by Dunn and later improved by Bezdek [14]. Here the numbers of clusters have to be known a priori. In brain MRI the number of clusters is generally taken as three: White matter, Gray matter and Cerebrospinal fluid. The FCM algorithm assigns pixel to each of the clusters by using fuzzy membership functions. The algorithm is an iterative optimization that minimizes the objective function defined as.

$$J = \sum_{j=1}^N \sum_{i=1}^c u_{ij}^m \|x_j - v_i\|^2 \quad (1)$$

Where u_{ij} represent the membership of pixel x_j in the i th cluster, v_i is the i th cluster center. m is a constant which gives the degree of fuzziness.

The cost function will be minimized when pixels close to the

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centroid of their clusters are assigned high membership values and low membership values are assigned to pixels far away from centroid [3]. The membership function gives the probability that a pixel belongs to a cluster. In FCM this probability is solely dependent on the distance between the pixel and the cluster center. The membership function and cluster centroids are updated as follows

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^{2/m-1}} \quad (2)$$

$$v_i = \frac{\sum_{j=1}^N u_{ij}^m x_j}{\sum_{j=1}^N u_{ij}^m} \quad (3)$$

The cluster center is taken randomly initially. Then new membership function and cluster centroid is evaluated iteratively until it converges to a threshold minimum. The drawback of standard FCM is that it doesn't take into consideration the neighboring pixels and their intensities. Moreover standard FCM is more sensitive to noise. And in abnormal brains pixels may be wrongly classified [8].

2.2 Spatial FCM

Spatial FCM make use of the property of correlation of image pixels. In an image the neighbouring pixels are highly correlated that it possesses similar feature values [4]. To incorporate this spatial information a new function is defined as

$$P_{ij} = \sum_{k \in N(x_j)} u_{ik} \quad (4)$$

A new membership function is defined by incorporating the spatial function as

$$u_{ij}^* = \frac{u_{ij}^s P_{ij}^t}{\sum_{k=1}^c u_{ij}^s P_{ij}^t} \quad (5)$$

The algorithm can be summarized as follows:

1. Set value of c, m and threshold ξ .
2. Randomly set cluster centers.
3. Evaluate membership function.
4. Evaluate the spatial function.
5. Evaluate modified membership function.
6. Evaluate cluster center.
7. if $|v_{new} - v_{old}| < \xi$
8. Terminate else go to step (3)

2.3 Validity functions

The efficiency of clustering can be evaluated using two cluster validity functions- fuzzy partition coefficient V_{pc} and partition entropy V_{pe} . The partition with less fuzziness indicates good performance [4]. Supreme clustering is achieved when value of V_{pc} is maximum and V_{pe} is minimum. The validity functions are defined as below.

$$V_{pc} = \frac{\sum_j^N \sum_i^c u_{ij}^2}{N} \quad (6)$$

$$V_{pe} = \frac{\sum_j^N \sum_i^c u_{ij} \log u_{ij}}{N} \quad (7)$$

3 EXPERIMENTAL RESULTS

The experiments were carried on T1 and T2 weighted brain MR images. Noise added images were also considered. The images were divided into three clusters: White matter, gray matter and cerebrospinal fluid. The degree of fuzziness m was taken as 2 and the threshold value ξ as 0.01. Simulation was done using python. Clustering results for these images using

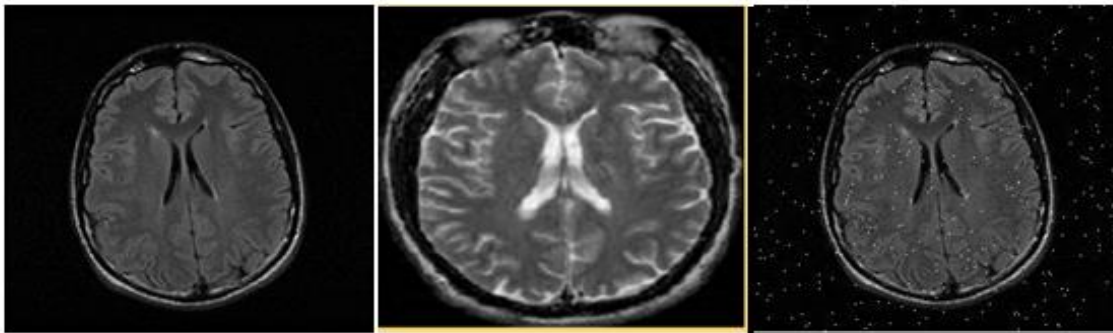


Fig 1: Image data (a) T1 weighted image (b) T2 weighted image (c) noise added image

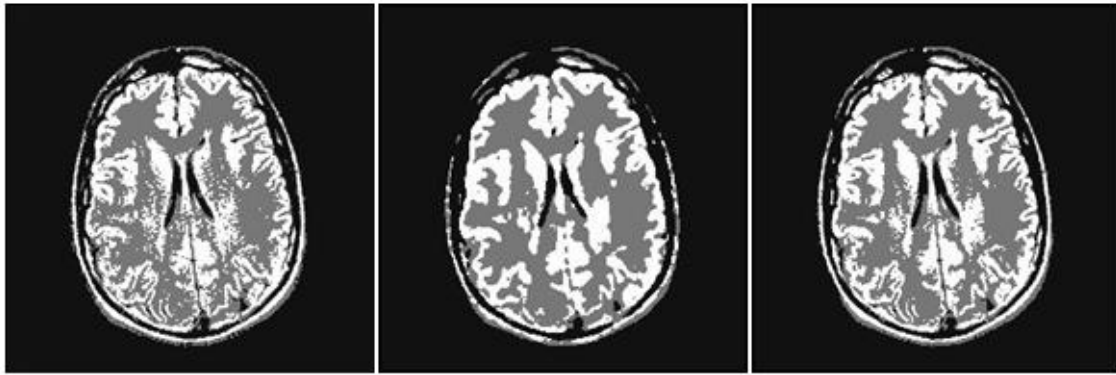


Fig 2: Segmented images of T1 weighted (a) FCM (b)sFCM₀₁ (c)sFCM₁₁

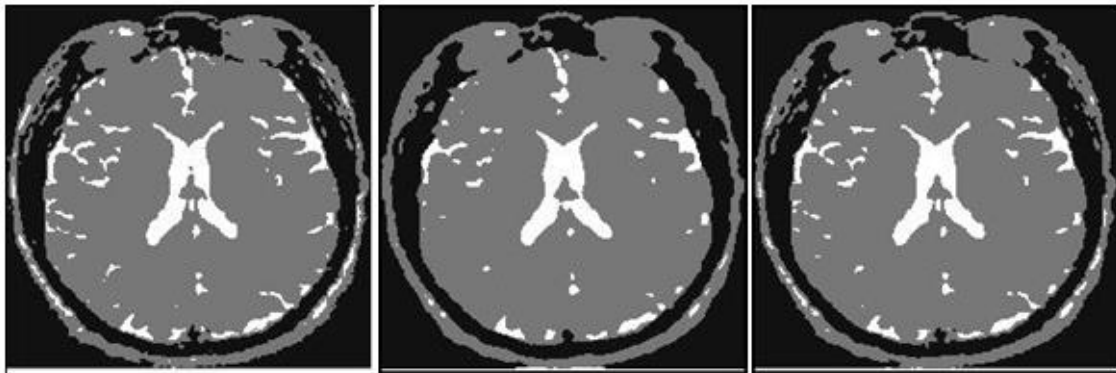


Fig 3: Segmented images of T2 weighted (a) FCM (b) sFCM01 (c) sFCM11

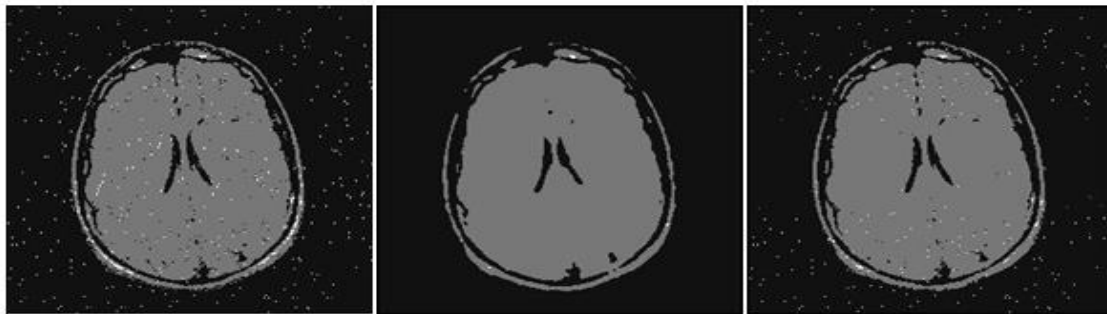


Fig 4: Segmented images of noise added image (a) FCM (b) sFCM01 (c) sFCM11

standard FCM was taken. The parameters s and t was varied to establish the effect of spatial function in clustering. Figure 1(a) shows the T1 weighted image, (b) the T2 weighted image and (c) and (d) shows the T1 and T2 weighted images added up with noise. Figure 2, 3 and 4 shows the segmentation results of the above said images using standard FCM and spatial FCM with different values of s and t such as $(s=0, t=1)$, $(s=0, t=2)$ and $(s=1, t=1)$ respectively. If $(s=1$ and $t=0)$ it is equivalent to standard FCM. Figure 2-4 shows the segmented results of the images in fig 1 using FCM and spatial FCM.

4 RESULT ANALYSIS

From the segmented results it is very clear that spatial FCM works much better than the standard FCM. As the effect of ' t ' is increased clustering become much smoother. But if t is increased much higher it may lead to blurring of higher details. The segmented images are more homogeneous is spatial FCM. The performance of clustering is analyzed by evaluating the clustering validity functions.

Higher value of V_{pc} indicates better clustering. From the table that follows it is clear that V_{pc} is maximum when $s=t=1$, which means better clustering is achieved in spatial FCM. Also in spatial FCM V_{pe} is minimum which again indicates good clustering.

Table1: Validity functions for various clustering methods

Images	Method	V_{pc}	V_{pe}
T1 weighted	FCM	0.165	0.110
	sFCM ₀₁	0.863	0.069
	sFCM ₁₁	0.900	0.046
T2 weighted	FCM	0.463	0.157
	sFCM ₀₁	0.779	0.142
	sFCM ₁₁	0.891	0.048
Noise added	FCM	0.583	0.118
	sFCM ₀₁	0.863	0.069
	sFCM ₁₁	0.921	0.031

5 CONCLUSION

Fuzzy C means has been widely used as a clustering algorithm for medical image analysis for over many years. Even though FCM works well for normal brains, it proved less efficient for segmented abnormal brains containing tumor, lesions etc. The enriched spatial FCM works very efficiently on abnormal brains also. Here instead of considering the pixel intensities alone, the neighbouring pixel intensities are also taken as feature. It incorporates the spatial information into the membership function to improve the segmentation results. This helps in eliminating noisy pixels and spurious blobs. The method was tested on brain MR images and the performance was evaluated using various validity functions.

ACKNOWLEDGMENT

Our thanks to the experts who have contributed towards development of this paper. Special thanks are due to the Professors of College of Engineering, Trivandrum.

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