A Parallel Fuzzy C Means Algorithm for Brain Tumor Segmentation on Multiple MRI Images

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Abstract. The Fuzzy C Means (FCM) algorithm has been extensively used in medical image segmentation. But for large data sets the convergence of the FCM algorithm is time consuming and also requires considerable amount of memory. In some real time applications, like Content Based Medical Image Retrieval (CBIR) systems, there is a need to segment a large volume of brain MRI images offline. In this paper, we present an efficient method to cluster data points of all the images at once. The gray level histogram is used in the FCM algorithm to minimize the time for segmentation and the space required. A parallel approach is then applied to further reduce the computation time. The proposed method is found to be almost twice as fast as conventional FCM.

1 Introduction

In the field of medical diagnosis a variety of imaging techniques is presently available, such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). MRI provides good contrast between the different soft tissues of the body, which makes it especially useful in imaging the brain. Image Segmentation is a process of partitioning an image into non-overlapped, consistent regions which are homogeneous with respect to some properties such as intensity, color and texture [1]. It is a vital step in analysis of medical images for computer aided diagnosis. The main objective of image segmentation in brain MRI images is to isolate a brain tumor from other regions of the brain.

In certain real time applications that support computer aided diagnosis like the CBIR systems, there is a need to process and analyze a large number of medical images. The processing of each image is time consuming owing to the large size of the image itself. Thus processing of large volumes of data must be done offline. In this paper we present a parallel histogram based fuzzy c means approach to efficiently cluster data points of all the MRI images together at once and segment the images to obtain the tumors.

2 Related Work

The computation of conventional FCM algorithm for the iterative operation is time consuming for large data sets and has a high amount of memory requirement for the

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membership matrix. Modifications to overcome the drawbacks of FCM have been proposed by researchers.

Moh'd Belal Al-Zoubi et al. [2] have proposed a fast fuzzy clustering algorithm that is based on eliminating data points with a membership value lower than a threshold value. The choice of the threshold value is based on experimentations; hence the algorithm is not very efficient. Ming-Chuan Hung and Don-Lin Yang [3] have proposed a faster FCM algorithm that uses a two phase approach. Though this approach reduces computation time, additional memory is required for k-d tree and storing additional information like statistical information of the patterns in each block. S.R. Kannan et al. [4] have proposed a center knowledge method in order to reduce the running time of proposed algorithm. But the drawback here is the memory required for the distance table that is dependent on the size of the image.

The algorithm proposed by Ye Xiu Qing et al. [5] uses the gray level histogram in the FCM algorithm to minimize the time for segmentation and the space required for the membership matrix. The algorithms proposed by Weiling Cai et al. [6] and S. Zulaikha Beevi and M. Mohamed Sathik [1], speed up the conventional FCM and significantly reduce the execution time by clustering on grey level histogram rather than on pixels. The proposed methodologies are found to be efficient and robust to noise. The histogram based approach is also adopted by He Yangming and Dai Shuguang [8] and achieves great speed up. The method proposed by Arpit Srivastava et al. [9] uses a membership suppression mechanism which creates competition among clusters to speed up the clustering process. The drawback here is that the execution time depends on the size of the dataset. S. Rahimi et al. [7] and S. Murugavalli and V. Rajamani [8] have proposed parallel FCM based approaches for image segmentation. The parallel algorithms proposed divide all the image pixels equally among the processors so that each processor handles n/p data points (n is the number of pixels and p is the number of processors involved in the computation). Thus, the processing time reduces significantly.

In this paper we adopt the histogram based approach [5], thus reducing the data points to the number of gray levels in the image instead of the number of pixels. The histogram of all images is computed and the membership matrix is initialized based on all the histograms. Thus, the FCM has to be applied only once to cluster all the images. In this paper we also modify the parallel approach [7] by assigning each cluster to different processors. Each processor computes its cluster center and updates the membership matrix after each iterative operation in the FCM algorithm.

3 Proposed Methodology

3.1 Conventional FCM

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. It is based on minimization of the following objective function:

$$J(U,C)=\sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^m \| x_i - c_j \|^2 \tag{1}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data and c_j is the d-dimension center of the cluster. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above. This iteration will stop when $\max_{ij} \left\{ | u_{ij}^{(k+1)} - u_{ij}^{(k)} | \right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k are the iteration steps.

Steps:

1. Initialize $U = [u_{ij}]$ matrix, $U^{(0)}$
2. At k-step calculate the centers vectors $C^{(k)} = [c_{ij}]$ with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{2}$$

3. Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|}\right)^{\frac{2}{m-1}}} \tag{3}$$

4. If $\| U^{k+1)} - U^{(k)} \| < \varepsilon$, then STOP; otherwise return to Step 2.

The convergence of the conventional FCM algorithm is time consuming which makes it impractical for image segmentation.

3.2 Histogram Based FCM

A single gray level histogram comprising of multiple brain MRI images is computed. This histogram is used in the FCM algorithm, which enhances the speed of segmentation and at the same time reduces the space required for the membership matrix. The objective function is given by

$$J(U,C)=\sum_{l=1}^{L}\sum_{i=1}^{v}(u_{il})^m H(l) d^2(l,c_i) \tag{4}$$

where, H is the histogram of all images comprising of L gray levels. The computation of membership degrees of $H(l)$ pixels is minimized to that of only one pixel with l as grey level value.

The membership function u_{ij} and center c_i for histogram based FCM can be calculated as

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{\frac{2}{m-1}}} \tag{5}$$

$$c_j = \frac{\sum_{l=1}^{L} u_{il}{}^{m} .H(l)l}{\sum_{i=1}^{L} u_{il}{}^{m}} \tag{6}$$

where l is the gray level ranging from 0 to 255.

3.3 Proposed Parallel Histogram Based Approach to FCM

The proposed algorithm computes the histogram H of multiple MRI images that need to be segmented. The performance of Histogram Based FCM can be further enhanced by distributing computation and main memory usage. Thus, each cluster is assigned to a different processor. Each processor corresponding to a cluster computes its center and updates the corresponding row of the membership matrix in each iteration of the modified FCM algorithm.

In this paper, the brain is segmented into 4 clusters. Each processor p_j corresponds to a cluster c_j where j is between 1 and 4. The initiating processor P assigns each cluster c_j corresponding to a row r_j of the membership matrix U is assigned to each processor p_j. Each processor p_j computes the center of its cluster as follows:

$$c_j = \frac{\sum_{l=1}^{L} u_{il}{}^{m} .H(l)l}{\sum_{i=1}^{L} u_{il}{}^{m}} \tag{7}$$

Each processor p_j sends the computed centers back to the initiating processor P. The processor P then reassigns each row r_j of the membership matrix to processor p_j and sends the centers vector to each processor p_j. Each processor p_j updates row r_j of the membership matrix U.

$$u_{jl} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_j - c_l \|}{\| x_j - c_k \|} \right)^{\frac{2}{m-1}}} \tag{8}$$

where j corresponds to the cluster or processor, l ranges from 0 to 255.

Proposed Methodology to Cluster Multiple Brain MRI Images

Step 1: Input Multiple Brain MRI Images
Step 2: Compute a single Histogram H of all the MRI images
Step 3: Initialize the membership matrix $U = [u_{jl}]$
Step 4: Initiating processor P assigns each cluster c_j to processor p_j
Step 5: Each processor p_j computes the center of its cluster
Step 6: Each processor sends the computed center c_j back to the initiating processor P
Step 7: Initiating processor P sends the center vector c to each processor p_j
Step 8: Each processor updates the row r_j of the membership matrix corresponding to its cluster c_j
Step 9: Each processor p_j sends the computed row r_j back to the initiating processor P
Step 10: If $\| U^{k+1)} - U^{(k)} \| < \varepsilon$ then, go to Step 4
Step 11: Output the Segmented Results

3.4 Extracting Tumor from Segmented Cluster

The cluster with the largest center value is chosen. All the points i.e. gray level values belonging to this cluster are stored in array C. Each brain MRI from the large set of MRI images is considered. The pixel values of points with gray value equal to gray values contained in array C to 255. Then perform opening and closing operations on the image using a disc as structural element. Check if blobs are present in the image. If the quality of the image is poor then the tumor may not be present in the cluster. Thus, the modified FCM algorithm must be applied again on the image if blobs are not present. If blobs are present then find the largest blob and set the pixel values of other blobs to zero. Fig. 2 shows results for extraction of tumors.

Steps of the Proposed Methodology to Cluster Multiple Brain MRI Images

Step 1: Input Multiple Brain MRI Images
Step 2: Set the pixel values of points with gray value equal to gray values con -tained in array C to 255
Step 3: Initialize the membership matrix $U = [u_{jl}]$
Step 4: Perform opening and closing operations on the image using a disc as structural element
Step 5: If blobs are present then, find largest blob
Else, Apply Modified FCM on the Input Brain MRI and go to Step 2
Step 6: Set the pixel values of other blobs to zero
Step 7: Output the Extracted Tumor

4 Results and Discussion

The proposed algorithm is found to be of reduced space and time complexity as compared to the conventional FCM.

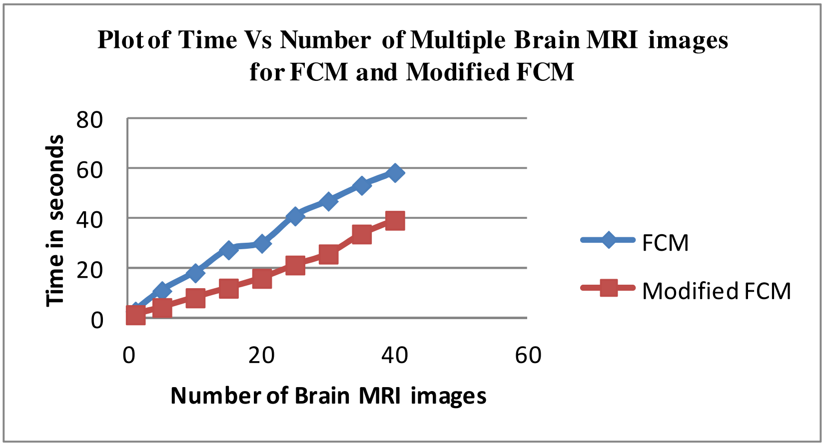

Fig. 1. Plot of Time Vs Number of Multiple Brain MRI images for FCM and Modified FCM

The proposed approach segments the brain MRI images into 4 clusters and uses 4 processors. The time required to cluster multiple MRI images is computed for the conventional FCM as well as the proposed parallel histogram based FCM and the results are compared. Fig. 1 shows the time taken to cluster the data set containing varied number of images.

The asymptotic efficiency of FCM and Modified FCM Algorithms are shown in Table 1.

Table 1. Space and Time Complexity of Clustering

Algorithm	Space Complexity (one image)	Space Complexity (n images)	Time Complexity (one image)	Time Complexity (n images)
FCM Modified FCM	O(dc) Cq	O(ndc) Cq	O(dc^2i) O(qci)	O(ndc^2i) O(nqci) Ω(qci)

The asymptotic efficiency of the algorithm has following notations:

i number FCM over entire dataset
d number of data points
c number of clusters
q number of grey levels

The tumors from these clustered images are then extracted and separated from other parts of the brain using the method elucidated in the proposed methodology. The Modified FCM is applied to a sample of 3 brain MRI images. The output in Figure 2 shows the removal of brain portion from the cluster containing tumor.

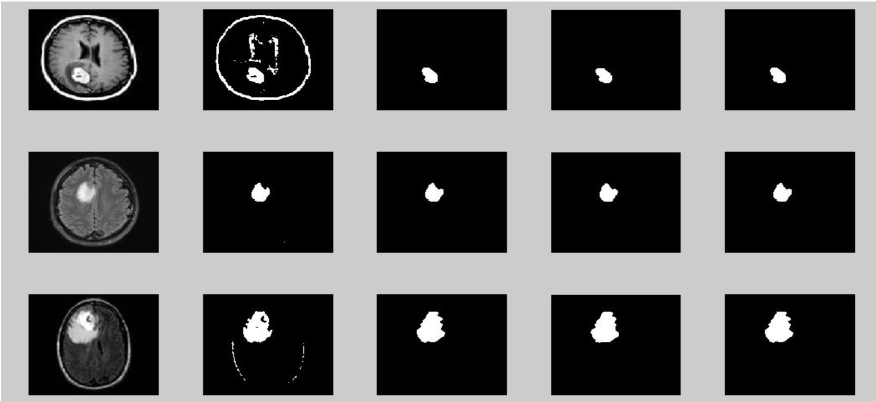

Fig. 2. Extraction of tumor from segmented cluster

5 Conclusion

The proposed parallel algorithm is found to be almost twice as fast as the conventional algorithm in spite of the overheads associated with parallelism. Large volumes of brain MRI images can be efficiently segmented at once using the proposed method. The proposed algorithm is independent of the size of the images to be segmented. Hence, it achieves a significant improvement over other parallel approaches which depend on the size of the image. The use of histogram based FCM in our algorithm reduces the space complexity significantly.

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