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Hybridized Algorithms for Medical Image Segmentation

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Abstract- ***Clustering analysisis a unsupervised pattern recognition and groups similar data items into same cluster while dissimilar data item will be moved into different clusters.The purpose of data clustering is to reveal the data patterns and gain some initial insights regarding data distribution.Similarly Image segmentation groups pixels of an image into multiple segments with respect to intensities. This in turn helps to segment objects of interest from the images. In this paper we discuss various segmentation algorithms such as Fuzzyc-means, Maximum Entropy optimized with Particle swarm Optimization to detect abnormalities present in the image. We apply these algorithms on MRI image and Ultra sound images. In order to improve the visibility of ultra sound images, we apply morphological filtering before segmentation. The results section of this paper show the outcome of the algorithms.***

KEYWORDS: FCM, Maximum Entropy,PSO,MRI and Ultra sound image.

I. INTRODUCTION

Imaging techniques are a challenging problem, due to poor resolution and weak contrast. Moreover the task is often made more difficult by the presence of noise and artifacts, due to instrumental limitations, reconstruction algorithms and patient movement. To extract and to study about the region of interest from the images, image segmentation is an ideal step and could be used in the form of image feature extraction and image recognition techniques**.** Fuzzy C-means is one of the clustering methods to group similar data and it has been widely applied to image segmentation [1,2,3]. The main advantage in fuzzy clustering algorithm is it allows each data element to belong to multiple clusters with reasonable degrees of membership grades which lies in the interval [0,1]. Fuzzy clustering does not necessitate any prior information about the elements in the dataset. Fuzzy clustering has been identified as one of the most important tools in segmentation of medical images and it provides information better than hard clustering methods.However,they require prior knowledge about the number of clusters inthe data, which may not be known for new data [4].

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II. FCMPSO

FCM was developed by Dunn in 1973[5] and modified in 1981 by Bezdek [6] used to detect similar patterns . It is an iterative algorithm produces partitions or clusters by minimizing Sum of Squared Error thus can be seen as the fuzzified version of basic widely used partitional K-Means clustering . Fuzzy clustering allow the data items to belong to several clusters with different degrees of membership, this behaviour is different from hard clustering in which data item either does or does not belong to a cluster . Sometimes fuzzy clustering is more efficient than hard clustering when data items lie on the boundaries and membership degrees of it are assigned between 0 and 1 indicating their partial membership. Fuzzy Partitioning of datasets are carried out through optimization of c-means objective function. The minimization of *c*-means represents a nonlinear optimization problem that can be solved by using genetic algorithms , simulated annealing , Ant Colony Optimization and Particle Swarm Optimization methods.

PSO is a population based stochastic optimization technique developed by Dr.Eberhart and Dr. Kennedy in 1995[7][8][9][10], inspired by social behaviour of bird flocking or fish schooling and has been rapidly applied to data mining tasks such as classification and clustering to optimize the results. In PSO, the potential solutions, called particles(M), searches the whole space guided by its previous best position(pbest) and best position of the swarm(gbest). The velocity and position of the particles are updated based on its best experience. The i^{th} particle of swarm in D dimension space represented as $\mu_i = (\overrightarrow{\mu_{i1}}, \overrightarrow{\mu_{i2}}, \overrightarrow{\mu_{i3}}, \ldots \overrightarrow{\mu_{iD}})$ where i= 1,2..M while the velocity for i^{th} particle is represented as $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})$. The best previous position (the position giving the best fitness value) of the i^{th} particle is recorded and represented as $p_i = \left(p_{i1}, p_{i2}, \ldots, p_{iD}\right)$. At each step, the particles are manipulated andpbest and gbest locations are identified for iteration t according to the following equations (1) and (2):

$$V_i(t+1) = \omega V_i(t) + c_1 rand()(pbest(t) - \mu_{id}(t)) + c_2 rand()(gbest(t) - \mu_i(t)) \quad (1)$$

ω represents the inertia weight to control the speed of each generation of particles and c1,c2 are two positive constants known as cognitive and social components. The velocity is calculated based on previous velocity,

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$$\mu_i(t+1) = \mu_i(t) + V_i(t+1) \qquad (2)$$

Here the problem of optimization is by iteratively updating the equation (1) and (2). And the termination criterion for iterations is determined according to whether the maximum generation or a designated value of the fitness is reached.

Procedure 1: FCMPSO

1. Set number of clusters C, Maximum iterations (T) and particle Swarm, in which each particle contains c cluster centers. For each particle, we randomly initialize the memberships, the personal best position pbest and the global best position gbest.
2. For(i=0;i<popsize;i++)
3. Evaluate fitness function.
4. Initialize the value of weight factor, ω;
5. while (termination condition is not true)
6. for(i=0;i<popsize;i++)
7. if(f(X[i])>pbest$_i$) pbest$_i$=X[i];
8. Update gbest;
9. Update(Position X[i], Velocity V[i]);
10. Evaluate f(X[i]);
11. Find the distance matrix between new gbest and original matrix
12. Update Membership
13. endfor
    Endwhile
    endfor

III. MEPSO

Intelligent optimization algorithms have been proved themselves as an effective tool to find optimal results. The system is initialized with a population of random solutions and searches for optima by updating generations.

ROI(Region Of Interest) detection of Medical images is a pre-processing step in medical image segmentation and 3D reconstruction and is detected according to some early brought forward algorithms but the performances of these algorithms depends on the type of medical image. Detection of abnormal structures with their location and orientation is an extremely important task in the diagnosis stage, in the planning and analysis of various treatments.

Ultrasound images have inbuilt noises and requires a highly experienced and skilled operator to detect a malignant region.A new technique to segment ultrasound images has been proposed [11] to extract pixels represent gall stones in the gall bladder. In which a combination of multiscale morphological gradients and maximum entropy has been applied to find threshold of an image. Further, the obtained threshold is optimized for good accuracy and reduced computation time.

Entropy based methods exploits the entropy on the distribution of gray levels, the maximum entropy being an indication of detecting objects of interest in the thresholded image. Threshold T lies in range (0<T<L-1, L=0, 1, 2….255) and the image is divided into two classes or two regions C_O and C_B based on T, where C_O is the object region and C_B is the background region. Shannon's entropy[14] is defined as $H = -\sum_{i=0}^{n} p_i \log(p_i)$ (3)

where p_i is the probability of occurrence of gray value i. The theory of maximum entropy is to select i which makes entropy as the maximum one.

When the sum of two class entropies, the image foreground and the image background reaches its maximum then the image is said to be optimally thresholded and it is defined as;

$$T_{opt} = \arg\max[H_F(T) + H_B(T)] \qquad (4)$$

$$H_F(T) = -\sum_{g=0}^{T-1} \frac{p_g}{P_F} \log \frac{p_g}{P_F} \qquad (5)$$

and

$$H_B(T) = -\sum_{g=T+1}^{255} \frac{p_g}{P_B} \log \frac{p_g}{P_B} \qquad (6)$$

Fitness=H(t) =H_F(t)+H_B(T) (7)

2-D maximum entropy considers distribution of the gray information as well as the spatial neighbor information to obtain entropy value. To optimize threshold value, PSO has been successfully applied with 2-D maximum entropy for segmenting infrared images in less computation cost[12]. Diversity controlled revised QPSO introduced by adding iterative equation with QPSO to prevent from local minima to be trapped has been tested against medical image registration[13]. The pseudo code of MEPSO thresholdingis presented below;

14. Generate random population of N solutions(particles);
15. For(i=0;i<popsize;i++)
16. Evaluate fitness f(X[i]) as in eqn (7);
17. Initialize the value of weight factor, ω;
18. while (termination condition is not true)
19. for(i=0;i<popsize;i++)
20. if(f(X[i])>pbest$_i$) pbest$_i$=X[i];
21. Update gbest;
22. Update(Position X[i], Velocity V[i]);
23. Evaluate f(X[i]);
24. Endfor Endwhile
25. If gbest(global best position)<X[i] Tseg=1; else Tseg=0;
26. Endif

The population size of particles refers the number of particles involved in obtaining solution at each iteration.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed work has been executed on the images obtained from open source repository. The image shown in figure 1.a is of size 100x9 has gall stones marked with an arrow. Figure 1.b is an image filtered using Morphological Processing and the result of MEPSO has been shown in figure 1.c. Figure 1.d shows the segmentation result of Figure 1.a using FCMPSO. Similarly the processing results of image with size 350x297 (Figure 2.a) shown in figures 2.b , 2.c. and 2.d respectively.Threshold obtained using MEPSO for image shown in figure 1.a is 112 and figure 2.a is 117.

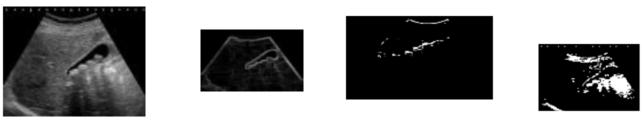

Figure 1.a **1.b** **1.c** **1.d**

Figure 1.a)Original image b) Image after Morphological Filtering c) Result after MEPSO d) segmentation results by FCMPSO

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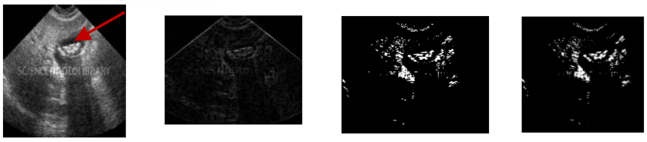

Figure 2.a **2.b** **2.c** **2.d**

Figure 2.a)Original image b) Image after Morphological Filtering c) Result after MEPSO d) segmentation results by FCMPSO

Figure 3.a is a MRI image of size 500x383 downloaded from (http://www.sandybearrdsley.com/sandys mri.html) where white matter represents lesion. Figure 3.b shows the histogram of Figure 3.a.The three classes of outputs obtained using FCMPSO shown in figures 3.b,3.c and 3.d respectively. The various levels of segmentation are mentioned in table 1. In this experiment the number of classes is set as three. The average intra distance obtained is 0.4585 and inter distance as 56.5810.

Figure 3.a **3.b** **3.c** **3.d** **3.e** **3.f**

Figure 3.a) Original MRI image b) Histogram of Figure 3. c) segmentation level1 3.d) segmentation level2 3.d) segmentation level3 3.f) MEPSO

Table 1. Various levels of Segmentation using FCMPSO

Image	Class1	Class2	Class3	Avg intra distance	Avg inter distance
Figure 3.a (MRI Image)	0.1706	0.4137	0.6922	0.4585	56.5810
Noisy image of Figure 3.a (Gaussian)	0.1549	0.3824	0.6373	0.4625	82.8684
Noisy image of Figure 3.a (Speckle)	0.1706	0.4098	0.6765	0.4625	82.8684
Noisy image of Figure 3.a (Salt and Pepper)	0.1745	0.4176	0.7078	0.4704	95.8318

Table 1 shows the segmentation levels of original MRI image and noisy images. The average Inter and intra distances of clusters are also mentioned in Table 1.

V. CONCLUSION

In this paper we have proposed two major methods Fuzzy C-means and Maximum Entropy optimized using PSO to segment Region of Interests from medical images obtained from free source repository. The analysis is carried out by comparing the segmentation results and intra and inters cluster distances. It has been observed that the accuracy of MEPSO is good compared to FCMPSO. The noises such as Gaussian, speckle and salt and pepper noise have been added to the original image to test the robustness of FCMPSO.

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