

Intelligent Medical Image Segmentation Using FCM, GA and PSO

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Abstract-- An important goal of medical image processing is to transfer images into better form for easy representation and evaluation. An important step in this transformation is image segmentation i.e. based on given homogeneity criteria to partition the image into segments. After this, the exact shape and appearance features of segments can be calculated and they can be used for clinical evaluation. Fuzzy c-means clustering method has been widely used for medical image segmentation. As medical images are frequently corroded by noise and the FCM algorithm is more sensitive to this noise. Thus in this paper, we propose optimization of this algorithm by using hybrid of genetic algorithm and particle swarm optimization algorithm. The results of this method are compared with basic segmentation methods like FCM and KFCM using quality parameters like: Rand index, Global consistency error and Variation. Experiments show that the proposed method is more effective and efficient.

Keywords-- Image Segmentation, Fuzzy Clustering, Rand Index, GCE, PSO.

I. INTRODUCTION

In computer vision, Image segmentation is known as a process of partitioning an image into several segments also known as super pixels. The important goal of image segmentation is to simplify or change the representation of an image into form that is more meaningful and is easy for analysis [1].

As we know that the medical images like CAT and X-ray images are corroded by noise from equipment and environment, so it is incertitude and blur. The segmentation is comparatively difficult for these images. At the present time many segmentation methods like Thresholding, Fuzzy clustering, neural networks and so on are used. From all these methods the FCM method is mostly used. The most prominent disadvantage of FCM is that it is sensitive to noise, including noise of CT-scan and any other equipment. This paper advances a new image segmentation method, which optimizes the basic FCM algorithm by using hybrid of Genetic algorithm and Particle swarm optimization. Thus by using optimization we can find best values for both pbest and gbest [2] [4].

II. FUZZY C-MEANS CLUSTERING

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters (soft clustering). This method is developed by Dunn in 1973 and improved by Bezdek in 1981. It is frequently used

in pattern recognition. It is based on minimization of the following objective function [10]:

$$J_m = \sum_{i=1}^N \sum_{j=1}^C S_{ij}^m \|x_i - c_j\|^2 \quad (1)$$

Where, m ($1 \leq m < \infty$) is any real number greater than 1, N is no. of data, c is no. of clusters, S_{ij} is the degree of membership of x_i in the cluster j , x_i is the i th of d -dimensional measured data, c_j is the d -dimension center of the cluster, and $\|\cdot\|$ is any norm that expresses the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

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

$$c_j = \frac{\sum_{i=1}^N S_{ij}^m \cdot x_i}{\sum_{i=1}^N S_{ij}^m} \quad (3)$$

This iteration will stop when

$$\max_{ij} \{S_{ij}^{(k+1)} - S_{ij}^k\} < \epsilon \quad (4)$$

Where, ϵ is a termination criterion between 0 and 1, and k is the no. of iterations. This procedure converges to a local minimum of J_m . The algorithm is composed of the following steps:

- Initialize $S=[S_{ij}]$ matrix, $S^{(0)}$
- At k -step: calculate the centers vectors $C^{(k)}=[c_j]$ with $S^{(k)}$

$$c_j = \frac{\sum_{i=1}^N S_{ij}^m \cdot x_i}{\sum_{i=1}^N S_{ij}^m}$$

- Update $S^{(k)}, S^{(k+1)}$

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

- If $\|S^{(k+1)} - S^{(k)}\| < \epsilon$ then stop; otherwise return to step 2.

III. KERNEL FUZZY C-MEANS CLUSTERING

The KFCM algorithm is a modification of basic FCM algorithm. It is based upon the minimization of the following objective function:

$$J_m = 2 \sum_{i=1}^N \sum_{j=1}^C S_{ij}^m (1 - K(x_i, c_j)) \tag{5}$$

Where, $K(x, y)$ is an inner product kernel function. Then similarly u_{ij} and c_j can be written as [12]:

$$S_{ij} = \frac{(1/(1 - K(x_i, c_j)))^{\frac{1}{m-1}}}{\sum_{k=1}^C (1/(1 - K(x_i, c_k)))^{\frac{1}{m-1}}} \tag{6}$$

$$c_j = \frac{\sum_{i=1}^N S_{ij}^m \cdot K(x_i, c_j) \cdot x_i}{\sum_{i=1}^N S_{ij}^m \cdot K(x_i, c_j)} \tag{7}$$

The KFCM algorithm is composed of the following steps:

- Fix $c, t_{max}, m > 1$ and $\epsilon > 0$ for some positive constant;
- Initialize the memberships S_{ij}^0 ;
- For $t=1,2,\dots, t_{max}$, do:
 - Update all prototypes u_{ij} by using:

$$S_{ij} = \frac{(1/(1 - K(x_i, c_j)))^{\frac{1}{m-1}}}{\sum_{k=1}^C (1/(1 - K(x_i, c_k)))^{\frac{1}{m-1}}}$$

- Update all memberships c_j by:

$$c_j = \frac{\sum_{i=1}^N S_{ij}^m \cdot K(x_i, c_j) \cdot x_i}{\sum_{i=1}^N S_{ij}^m \cdot K(x_i, c_j)}$$

- Compute $E^t = \max_{ij} |S_{ij}^t - S_{ij}^{t-1}|$,
if $E^t \leq \epsilon$, stop; else $t=t+1$.

IV. GENETIC ALGORITHM

Genetic algorithm is a part of evolutionary computing, which is a rapidly growing area of artificial intelligence. It generates solutions to optimization problems using techniques that are inspired by natural evolution, such as inheritance, selection, mutation and crossover. Algorithm starts with a number of solutions or chromosomes also called as population. Then the solutions from one population are taken and are used to form a new population which is better than the old one. The Solutions which are selected to form new solutions (offspring) are selected based on their fitness. This procedure is repeated until some condition (for example number of populations or improvement in the best solution) is satisfied. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. For example, small population sizes might lead to premature convergence and yield substandard solutions [19]. On the other hand, large population sizes lead to unnecessary expenditure of valuable computational time. The basic outline steps of GA are:

- **[Start]** Generate random population of n chromosomes (suitable solutions for any problem)
- **[Evaluation]** Evaluate fitness $f(x)$ of each chromosome x in the population
- **[New population]** Create a new population by repeating following steps until the new population is complete.
 - **[Selection]** Two chromosomes from a population are selected according to their fitness (the better is the fitness, the bigger chance to be selected)
 - **[Crossover]** Selected parents are Crossover to form a new offspring (children). If no crossover was performed, then the offspring is an exact copy of parents.
 - **[Mutation]** Mutate new offspring at each position in chromosome.
 - **[Accepting]** Placing the new offspring in new population
- **[Replacing]** Use new generated population for further steps of the algorithm.
- **[Testing]** If the end condition is satisfied, then stop, and return the best solutions in the current population
- **[Loop]** Return to step 2

V. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a population-based search algorithm and is initialized with a population of randomly selected solutions, called particles. In PSO, each single solution is like a ‘bird’ in the search space, which is called ‘particle’. All particles in PSO have their own fitness values which can be evaluated by the fitness function to be optimized, and also have velocities which direct the flying of the particles [18]. These particles fly through the entire problem space by following the particles with the best solutions so far. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating each generation [17]. Fig.1. shows the basic Particle swarm optimization algorithm steps.

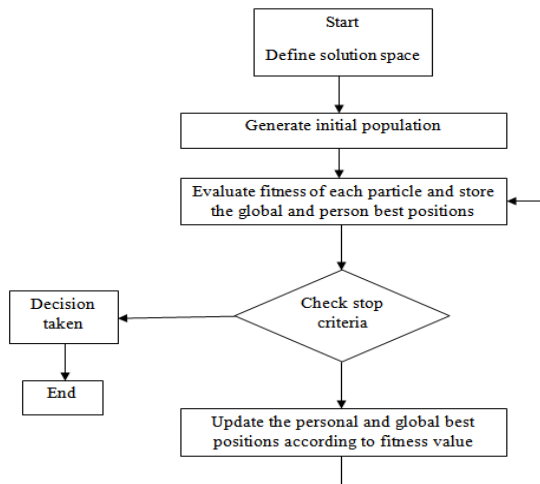


Fig.1. Simple PSO algorithm [14].

VI. PROPOSED METHOD

As we all know that the medical tests are mostly in the form of noisy images, thus it is very difficult to perform any type of processing over these. For the segmentation of these images mostly the FCM method is used, which is very sensitive to noise. Thus we proposed a new method based on the hybrid mechanism of GA and PSO, which optimizes the results of FCM and thus comparatively give good results. The basic diagram showing the steps of this method are shown as follows.

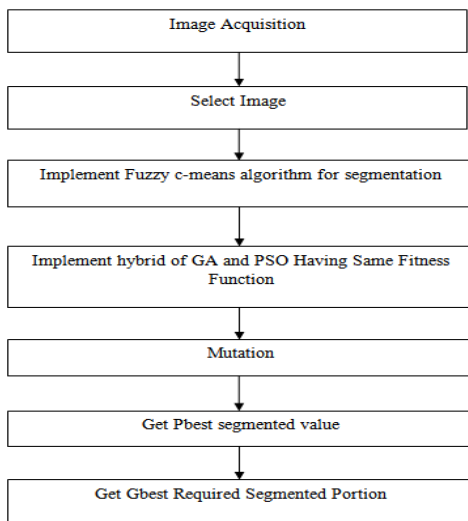


Fig.2. Steps of proposed method

A. Hybrid of GA and PSO

The two evolutionary algorithms: GA and PSO are hybrid together to overcome their drawbacks, and to provide better results. Hybrid of genetic algorithm and particle swarm optimization algorithm provides better optimization than single methods.

1) *Need of hybrid mechanism in PSO:* PSO is faster in finding quality solutions; however it faces some difficulty in obtaining better quality solutions while exploring complex functions. The two main drawbacks of PSO are:

(a) The first drawback of PSO is that the swarm may prematurely converge. That is for the global best PSO, particles converge to a single point, which is on the line between the gbest and the pbest values. This point is not guaranteed for a local optimum. Another reason for this problem is the fast information flow between particles, resulting in the creation of similar particles with a loss in diversity that increases the possibility of being trapped in local optima.

(b) The second drawback of PSO is that its performance is problem-dependent. It depends upon the parameter settings of the algorithm. This performance can be addressed through hybrid mechanism.

2) *Relationship between PSO and GA:* The PSO and GA, both are evolutionary computing techniques. Both begin with a group of a randomly generated population and both utilize a fitness value to evaluate the population. They update the population and search for the optimum. In GA there are three main operators: recombination, mutation and selection operator. PSO does not have a direct recombination operator. However, the stochastic acceleration of a particle towards its previous best position, as well as towards the best particle of the swarm, resembles the recombination procedure in GA.

VII. SIMULATION RESULTS

To show the performance of proposed method, simulation results are shown. The following figures show the simulation results of the segmentation methods like: FCM, KFCM and also the results of proposed method. Fig.3, 4, 5&6 shows the original image, KFCM segmented image, FCM segmented image and the image segmented using the proposed algorithm respectively. These simulation results provide qualitative analysis of methods. These all results are obtained by implementing the listed algorithms in MatLab using image processing toolbox.



Fig.3. Original image.



Fig.4. KFCM segmented image.



Fig.5. FCM segmented image.



Fig.6. image segmented by using proposed method.

VIII. COMPARISON

A comparison of all techniques that are discussed in this paper i.e. FCM, KFCM, FCM+GA-PSO, is done using three quality parameters. These quality parameters are:

A. The Rand Index (RI) [3]

Rand index is a measure of similarity between two clusters. Let a set of m elements and two partitions of S to compare. Then the Rand index I is:

$$I = \frac{a + b}{a + b + c + d} = \frac{a + b}{\binom{m}{2}} \quad (8)$$

Where, a is no. of pair of elements in S that are in same set in X and Y , b is no. of pair of elements that are in different sets in X and Y , c is no. of pair of elements in S that are in same set in X and in different sets in Y , d is no.

of pair of elements in S that are in different sets in X and in same set in Y , $a + b$ is no. of agreements between X and Y and $c + d$ is no. of disagreements between X and Y .

The rand index has a value between 0 and 1, 0 means two data clusters do not agree on any pair of points and 1 indicates that the clusters are exactly the same.

B. Global Consistency error (GCE)

It measures the extent to which one segmentation can be viewed as a refinement of other. The related segmentations are considered consistent. The formula for GCE is as follows [3]:

$$GCE = \frac{1}{m} \min \left\{ \sum_i E(S1, S2, pi), \sum_i E(S1.S2, pi) \right\} \quad (9)$$

Where, $S1$ and $S2$ are two segmentations and Pi is any pixel. The Value of GCE lies between 0 and 1. Where 0 means no error.

C. Variation of Information (VOI)

This metric measures the amount of randomness in one segmentation which cannot be explained by other. Let we have two clusters X and Y . Then variance is:

$$V(X, Y) = E(X) + E(Y) - 2I(X, Y) \quad (10)$$

Where, $E(X)$ is entropy of X and $I(X, Y)$ is mutual information between X and Y .

TABLE I

COMPARISON OF FCM, KFCM AND PROPOSED METHOD

Method	Rand Index	GCE	VOI
KFCM	0.495486	0.949912	7.71968
FCM	0.464881	0.946671	6.18949
Proposed Method	0.514349	0.940226	6.11582

Table shows the values of RI, GCE and VOI for methods FCM, KFCM and FCM optimized using hybrid of GA and PSO. These values qualitatively show that the values of these three metrics for FCM+GA-PSO are better than other methods, thus it can be said that this method gives better segmentation results over others.

IX. CONCLUSION AND FUTURE SCOPE

In this paper, a new method for the segmentation of medical images is introduced. In this method the results of FCM algorithm are optimized using hybrid of GA and PSO. Then the results of this method are compared with basic methods both qualitatively and quantitatively. This comparison shows that the proposed method is better than the existing and gives efficient and effective results. In future, this method can be used to segment MRI images which are more prone to noise. As well as it can be used over RGB images.

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