Genetic Approach on Medical Image Segmentation by Generalized Spatial Fuzzy C- Means Algorithm

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Abstract - **Medical Image segmentation is an important tool in viewing and analyzing magnetic resonance (MR) images and solving a wide range of problems in medical imaging. The Fuzzy C means clustering algorithm performs well in the absence of noise as well as it considers only the pixel attributes and not its neighbors. This leads to accuracy degradation in the image segmentation process. This can be addressed by using Generalized spatial Fuzzy C-means clustering algorithm (GSFCM), which utilizes both given pixel attributes and the spatial local information. This algorithm corresponds to the weights of the neighbor elements based on their distance attributes. Though GSFCM gives good output, the main drawback behind this method is the inability of generating global minima for the objective function. To improve the efficiency of this clustering algorithm, this paper proposes the genetic algorithm (GA) based GSFCM algorithm called GAGSFCM. By using GAGSFCM, the global minima of the clustering objective function can be reached. Although this algorithm has high computational complexity, it greatly improves the accuracy of the segmentation on medical images.**

Keywords: **Segmentation, Clustering, FCM, GSFCM, GA, Optimization**

I. INTRODUCTION

Segmentation is an important process in the analysis of MR (Medical Resonance) Images for medical diagnosis. It divides the MR image into different types of classes and groups the homogeneous pixels into clusters. This is used in medical diagnosis in many ways, detecting brain tumor, tissue analysis, bone fractures and similar problems. Many processing techniques have been proposed for brain MRI segmentation such as thresholding, region growing and clustering [2]-[6]. Clustering is one of the preprocess technique in image segmentation. It separates the heterogeneous pixels from the image. But it takes only the pixel attributes for clustering. This leads to inaccuracy with segmentation because medical images have limited spatial resolution, poor contrast, noise and non-uniform intensity variation. K-means clustering is one of the most commonly used technique for segmentation [9],[10]. But compared to FCM it is poor at detecting the noise from the MRI. The fuzzy-based methods are good at clustering algorithms compared to the crisp methods. The field of medicine is greatly improved by using the fuzzy-based theory [11]. FCM is one of the fuzzy clustering methods which was proposed by J.C. Bezdek in 1981. This is a powerful clustering technique for medical image segmentation. But the FCM clustering algorithm sometimes degrades the accuracy of the image because it takes only the pixel attributes for clustering. To avoid this drawback, Huynh Van Lung and Jong-Myon Kim proposed the GSFCM algorithm for medical image segmentation [1]. It avoids the drawbacks of the FCM and improves the FCM clustering by taking into account the effect of the local neighborhood which depends on their distances to the considered pixel. This GSFCM is limited to the local minima of the objective function. To avoid this, this paper proposes the GAGSFCM algorithm for medical image segmentation. This algorithm takes the advantages of GSFCM as well as avoids the limits of the local minima in an objective function. The Genetic algorithm is an optimization method for calculating global minima [2],[3]. Further this algorithm can be validated by the different cluster validity functions (v_{pc}, v_{pe}, v_{fs}) which outperform the traditional FCM algorithm and GSFCM algorithm.[1]

II. BACKGROUND INFORMATION

A. *Traditional FCM Algorithm:*

Segmentation is greatly being improved by using the FCM algorithm instead of using K-Means Clustering algorithm. It divides the images into number of homogenous classes effectively. It has some success to detect the noise from an image.

The Traditional FCM algorithm is an iterative algorithm that produces optimal C partitions, centers $V=\{v_1,v_2,\ldots,v_c\}$. Let unlabelled data set $X=\{x_1,x_2,\ldots,x_n\}$ be the pixel intensities, where n is the number of image pixels to determine their membership. The FCM algorithm tries to partition the dataset X into C clusters. The standard FCM objective function is defined as follows.

$$J_m(U,V)= \sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m d^2(x_k,v_i) \qquad (1)$$

Where $d^2(x_k,v_i)$ represents the square of the equclidean distance between the pixel intensity value x_k and the centroid value v_i along with constraint $\sum_{i=1}^{c} u_{ik} = 1$, and the

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degree of fuzzification $m \geq 1$. A data point x_k belongs to the specific cluster v_i that is given by the membership value u_{ik} of the data point to that cluster. Local minimization of the objective function $J_m(U,V)$ is accomplished by repeatedly adjusting the values of u_{ik} and v_i according to the following equations

$$U_{ik} = \left[\sum_{j=1}^{c} \left(\frac{d^2(x_k, v_i)}{d^2(x_k, v_j)} \right)^{\frac{1}{(m-1)}} \right]^{-1} \quad (2)$$

Where V_i is calculated by the following equation

$$V_i = \sum_{k=0}^{n} (u_{ik})^m x_k \Big/ \sum_{k=0}^{n} (u_{ik})^m \quad (3)$$

As J is iteratively minimized, the centroid matrix is more stable. This iteration is terminated when the difference between the maximum of current centroid value, maximum of previous iteration centroid value is less than the 0.0001. The value 0.0001 is predefined termination threshold. Finally, all homogeneous pixels are grouped into the same class to evaluate the Fuzzy C-means algorithm.

B. GSFCM Algorithm:

1. Calculate the fuzzy membership matrix by using uniform distribution then calculate the P_{ik} value using the following formula

$$P_{ik} = \sum_{j=0}^{Nk} g(u_{ij}) \sum_{i=0}^{k} (d^2(x_k, x_j)/d2(xk,xj))^{-1} \quad (4)$$

Where $g(u_{ij})$ is the fuzzification matrix Where d is the Euclidean distance among two pixels x_k, x_j calculated by the following formula $D_{ij} = \sqrt{(x_k - x_j)^2}$

2. Calculate the $f(P_{ik}) = 1/P_{ik}$

Calculate the ω_{ik} by using the following formula

$$u_{ik} f^{1/1-m}(P_{ik}) \Big/ \sum_{j=1}^{c} u_{ik} f^{1/1-m}(P_{ik}) \quad (5)$$

Here m is the fuzzification parameter (m>1) Calculate the new centroid value V by using the following formula

$$\sum_{k=0}^{n} \omega_{ik}^m x_k \Big/ \sum_{k=0}^{n} \omega_{ik}^m \quad (6)$$

Here m is the fuzzification parameter (m>1), ω_{ik} is the fuzzification matrix, and n is the number of pixels

3. Repeat the steps 3 until the change in U_{ik} matrix is less than the epsilon value (epsilon=0.0001)

4. Assign all pixels to belong to clusters by using the maximum membership value of every pixel.

III. GENETIC ALGORITHM

Most of the clustering methods minimize the objective function J. Genetic algorithm (GA) is an optimization problem to minimize the objective function. Three major functions are carried out by the genetic algorithm such as initialization, mutation and cross over. The cluster centers are assigned as the Initialization vector from the uniform distribution. Suppose it reaches the local minima, GA selects the mutation method to take off it. The incorporation of mutation enhances the ability of the genetic algorithm to find near optimal solutions. The pixel intensity is converted in to the bit strings. The mutation operator in this bit string flips each bit of the bit string with a small probability. The roulette wheel selection method which is used for selecting a small probability value.

Consider the chromosomes of the dataset. We can create the new chromosome from the existing chromosomes during the reproduction is the process of crossover. The basic of the crossover is as follows: consider a1=10001111, a2=10110011 then derive the new chromosomes from the a1 and a2 namely a_{new}^1 and a_{new}^2.

$a_{new}^1 = 10000011$

(first 4 bits from a1 and last 4 bits from a2)

$a_{new}^2 = 11111011$

(last 4 bits from a1 and first 4 bits from a2). In this way we generate the new chromosome by using the crossover operator. Where a1,a2 are the parent chromosomes of the a_{new}^1 and a_{new}^2. This two are the children of the parent chromosomes. Well the mutation method flips the bit string of the pixel intensity value. Example consider the a1 value it may be flipped like 10001001. Now GA can be evaluated in the MRI by the following ways.

1. The fitness function:

We set the fitness function as one of the iteration of GSFCM algorithm. Since we want to minimize the J value, we take our fitness function as 1/J.

2. Apply Cross Over to the Chromosomes

2.1 Set chromosomes as vector containing the centroids of the clusters. In our implementation, we set population as 10 and the number of generations as 12.

2.2 Using the roulette wheel selection, it ensures that the chromosomes with higher fitness values have better chance to get selected.

2.3 Using mutation ensures that the algorithm converges to the global minima instead of getting stuck in local minima. Based on the Mutation and roulette wheel selection, the GA approach is implemented.

2.4 Finally we get the clustering image.

IV. EXPERIMENTAL RESULT AND DISCUSSION

The GAGSFCM algorithm is an iterative approach that can be suitable for large sets. The main aim of this algorithm is to avoid the local minima. So, the problem is with local minima well solved by Genetic approach. This GAGSFCM algorithm compares with the GAFCM, FCM and GSFCM. The performance of clustering was measured for several brain images in terms of the three cluster validity functions (Vpc,Vpe,Vfs)[1].

Image 1

Image2

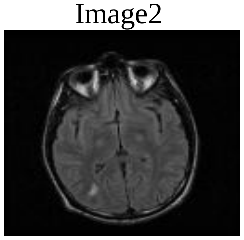


Image 3

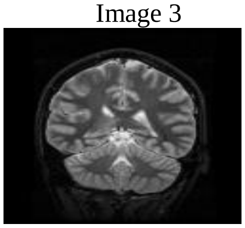
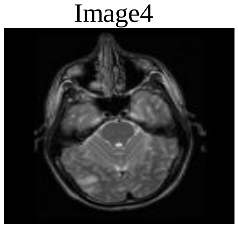
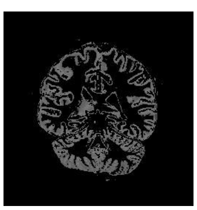


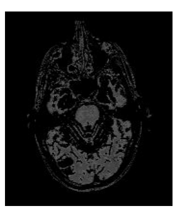
Image4



Segmentation results of brain images using GSFCM

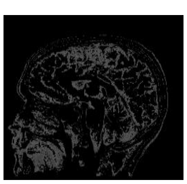
Image 1 Image 3 Image 4

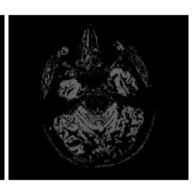




Segmentation results of brain images using GAGSFCM

Image 1 Image 3 Image 4





This section evaluates the performance of the proposed GAGSFCM method for clustering four different images into 5 clusters using the cluster validity functions as given in[1].

Image	Number of clusters	V_{pc}	V_{pe}	$V_{fs\,(10^6)}$	Technique
Image 1	5	0.735353	0.482560	-66.1532	GSFCM
		0.790487	0.420240	-87.6507	GAGSFCM
Image 2	5	0.750153	0.535817	-115.267	GSFCM
		0.771846	0.550134	-140.076	GAGSFCM
Image 3	5	0.564941	0.782236	-105.555	GSFCM
		0.592724	0.492447	-244.378	GAGSFCM
Image 4	5	0.479080	1.03016	-290.850	GSFCM
		0.739123	0.813433	-440.370	GAGSFCM

V. CONCLUSION

The presented GAGSFCM algorithm is an optimization algorithm which applies the global minima finding capability of genetic algorithms to find the optimal cluster partitions using the GSFCM method. The GAGSFCM method allows higher accuracy than traditional FCM and GSFCM algorithms. The results are experimented by using four different MR images and validated the output using cluster validity functions. This paper has some limits, the computational complexity of the objective function is very high compared to the traditional FCM and GSFCM. By comparing these two algorithms the GAGSFCM is best optimization algorithm as we experimented.

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