International Journal of Pure and Applied Mathematics
Volume 117 No. 22 2017, 179-183
ISSN: 1311-8080 (printed version); ISSN: 1314-3395 (on-line version)
url: http://www.ijpam.eu
Special Issue
ijpam.eu

Comparative analysis on optimal segmentation of tumors from magnetic resonance images using Fuzzy clustering and Convergent Heterogeneous Particle swarm intelligence with maximum Entropy

R. Krishna Priya[1], P. S. Godwin Anand[2], and Susamma Chacko[3]
Caledonian college of Engineering, University college, Sultanate of Oman, Muscat,
(e-mail: godwin.priya@gmail.com)[1,3], Saintgits College of Engineering,Kottayam, India.[2]

***Abstract*—this research paper underpins a comparative analysis of medical image segmentation based on fuzzy c-means clustering and swarm intelligence parameter optimization. Maximum information extracted from the image has been carried out by the fuzzy entropy function and the best parameter for segmenting the tumors has been decided on using Convergent Heterogeneous Particle Swarm Optimization (CHPSO).The proposed comparative analysis among the various approaches highlights the efficiency of CHPSO algorithm in searching the problem space by dividing the main swarm into four sub-swarms. The CHPSO algorithm utilizes sub-swarm particles to search for best solution separately that in turn leads to better exploitation and cooperate with each other sub-swarms to obtain the best global position. The results of the objective function are better exploration and best convergence that avoids the trapping in the local optimal solution. Medical images need the maximum information about the region of interest. Hence fuzzy entropy is considered as the objective function and its parameters are optimized via swarm intelligence to obtain a best threshold. The effectiveness of the comparative analysis has been carried out on two different MR Brain Images and simulated experimental result is compared against the classical thresholding technique of Otsu and conventional PSO. The result from the comparative analysis indicates that the swarm intelligence by CHPSO outperforms other conventional methods.**

***Index Terms*— Fuzzy entropy, PSO, CHPSO**

1. INTRODUCTION

Image segmentation has been applied in numerous applications such as medical diagnosis [1,2,3], satellite images [4], character recognition and so on [5]. However, it might be a complex procedure if the input images are degraded by disturbances like noises from equipment or surrounding environments. Different approaches in performing image segmentation, includes region extraction, edge detection, histogram thresholding, and clustering algorithms and threshold based segmentation [6,7,8]. The finite method of proper segmentation demands in locating the exact threshold point/value [9,10]. This method can be of two types, either bi-level or multilevel depending upon the image to be used. Bi-level thresholding method can produce adequate outcomes in cases where the image includes two levels only, however, if it has been used with multilevel the computational time will be often high . FCM is a method of clustering which allows one piece of data to belong to two or more clusters. The clusters are formed according to the distance between data points and cluster centers This method is frequently used in pattern recognition. If the requirement of number of thresholds is less, classical methods are acceptable; but if there are more threshold numbers, it would always be the best practice to perform swarm intelligence (SI) technique to optimize this task . Heuristic and Meta-heuristic optimization algorithms are identified to provide better optimization with less computational time and proved to deliver acceptable performance for multi-dimensional problems . Heuristic optimization method can find the best threshold values for the objective function iteratively by maximizing or minimizing fitness function .

2.1 FUZZY C-MEANS COMPARITIVE APPROACH FOR BILEVEL SEGMENTATION

FCM is a data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to each cluster to a certain degree [12]. It starts with an initial guess for the cluster centers, which are intended to mark the mean location of 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. The objective is to minimize the distance from any given data point to a cluster center weighted by that data point's membership grade within the fuzzy boundary limits between 0 and 1 [14,].Due to this, fuzzy set theory which uses the idea of partial membership's described by a MF, was applied. FCM minimizes an objective function J_{FCM} , with respect to fuzzy membership U, and a set of cluster centroids which is discussed in Equation (1)

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

where $X=\{x_1,x_2,....,x_s\}\subseteq R^p$ [12,14]

The algorithm corresponding to the segmentation using FCM is given below:

Step1: Input image is fed to the FCM algorithm

Step 2: RGB to gray scale image conversion along with image resizing is performed to obtain an optimum result.

Step 3: Grouping of pixels into clusters.

Step 4: Centroid or center pixel value is initialized using FCM.

Step 5: Euclidean distance between the center and the neighboring pixels are calculated for each clusters.

Step 6: Pixels with least Euclidean distance is grouped with the centroid value for each clusters.

Step 7: This grouping process is done recursively till a maximum objective function is reached.

2.2 CONVERGENT HETEROGENEOUS PARTICLE SWARM OPTIMIZATION (CHPSO)

The conventional PSO algorithm and MPSO, which have been cited to be one among the fastest convergent optimization algorithms, used to get trapped in the local minimum due to its homogeneous searching behavior in its initial iteration search. [20,22]. A comparatively acceptable and effective approach in solving the local minima trapping problem, is to use multi-swarm intelligence optimization techniques. This can provide both exploration and exploitation ability of the original heuristic optimization algorithms.

The design of CHPSO is in such a way to extent the entire particles for the search space into four sub-swarms, of which each sub-swarm can later search individually in the problem search space. Among the four sub-swarms, two of them are entitled as basic sub-swarm, which serves the purpose of exploitation search and the others are entitled as adaptive sub-swarm and the exploration sub-swarm. The basic sub-swarm provides the information to the adaptive sub-swarm sets to take the flight path for the search domain. The collective information gathered by other sub swarms, empower the exploration sub-swarm to widen its search into the unknown area in the problem search space. The four sub-swarms will search the entire problem space for the optimum solution heterogeneously [20,21] .The new updated rules based on positions, velocities and the value of fitness function are redefined for CHPSO. The updated velocity and fitness value information has been provided by the basic sub-swarms to the adaptive sub-swarm to determine an exact trajectory for the whole particles. The convergence of this algorithm has been decided by the exploration sub–swarm. This enables the algorithm to avoid it's trapping in the local optima position. Thus the algorithm could enter into the wide areas of unseen problem space.

The schematic sketch of CHPSO is shown in Figure 1 [22].

From the illustrations of the figure above, the global position G_{best} is evaluated based upon the global position of the four sub-swarms and is described in equation (2).

$$G_{best} = \arg\min\{f(P_{best(sub(s))} | s = 1,2,3,4)\} \qquad (2)$$

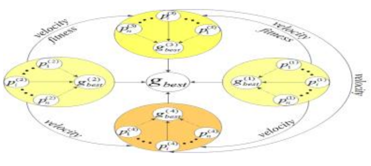


Fig. 1 CHPSO Schematic

where, $P_{best(sub(s))}$ is the particle best selected among the sub-swarms. The velocity of the basic sub-swarms is thus

$$\begin{cases} V_{i(sub(1\&2))}(t+1) = \omega V_{i(sub(1\&2))}(t) + c_1 R(P_{i(sub(1\&2))}(t) - \\ X_{i(sub(1\&2))}(t)) + c_2 R(G_{best} - X_{i(sub(1\&2))}(t)) \end{cases}$$

updated [22] using equation (3).

(3)

where c_1 and c_2 are constants that decide to control the exploration and exploitation in the entire search space with uniformly distributed random vector R with a range from 0 to 1. The inertia weight constant □ scales the effect of the velocity in the previous iteration, $P_{i(sub(1\&2))}(t)$ and G_{best}, best global position in the sub-swarm and has been observed as the best position gained among the entire search space within the constrained time of search [21,22].

$$\begin{cases} V_{i(sub(3))}(t+1) = \omega\left[\dfrac{\chi}{\chi_1} V_{i(sub(1))}(t+1) + \dfrac{\chi}{\chi_2} V_{i(sub(2))}(t+1) + V_{i(sub(3))}(t)\right] \\ + c_1 R(P_{i(sub(3))} - X_{i(sub(3))}(t)) + c_2 R(G_{best} - X_{i(sub(3))}(t)) \end{cases}$$

$$\chi = \chi_1 + \chi_2 \qquad (4)$$

The fitness values of the particles has been denoted as χ_1 and χ_2 in the basic sub-swarms sub(1) and sub(2), and other parameters remains the same in the equation (3)

$$\begin{cases} V_{i(sub(4))}(t+1) = V_{i(sub(1))}(t+1) + \\ V_{i(sub(2))}(t+1) - V_{i(sub(3))}(t+1) \end{cases} \qquad (5)$$

$$\begin{cases} X_{i(sub(4))}(t+1) = \alpha_1 X_{i(sub(4))}(t) + \\ \alpha_2 P_{i(sub(4))} + \alpha_3 G_{best} + V_{i(sub(4))}(t+1) \end{cases} \qquad (6)$$

□1, □2 and □3 are labeled as impact factors that indicate the depth of prior information gained from the particle that can contribute in updating process and this information is anticipated to satisfy □1□□2□□3□1.

2. APPROACH WITH FUZZY ENTROPY TO SET THRESHOLD FOR SEGMENTATION USING FUZZY LOGIC

Fuzzy entropy function extracts the maximum information about the tumor by the fuzziness of a fuzzy set generated for the input image[17,18,22]. It is a measure of the uncertainty of a fuzzy set [25]. The domain can be set as Z for an input image as

$$Z = \{(i,j): i = 0,1,2,\ldots,M-1;\ j = 0,1,2,\ldots,N-1\} \qquad (7)$$

and the gray level intensity of the input image as $G = \{0,1,\ldots,L-1\}$ where M, N and L are three positive integers [25]. The intensity of gray level value of the input image for a pixel (x,y) is $A(x,y)$. Hence the domain Z can be shown as:

$$Z_k = \{(x,y): A(x,y) = k, (x,y) \in G\}, k = 0,1,\ldots,L-1 \qquad (8)$$

The original image can be classified into two different groups, F_d and F_b from the domain Z , which comprises of pixels with low gray intensity levels and high gray intensity levels based on a threshold limit T.

The parameter's a , b and c of the fuzzy membership function, decides the threshold T for segmentation of the region of interest, i.e tumor in the MR brain test input image [10,17].

2.1 Classification of Fuzzy MF Parameters with Z-type and S-type MF

The image constraint for classification lies within $0 \le a \le b \le c \le 255$. The parameters a,b,c of the fuzzy MF should limt in this constraint to perform the classification of dark and bright pixels. The best chosen type of membership function to accommodate the two classifications has been termed as Z-type and S-type.[ ] The Z-type MF, corresponds to dark category of pixels $Z(k,a,b,c)$ noted as $\mu_d(k)$ while the S-type of MF corresponds to the bright class. $S(k,a,b,c)$ and noted as $\mu_b(k)$.The segmentation threshold T can be obtained from the Equation(9) [17,18,22].

$$T = \begin{cases} a+\sqrt{(c-a)*(b-a)/2}, & (a+c)/2 \le b \le c \\ c-\sqrt{(c-a)*(c-b)/2}, & a \le b \le (a+c)/2 \end{cases} \quad (9)$$

2.2 Maximum Fuzzy entropy function

The total maximum fuzzy entropy function $H_{\max}(a,b,c)$ depends on the fuzzy MF parameters a,b,c and is shown in Equation (10) for the input image [10,18,23].

$$H_{\max}(a,b,c) = H_{dark} + H_{bright} \quad (10)$$

The fuzzy membership function parameters thus obtained were optimized using the CHPSO. The heuristic algorithm delivers the globally best values for fuzzy membership function parameters a,b,c ,that can provide the best threshold for segmentation.

3. Simulation of Experimental results and Discussion

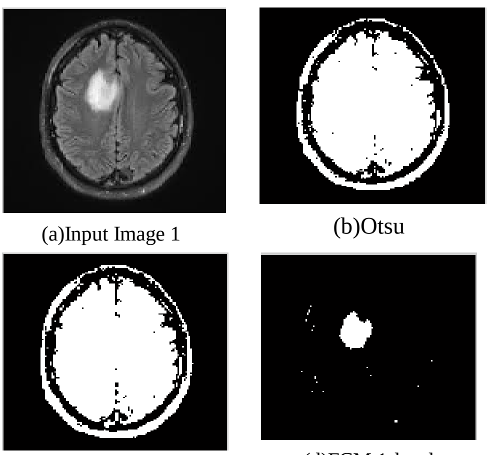
The simulation is carried out using MATLAB 7.10 on a computer with Intel® Core™ i7-Processor and 8GB RAM.

The parameter settings for FCM for MR brain image segmentation and is depicted in Table 1 The parameters are set based upon the concept of parameters specifications as discussed in section 2.

TABLE 1
parameter settings for FCM segmentation

Parameters	Value
Number of Iterations	55
Number of Clusters	2
Fuzziness Parameter	{0,1}

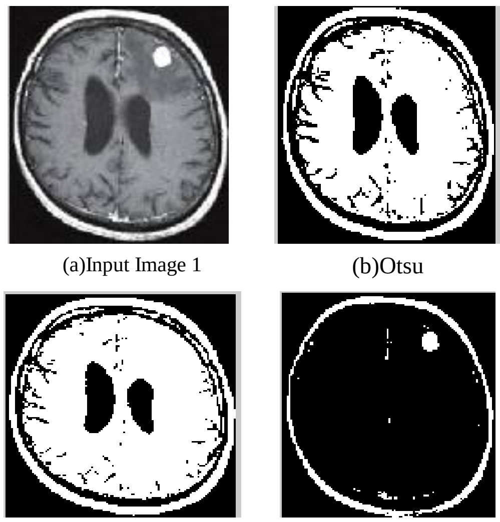
The Otsu method [10,18] which chooses the threshold to minimize the intraclass variance of the black and white pixels from an image is used to compare with FCM. The segmented output of the input image 1 is shown in Figure 2.



(a)Input Image 1 (b)Otsu

(c)FCM 0-Level (d)FCM 1-level

Figure 2 (a) shows the Test image 1. Figure 2 (b) shows the segmentation performed by Otsu segmentation method with a threshold value of T=82.290, Figure 2 (c) shows the segmentation performed by the FCM for Level-0 (0.2185), with a threshold value of T = 76.50. Figure 2 (d) shows the segmentation performed by FCM for level-1 (0.5807), with a threshold value of T = 184.499. The segmented output of the input image 2 using FCM in comparison with Otsu method, are shown in Figure 3.



(a)Input Image 1 (b)Otsu

Fig. 3 Segmented outputs for (a) test image 2, (b)using Otsu, and FCM method (c) FCM 0-level and (d) FCM 1-level

Figure 3 (a) shows the Test image 2. Figure 3 (b) shows the segmentation performed by Otsu segmentation method with a threshold value of T=74.586, Figure 3 (c) shows the segmentation performed by the FCM for Level-0 (0.320408), with a threshold value of T = 68.71. Figure 4.2 (d) shows the segmentation performed by FCM for level-1 (0.724490), with a threshold value of T = 196.213. By observing these figures, both input images, the tumor areas are properly segmented in FCM level-1only, whereas in Otsu segmentation, the tumor area is not identified.

FCM evaluation for test input images

Table 2 shows the comparison of the results obtained using Otsu segmentation and FCM for all the test images.

TABLE 2 Comparison results of FCM WITH OTSU

Image	Otsu Threshold	Time (Sec)	Level -0		Level-1		Time (Sec)
			Threshold (T)	Segmented Pixel value	Threshold (T)	Segmented Pixel value	
Image 1 (225x225)	82.290	0.327	76.50	47542	184.49	3083	2.2
Image 2 (630x612)	74.586	0.51	68.71	343609	196.21	41951	10.34

The PSO, CHPSO parameters were initialized as mentioned in Table 3 given below.

TABLE 3 SWARM INTELLIGENCE PARAMETER SETTINGS

Swarm Intelligence Method	Iterations/Bird step	Number of Particles	Acceleration constants c1 and c2	Inertia weight
PSO	180	30	2	1
CHPSO	180	30	1.50	0.5-0.9

Figure 4 shows the segmented output using CHPSO, PSO, and Otsu method for input image 1. From these figures it is observed that, CHPSO segments the affected area is more precisely than PSO, whereas the resulting performance of Otsu segmentation method is not in acceptable range.

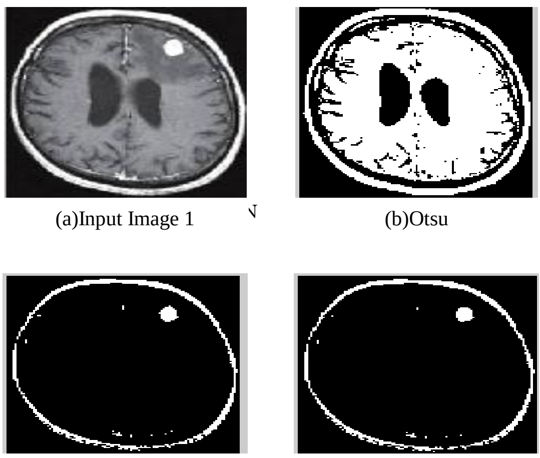
TABLE 4 COMPARISON OF OUTPUT PARAMETERS FOR INPUT IMAGE 1

Method	Fuzzy MF parameters a, b, c	Threshold (T)	Fuzzy Entropy (H)	Time(sec)
Otsu	NA	82.290	4.982	0.42
PSO	94, 210, 240	195.48	5.211	2. 07
CHPSO	100, 207, 238	205.204	5.698	1.981

Table 4 shows the comparison of the results obtained using the three different methodology with respect to threshold, entropy and computational time. Among the 3 results performed, whereas the resulting performance of Otsu segmentation method is not in acceptable range. The comparison of the results for input image 2 is depicted in Table 5. When compared with PSO, CHPSO take less time to segment with high entropy.

TABLE 5
COMPARISON OF OUTPUT PARAMETERS FOR INPUT IMAGE 2

Method	Fuzzy MF parameters a, b, c	Threshold (T)	Fuzzy Entropy (H)	Time(sec)
Otsu	NA	74.586	5.935	0.51
PSO	86, 222, 246	208.30	6.398	3.46
CHPSO	95, 225, 245	210.74	6.921	3.21


(a)Input Image 1 (b)Otsu

(b)PSO (c)CHPSO

Figure 5 Segmented outputs for test image 2 using Otsu, PSO and CHPSO methods

s of total fuzzy entropy-swarm intelligences (PSO and CHPSO) along with FCM on MR brain images. The multi-swarm can improve the performance of a heuristic algorithm for the problem of image thresholding. Simulation testing for two sets of MRI brain image shows that among the comparative approaches, the CHPSO method is significantly robust with improved convergence, in comparison to other analogous techniques and conventional (PSO). The CHPSO outperforms the conventional Otsu method and PSO optimized methods in terms of faster converging time with total/maximum fuzzy entropy in evaluating the optimal threshold value.

REFERENCES

[1] Hamamci A, Kucuk N, Karaman K, Engin K, Unal G. "Tumor-cut: segmentation of brain tumors on contrast enhanced MR images for radiosurgery applications, ". *Med Imaging, IEEE Trans*, Vol 31(3), 2012, pp. 790-804.

[2] Zhao, F., Xie, X.: An overview of interactive medical image segmentation. Annals of the BMVA **7**, 1–22 (2013).

[3] Pare, S., Bhandari, A.K., Kumar, A., Singh, G.K., Khare, S.: Satellite image segmentation based on different objective functions using genetic algorithm: a comparative study. In: 2015 IEEE International Conference on Digital Signal Processing (DSP), pp. 730-734. IEEE (2015)

[4] Dawngliana M, Deb D, Handique M, Roy S. "Automatic brain tumor segmentation in MRI: Hybridized multilevel thresholding and level set," In: *International Symposium on Advanced Computing and Communication, 2015*, pp. 219-223.

[5] El Aziz, Mohamed Abd, et al. "Multi-objective Whale Optimization Algorithm for Multilevel Thresholding Segmentation." *Advances in Soft Computing and Machine Learning in Image Processing*. Springer, Cham, 2018. 23-39.

[6] Krishnamoorthy, Dr, et al. "A Novel Approach towards Lowest Energy Usage Routing Protocol (LEuRP) in Wireless Mobile Ad-Hoc Network (WMANet)." (2017)..

[7] Horng M-H. Multilevel thresholding selection based on the artificial bee colony algorithm for image segmentation. *Expert Syst Appl*. 2011;38(11):13785-13791.

[8] Ayala HVH, dos Santos FM, Mariani VC, dos Santos Coelho L. Image thresholding segmentation based on a novel beta differential evolution approach. *Expert Syst Appl*, Vol. 42(4), 2015, pp.2136-2142.

[9] Zhou C, Tian L, Zhao H, Zhao K. A method of two-dimensional Otsu image threshold segmentation based on improved firefly algorithm. In: *2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems,*2015, pp. 1420-1424.

[10] Remamany Krishna Priya, Chelliah Thangaraj, Chandrasekaran K, Subramanian K. Brain Tumor Segmentation in MRI Images Using Integrated Modified PSO-Fuzzy Approach. *Int Arab J Inf Technol*, Vol 12(6A), 2015, pp.797-804.