

Segmentation of Brain MR Images Using Fuzzy Clustering Method with Silhouette Method

¹T. Bala Ganesan and ²R. Sukanesh

¹Department of Information Technology, Sree Sowdambiga College of Engineering,
Aruppukottai, Tamil Nadu, India

²Department of Electronics and Communication Engineering,
Thiyagarajar College of Engineering, Madurai, Tamilnadu, India

Abstract: Segmentation of images is the key step in image analysis. This study deals with Brain Magnetic Resonance Image segmentation. Any medical image of human being consists of distinct regions. These regions could be represented by Wavelet Coefficients. Classification of these features may be performed using Fuzzy Clustering Method (FCM-Fuzzy C-Means Algorithm). Edge detection technique is used to detect the edges of the given images. Silhouette method is used to find the strength of clusters. Finally, the different regions of the images are demarcated and color coded.

Key words: Wavelet coefficients, fuzzy C means algorithm, edge detection technique

INTRODUCTION

Digital image processing refers to processing of 2 dimensional picture by a digital computer (Struyf *et al.*, 1997). Various problems encountered in image processing are Image representation and modeling. Image Enhancement, Image restoration, Image Analysis, Image reconstruction and Image data compression. Segmentation is one of the most important part in image analysis. Segmentation refers to the process of extracting the desired object (or objects) of interest in an image. This paper deals with Segmentation of medical images. Medical image segmentation is a key step in medical image analysis. Segmentation of medical imagery is a challenging task due to the complexity of the images, as well as to the absence of the models of the anatomy that fully capture the possible deformations in each structure. Presently, the medical images are viewed by respective experts in the field of radiology to diagnose the nature of the image for abnormalities if any. In this proposed study, an attempt is made to segment the medical images, in particular MR images of the Brain. Brain tissue is a particularly complex structure and its segmentation is an important step for derivation of computerized anatomical atlases, as well as pre and intra-operative guidance for therapeutic intervention. Medical Image analysis is usually performed manually (Jovan *et al.*, 2003) by trained radiologists.

One Important task facing radiologists is the delineation of the contour of anatomical structure, also called segmentation. The roles of segmentation include: quantification of tissue volume, diagnosis, localization of pathology, study of anatomical structure, treatment planning and Computer integrated surgery. Before segmentation of brain tissue, non-brain material must be identified or removed from the image before the brain as a whole can be measured and its external features identified. This will result in demarcating the normal portion of the Brain from any unwanted growth or blood clot inside the Brain. The different regions of the brain may suitably be color-coded so that the diagnosis after segmentation becomes easier and accurate.

MATERIALS AND METHODS

Segmentation of medical images is vital for diagnosis. Any medical image of human being (ex. MRI, X-ray, CT Scan) consists of distinct regions. These regions could be represented by wavelet co-efficient. Classification of these features may be performed using Fuzzy Clustering Method (FCM-Fuzzy C Means Algorithm) (Timothy, 1997). Sobel edge detection technique is used to detect the edges of the given images.

The resultant MRI is converted into data matrices (Haralick, 1980) and entries of data matrices have rearranged in term of appropriate clusters and then the

new separated elements of group of matrix (same matrix, same dimensions but the elements have been grouped with their nearest clusters) has introduced. After getting the matrix with elements has been grouped with their nearest clusters, the silhouette method has introduced to analyze the strength of the groups of matrix that whether the groups have been classified properly or not. To do this, some threshold value introduced with the use of silhouette. The silhouette threshold can change the number of cluster, in case the earlier groups of matrix have not classified properly.

After over the above process the new image has been introduced. The results compared between the previous image and new image which is classified with the use of above methods by visually. Finally, the different regions of the images are color coded.

In the proposed method input image is divided into small blocks. The block size is in the order of powers of 2 (2×2 , 4×4 , 8×8 etc.). These blocks are given as input to the feature extraction.

Features are extracted by wavelet transform, because it does not have the ring problem and its energy compaction is very high. After applying wavelet transform (Raghuveer and Bopardikar, 2000) to the individual blocks, the wavelet coefficients are obtained as haar wavelets because it is very simple and it has high energy compaction property and compression ratio.

After applying haar wavelet transform to that blocks, approximation and detailed co-efficient are obtained. Approximation coefficients contain the most of energy (information) in an image. These coefficients are arranged row-wise. Detailed coefficients contain the horizontal, vertical and diagonal details of the image. There are 2 basic approaches for clustering, which we call supervised and unsupervised. In the case of unsupervised classification or clustering, we do not have labels. If we know the labels of our input data, the problem is considered supervised, or otherwise it is called unsupervised.

Clustering (<http://www2.es.uregina.ca/hamilton/courses/831/notes/clustering/cluster.html>) is a grouping of data with similar characteristics. To divide the data into several groups similarity of objects are used, here the distance functions are being used to find the similarity of 2 objects in the data set. This approximation coefficient matrix from the previous step is given as the input to the fuzzy classification.

Fuzzy C-Means (FCM) was chosen to classify the different object in an image because of its good to very good performance in diverse applications. FCM starts

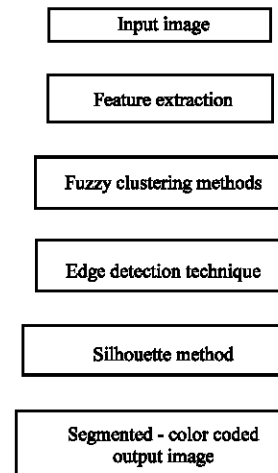


Fig. 1: Block diagram of the proposed work

with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster (Syoji *et al.*, 2001). The initial guess for these centers is mostly likely incorrect. Additionally, FCM assigns every data point a membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point. FCM iteratively moves the cluster centers to the right location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade (Fig. 1).

FCM ALGORITHM (Masulli *et al.*, 1998)

Step 1: Fix the number of Clusters (cl). The value of the 'cl' is ≥ 2 ($2 \leq cl \leq n$).

Step 2: Each iteration in this algorithm will be labeled as r , where $r = 0, 1, 2, 3, \dots, 100$.

Step 3: Choose the stopping criteria (ϵ), where $\epsilon = 0.01$.

Step 4: Randomly initialize the partition matrix U^r . Here, partition matrix U^r depends upon the number of clusters and approximation coefficients.

Step 5: Cluster centers are represented by the variable ' V^r '. Here, V^r is a 2 dimensional matrix. So, the number of cluster is assigned to the number of rows in this matrix and the number of columns in approximation coefficients is assigned to the columns in this matrix.

$$v_{ij} = \frac{\sum_{k=1}^n (u_{ik})^2 x_{kj}}{\sum_{k=1}^n (u_{ik})^2} \quad (1)$$

Step 6: We compute the distances (d_{ik}) from the sample x_{kj} to the center v_{ij} .

$$d_{ik} = \left[\sum_{k=1}^n (x_{kj} - v_{ij})^2 \right]^{1/2} \quad (2)$$

Here, i varies from 1 to cl

Step 7: With the distance measures, we can now update partition matrix U^{r+1} using the Eq. 3:

$$U_{ik}^{r+1} = \left[\sum_{j=1}^{cl} (d_{ik}^r / d_{jk}^r)^2 \right]^{-1} \quad (3)$$

Step 8: To determine the maximum absolute value of pair wise comparisons of each of the values in U^r and U^{r+1} . If $|U^{r+1} - U^r| \leq \square$ then stop otherwise set $r = r + 1$ and return to step 5.

FCM algorithm gives the following outputs:

- Center value of each cluster
- Final fuzzy partition matrix (membership function matrix)
- Values of the objective function during iterations

Membership function matrix can be used to classify the different objects in an image. It can be used to reconstruct the output image also.

In this work, sobel edge detection technique is used to detect edges of the output image (Haralick, 1980).

The Sobel operator Ganesan and Bhattacharya (1995) is more sensitive to diagonal edges than vertical and horizontal edges. The Sobel 3×3 templates are normally given as:

$$\begin{aligned} \text{X-Direction} & \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \\ \text{Y-Direction} & \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 2 & 1 \end{bmatrix} \end{aligned}$$

Silhouette method Jovan *et al.* (2003) is used to find the strength of clusters, not only clusters, even

it gives result in visually the quality if clustering for every object. Using the confirmation the appropriate number of clusters identified in the data set. For each object, we denote by the cluster to which it belongs and compute:

$$a(i) = \frac{1}{|A|} - 1 \sum_{j \in A, j \neq i} d(i, j) \quad (4)$$

where, $a(i)$ is a average dissimilarity of i to all other objects of A and A is a cluster.

Now consider a second cluster C different from A and put:

$$d(i, C) = \frac{1}{|C|} \sum_{j \in C} d(i, j) \quad (5)$$

$d(i, C)$ = average dissimilarity of i to all objects of C , clusters $C \neq A$.

After computing $d(i, C)$ for all C , we take the smallest of those.

$$b(i) = \min_{C \neq A} d(i, C) \quad (6)$$

The cluster B , which attains this minimum (that is, $d(i, B) = b(i)$) is called the neighbor of object i . this is the 2nd-best cluster for object i .

The silhouette value $s(i)$ of the object is defined as

$$s(i) = (b(i) - a(i)) / \max(a(i), b(i)) \quad (7)$$

Clearly $s(i)$ always lies between -1 and 1. The value $s(i)$ may be interpreted as follows:

s (i) equivalence 1: Object i is well classified in A .

s (i) equivalence 0: Object i lies intermediate between 2 clusters (B and A).

s (i) equivalence-1: Object i is badly classified (closer to B than to A).

The average of all $s(I)$ is called average Silhouette Width (SW) and it uses to justify the total number of clusters. The overall of average SW is called silhouette coefficient of cluster k (No. clusters). If the SW value is exceeded 0.50 then the structure in data found correctly or otherwise structure is weak. Finally the output is properly color coded. Display of different object in an output image and its histogram is in Fig. 2.

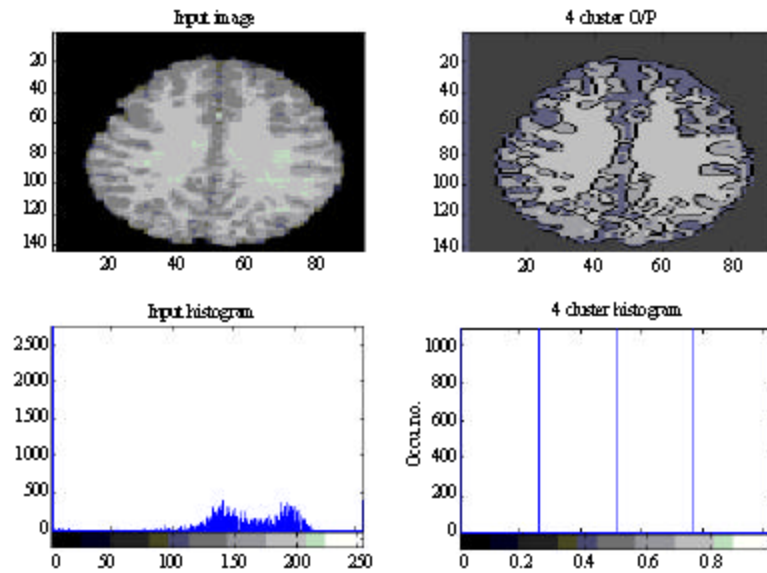


Fig. 2: Result of different object in an output image

RESULTS AND DISCUSSION

In this research, segmentation of Magnetic Resonance images has been performed with wavelets coefficients as features and FCM as the classifier and strength of the cluster is found by Silhouette Width. Various experiments were performed on different Magnetic Resonance Images by using the haar wavelets. This scheme has its capability to identify distinct regions which are supposed to be abnormal (or) unwanted growth in MR image.

This research also brings together FCM, Silhouette width, Raw data, MR images and program to convert data matrices from MRI and MR images from the data matrices.

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