

Brain Tumor Segmentation in MRI Images Using Integrated Modified PSO-Fuzzy Approach

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Abstract: An image segmentation technique based on maximum fuzzy entropy is applied for Magnetic Resonance (MR) brain images to detect a brain tumor is presented in this paper. The proposed method performs image segmentation based on adaptive thresholding of the input MR brain images. The MR brain image is classified into two Membership Function (MF), whose MFs of the fuzzy region are Z-function and S-function. The optimal parameters of these fuzzy MFs are obtained using Modified Particle Swarm Optimization (MPSO) algorithm. The objective function for obtaining the optimal fuzzy MF parameters is considered to be the maximum the fuzzy entropy. In the course of a number of examples, the performance is compared with those using existing entropy-based object segmentation approaches and the superiority of the proposed MPSO method is demonstrated. The experimental results are compared with the exhaustive search method and Otsu segmentation technique. The result shows the proposed fuzzy entropy based segmentation method optimized using MPSO achieves maximum entropy with proper segmentation of tumor and with minimum computational time.

Keywords: Fuzzy entropy, particle swarm optimization, MRI, segmentation.

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1. Introduction

The classification of Magnetic Resonance Imaging (MRI) brain tumor is progressively vital within the medical arena since it's crucial for surgical designing and intervention [6]. The most significant and highly complicated image analysis tasks are image segmentation. The image segmentation is a process to extract meaningful objects or specified regions from an image based on threshold levels. Various research studies shows threshold based segmentation is most effective [12, 15, 17]. To separate a particular object from the background of an image by applying different threshold values remains as a challenge. In [9, 13] maximum entropy is derived from the histogram of an image. Of all the thresholding methods, entropy-based method is broadly studied and is considered effective. The entropic correlation defined by Yen *et al.* [21] obtains an optimum threshold that maximizes it. From various researchers [1, 16] the maximization of the entropies computed from auto correlation functions to set a threshold value to characterize the segmentation of the image was inferred. A significant role played by fuzzy sets in deploying systems with their capability to model non-statistical imprecision is discussed in [4]. A function on fuzzy sets defined as fuzzy entropy converges to low value when the sharpness of its fuzzy set argument is improved.

Luca and Termini [10] introduced the concept of fuzzy entropy. There have been numerous applications

of fuzzy entropies in image segmentation. A thresholding approach based on the fuzzy relation and the maximum fuzzy entropy principle using fuzzy partition on a two-dimensional histogram has been discussed by Cheng *et al.* [2]. An optimum threshold is set among the least sum of entropies for an image and the importance of fuzzy memberships in indicating depth of gray value in an image's background is well expressed in [18]. A probability partition and fuzzy c-partition was discussed in [22] to measure the compatibility among these two. A novel methodology to segment tumor from Magnetic Resonance (MR) brain image based on fuzzy entropy through probability analysis, using fuzzy partition and entropy theory is defined. The image is partitioned into two parts, namely the dark and the gray, where Z membership function corresponds to dark and S membership function corresponds to bright.

In this paper, we examine the performance of segmentation techniques applied on MR brain images using proposed Modified Particle Swarm Optimization (MPSO), Particle Swarm Optimization (PSO), Otsu method [11] and exhaustive method. To obtain the optimal threshold value, it is required to search all the possible fuzzy combinations. Therefore, the segmentation problem is formulated as an optimization problem. Various researches proved that PSO can deploy good result for many engineering problems [5, 7, 8]. Hence, MPSO method is found to obtain effective optimal fuzzy membership parameters. This

paper, explores how MPSO is applied to find the optimal fuzzy MFs parameters to obtain maximum fuzzy entropy for the MR brain image. This paper is organized as follows. In section 2, for the integrity of this paper, we simply describe the object segmentation method based on probability analysis and fuzzy entropy, which is similar to the method presented in [14, 19]. In section 3, how to use modified MPSO approach to find the optimal combination of all fuzzy parameters is presented. In section 4, we evaluate the performance of the proposed thresholding approach using MR brain images and compare it with techniques from the literature. Finally, section 5 concludes this paper.

2. Image As A Fuzzy Event

Consider an image A of size $M \times N$ with L gray levels ranging from L_{min} to L_{max} . Let a_{ij} denote the gray level of the image A at the $(i, j)^{th}$ pixel. The histogram of the image is denoted as h_k and is defined as:

$$h_k = \frac{n_k}{M \times N}, k=0, \dots, L-1 \tag{1}$$

Where n_k denotes the number of occurrences of gray levels in A . We can model an image by a triplet (G, K, P) , where $G = \{r_0, r_1, r_2, \dots, r_{L-1}\}$, P is the probability measure of the occurrence of gray levels, i.e., $Pr\{r_k\} = h_k$. A probability space based fuzzy event can be modeled for an image. According to fuzzy set theory, the image A can be transformed into an array of fuzzy singletons S by a membership function.

$$S = \{\mu_A(a_{ij}), i=1, 2, \dots, M; j=1, 2, \dots, N\} \tag{2}$$

Then, the degree of some properties of the image such as brightness, darkness, etc., possessed by the $(i, j)^{th}$ pixel is denoted by the membership function $\mu_A(I_{ij})$ of the fuzzy set, $A \in G$. In fuzzy set notation, A can be written as:

$$A = \frac{\mu_A(r_1)}{r_1} + \frac{\mu_A(r_2)}{r_2} + \dots + \frac{\mu_A(r_k)}{r_k} \tag{3}$$

$$A = \sum_{r_k \in G} \frac{\mu_A(r_k)}{r_k} \tag{4}$$

Here, $+$ indicates union. The equation to obtain the probability of A is given as:

$$\sum_{k=0}^{L-1} \mu_A(r_k) Pr(r_k) \tag{5}$$

And the equation corresponding to conditional probability tends to be:

$$p[\{r_k\} | A] = \frac{\mu_A(r_k) h_k}{P(A)} \tag{6}$$

Fuzzy entropy describes the fuzziness of a fuzzy set. It is a measure of the uncertainty of a fuzzy set. The domain of the image be given as Z :

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

And the gray level of the image as $G = \{0, 1, \dots, L-1\}$ where M, N and L are three positive integers. If the gray level value of the image at the pixel (x, y) is $A(x, y)$ then:

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

Let the threshold of the image A be T that segments an image into its target and background. The domain Z of the original image can be classified into two parts, F_d and F_b , which is composed of pixels with low gray levels and high gray levels, respectively. An unknown probabilistic partition of Z denoted as $\Pi_2\{F_d, F_b\}$ describes its probability distribution as:

$$p_d = P(F_d) \tag{9}$$

$$p_b = P(F_b) \tag{10}$$

For an image with 256 gray levels, μ_b and μ_d indicates the membership functions that corresponds to the bright and dark pixels. Let a, b and c be the three parameters of the membership function, which means that the threshold T depends on a, b and c . Consider:

$$Z_{kd} = \{(x, y) : I(x, y) \leq T, (x, y) \in Z_k\} \tag{11}$$

$$Z_{kb} = \{(x, y) : I(x, y) \leq T, (x, y) \in Z_k\} \tag{12}$$

For each $k = 0, 1, \dots, 255$, then the following Equations hold:

$$p_{kd} = P(Z_{kd}) = p_k * p_{d|k} \tag{13}$$

$$p_{kb} = P(Z_{kb}) = p_k * p_{b|k} \tag{14}$$

The conditional probability of a pixel, obviously set as $P_{d|k}$ and $P_{b|k}$ is categorised into the class ‘dark’ and class ‘bright’, with the constraint that the pixel belongs to D_k with:

$$p_{d|k} + p_{b|k} = 1, (k = 0, 1, \dots, 255) \tag{15}$$

The grade of pixels classified into class ‘dark’ and class ‘bright’ having the gray level value k , be equal to its conditional probability $P_{d|k}$ and $P_{b|k}$, respectively [2, 9, 12, 14]. The equations for probability P_d and P_b hold as follows:

$$P_d = \sum_{k=0}^{255} p_k * p_{d|k} = \sum_{k=0}^{255} p_k * \mu_d(k) \tag{16}$$

$$P_b = \sum_{k=0}^{255} p_k * p_{b|k} = \sum_{k=0}^{255} p_k * \mu_b(k) \tag{17}$$

3. Fuzzy Membership Functions

The two MFs, $S(MF)$ and $Z(MF)$ are applied for calculating the fuzzy entropy function which is shown in Figure 1. In most of the applications in which the fuzzy MF does not appear in explicit form, it is assumed as S -shaped MF or Z shape MF’s [3]. Here, $Z(k, a, b, c)$ function denotes the membership function $\mu_d(k)$ of the class ‘dark’ and $S(k, a, b, c)$ function denotes the membership function $\mu_b(k)$ of the class ‘bright’. The fuzzy parameters a, b and c must satisfy the constraint $0 \leq a \leq b \leq c \leq 255$.

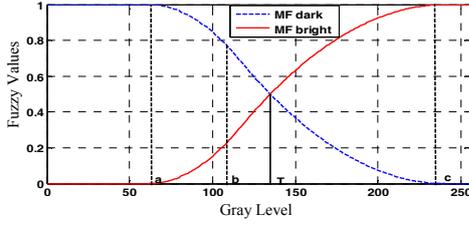


Figure 1. Membership function showing the intersection of Z MF and S MF.

Equation 18 shows the MF of $Z(k, a, b, c)$. Equation 19 shows the MF of $S(k, a, b, c)$.

$$\mu_d(k) = \begin{cases} 1, & k \leq a \\ 1 - \frac{(k-a)^2}{(c-a)*(b-a)}, & a < k \leq b \\ \frac{(k-c)^2}{(c-a)*(c-b)}, & b < k \leq c \\ 0, & k > c \end{cases} \quad (18)$$

$$\mu_b(k) = \begin{cases} 0, & k \leq a \\ \frac{(k-a)^2}{(c-a)*(b-a)}, & a < k \leq b \\ 1 - \frac{(k-c)^2}{(c-a)*(c-b)}, & b < k \leq c \\ 1, & k > c \end{cases} \quad (19)$$

Fuzzy entropy function for dark class, H_d is calculated based on Equation 20 and for bright class, H_b is calculated based on Equation 21 as shown below:

$$H_d = -\sum_{k=0}^{255} \frac{p_k * \mu_d(k)}{p_d} * \log\left(\frac{p_k * \mu_d(k)}{p_d}\right) \quad (20)$$

$$H_b = -\sum_{k=0}^{255} \frac{p_k * \mu_b(k)}{p_b} * \log\left(\frac{p_k * \mu_b(k)}{p_b}\right) \quad (21)$$

The total fuzzy entropy function $H(a, b, c)$ is given as:

$$H(a, b, c) = H_d + H_b \quad (22)$$

This total fuzzy entropy depends on the fuzzy parameters a, b, c . The combination of these three parameters is chosen such that the total fuzzy entropy $H(a, b, c)$ attains a maximum value. Equation to segment the image into two classes using appropriate threshold is as follows:

$$\mu_d(T) = \mu_b(T) = 0.5 \quad (23)$$

Threshold T is the point of intersection of $\mu_d(k)$ and $\mu_b(k)$. The solution to derive T can be obtained from Equation 24:

$$T = \begin{cases} a + \sqrt{(c-a)*(b-a)/2}, & (a+c)/2 \leq b \leq c \\ c - \sqrt{(c-a)*(c-b)/2}, & a \leq b \leq (a+c)/2 \end{cases} \quad (24)$$

4. Modified Particle Swarm Optimization

The PSO algorithm is a population based, stochastic search technique developed by Eberhart and Kennedy [7]. The searching process of the algorithm was inspired by social behaviours of animals such as bird flocking and fish schooling. It is similar to other population based optimization methods, PSO starts with the random initialization of a population in the

search space. PSO algorithm works on the social behaviour of particles in the swarm. The most notable of these are its characteristics of stable convergence, that it can generate a high quality solution in a shorter execution time than other stochastic methods. The concept of modification of a search point by PSO is shown in Figure 2.

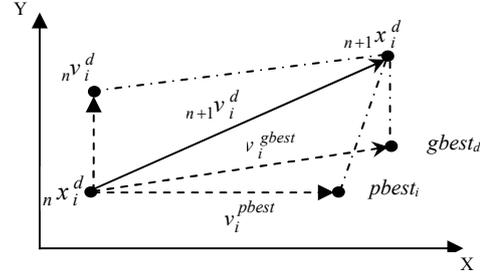


Figure 2. Concept of modification of a search point by PSO.

Where $n x_i^d$ is the current position, $n+1 x_i^d$ is modified position, $n v_i^d$ is the current velocity, $n+1 v_i^d$ is the modified velocity, v_i^{pbest} is the velocity based on $pbest_i$ and v_i^{gbest} is the velocity based on $gbest_d$.

The velocity v_i^d and positions x_i^d are up dated based on the Equation given below [7]:

$$n+1 v_i^d = \omega_n v_i^d + c_1 r_1^d (pbest_i^d - n x_i^d) + c_2 r_2^d (gbest^d - n x_i^d) \quad (25)$$

$$n+1 x_i^d = n x_i^d + n+1 v_i^d \quad i = 1, 2, 3, \dots, N, \quad d = 1, 2, 3, \dots, D \quad (26)$$

Where $x_i = (x_i^1, x_i^2, x_i^3, \dots, x_i^D)$ is the position of the i^{th} particle, $pbest = (pbest^1, pbest^2, \dots, pbest^D)$ is the best local best position of a particle, $gbest = (gbest^1, gbest^2, \dots, gbest^D)$ is the global best position discovered by the entire population, $v_i = (v_i^1, v_i^2, v_i^3, \dots, v_i^D)$ is the velocity of a particle i , c_1 and c_2 are the acceleration constants, n is the migration number, r_1 and r_2 are the random variables and ω is the inertia weight.

A linearly time-varying acceleration constant is introduced in evolutionary procedure as suggested in [20] applied as a modification in the standard PSO, hence MPSO. The MPSO modifies the constants c_1 and c_2 in Equation 25 with a high cognitive constant c_1 and low social constant c_2 at the start of the algorithm and gradually c_1 is decreased and c_2 is increased to move the particle around the entire search space instead of converging toward a local minima. In the latter part of the optimization the particles are allowed converge to the global optima.

$$c_1(ite) = (c_{1, min} - c_{2, max}) \frac{ite}{ite_{max}} + c_{1, max} \quad (27)$$

$$c_2(ite) = (c_{2, max} - c_{1, min}) \frac{ite}{ite_{max}} + c_{2, min} \quad (28)$$

Where ite is the current iteration number and ite_{max} is the maximum iteration number. Then, $n+1 v_i^d$ and $n+1 x_i^d$ should be under the constrained conditions as follows:

$$n+1 v_i^d = \begin{cases} n+1 v_i^d, & -v_{max} \leq n+1 v_i^d \leq v_{max} \\ v_{max}, & n+1 v_i^d > v_{max} \\ -v_{max}, & n+1 v_i^d < -v_{max} \end{cases} \quad (29)$$

Where v_{max} is the maximum value of v , x_{max} and x_{min} are the maximum and minimum value of x , respectively.

$$n+1x_i^d = \begin{cases} n+1x_i^d, & x_{min} \leq n+1x_i^d \leq x_{max} \\ x_{init}, & n+1x_i^d > x_{max} \\ x_{init}, & n+1x_i^d < x_{min} \end{cases} \quad (30)$$

$$x_{init} = x_{min} + rand() * (x_{max} - x_{min}) \quad (31)$$

5. Fuzzy Parameter Optimization Using MPSO

The three parameters a , b and c are used to design fuzzy MFs . The two membership functions are constructed by these three parameters subject to the constraint; $0 \leq a \leq b \leq c \leq 255$. The flowchart for obtaining the optimal threshold based on maximum fuzzy entropy using MPSO is illustrated in Figure 3.

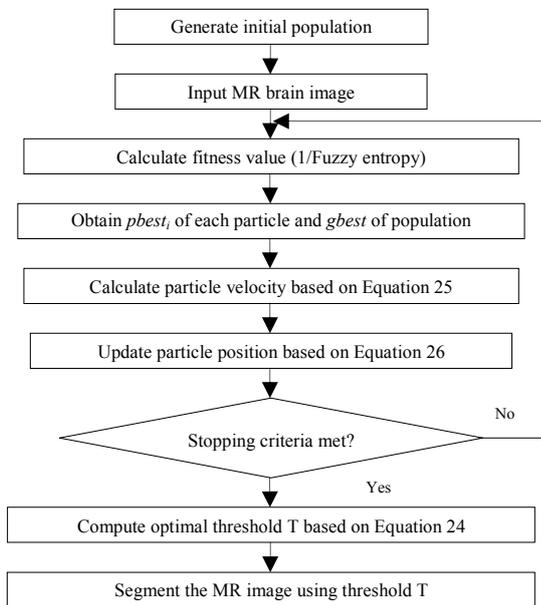


Figure 3. MPSO MR image segmentation flowchart.

These three parameters are optimized using MPSO. Since, MPSO uses objective function to find its optimal solution, entropy is considered as the objective function based on Equation 22. This optimization is considered as a minimization problem hence the fitness function is considered as inverse of objective function. The threshold is calculated from the optimal fuzzy MFs parameters and segmentation is carried out.

The procedure can be summarized as follows: First initialization of the particle swarm for the position matrix X and the velocity matrix V are given below as:

$$n x_i^d = x_{min} + (x_{max} - x_{min}) * rand() \quad (32)$$

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \dots & \dots & \dots \\ x_{N1} & x_{N2} & x_{N3} \end{bmatrix} \quad (33)$$

$$n v_i^d = -v_{max} + 2v_{max} * rand() \quad (34)$$

$$V = \begin{bmatrix} v_{11} & v_{12} & v_{13} \\ v_{21} & v_{22} & v_{23} \\ \dots & \dots & \dots \\ v_{N1} & v_{N2} & v_{N3} \end{bmatrix} \quad (35)$$

Where x_{max} and x_{min} are the maximum and minimum value of position x , where $x_{max} = L_{max}$, $x_{min} = L_{min} + 1$, $x_{i2} - x_{i1} \geq 2$ and $x_{i3} - x_{i2} \geq 2$; L_{max} and L_{min} are the corresponding maximum and minimum gray levels of the image.

For each particle, fitness value is calculated using the fuzzy entropy function. The evaluated current fitness values are compared with that of the fitness value of its best previous position. If the current fitness value is found to be better, then the best previous position is set as the current best position. Then compare the evaluated fitness value of each particle with the fitness value of the whole swarm's best previous position, $pbest$. If the current value is better, subsequently set the current position as the whole swarm's best previous position. Update the velocity of each particle using to Equation 25, Update the position of each particle with Equation 26, subject to constrains, Equations 29 and 30. The predefined maximum iterative time is the stopping criterion. If the terminating criterion is not satisfied, the MPSO will search for the next best particle in the swarm. When the terminating criterion is satisfied, the threshold T is calculated based on the optimal fuzzy MF parameters (a , b , c) then segmentation is carried out.

6. Experimental Results

The entire simulation is carried out using MATLAB 7.1 on a Desktop with Intel® Core™ i5-Processor and 4GB RAM. The MPSO parameters were initialized as mentioned in Table 1.

Table 1. MPSO parameter settings.

Parameters	Value	
Swarm Size	25	
Self-Recognition Coefficient, c_1	c_{1min}	0.5
	c_{1max}	2.5
Social Coefficient, c_2	c_{2min}	0.5
	c_{2max}	2.5
Inertia Weight, ω	1	
Bird Step	150	

The parameter settings for PSO which is used for comparison is given in Table 2.

Table 2. PSO parameter settings.

Parameters	Value
Swarm Size	25
Self-Recognition Coefficient, $C1$	2
Social Coefficient, $C2$	2
Inertia Weight, Ω	1
Bird Step	150

In order to, substantiate this work, a set of MR brain images is used as the experimental data. Each MR brain image includes a tumor that should be segmented. In order to validate the effectiveness of the proposed MPSO method, the performance of segmentation is compared with that of existing methods such as: PSO method, Otsu's segmentation method [11] and finally with exhaustive search method.

The simulation results of four MR brain images are shown in Figures 4, 5, 6 and 7. Each figure shows the test MR brain image, the segmented images using the proposed method as well as other methods used in comparison. The test images used for segmentation include Figure 4-a a tumor in the left medial parietal cortex, Figure 5-a the tumor located in the supersellar region, Figure 6-a the tumor is located in the left occipito-parietal region and Figure 7-a the tumor is located in the medial parietal cortex. These images were taken from MNI brain web.

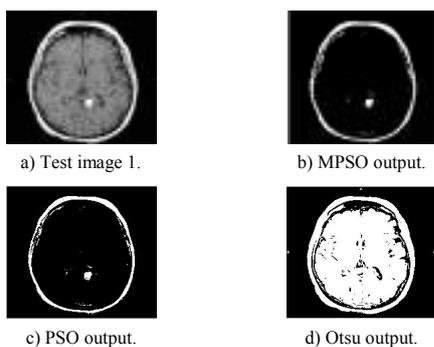


Figure 4. Simulated segmentation output for test image 1.

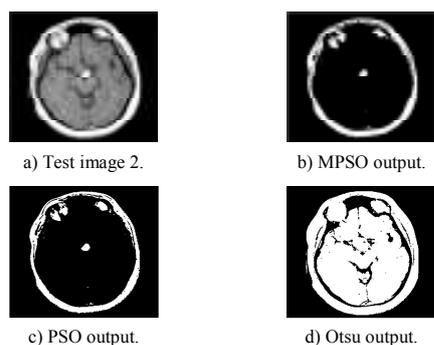


Figure 5. Simulated segmentation output for test image 2.

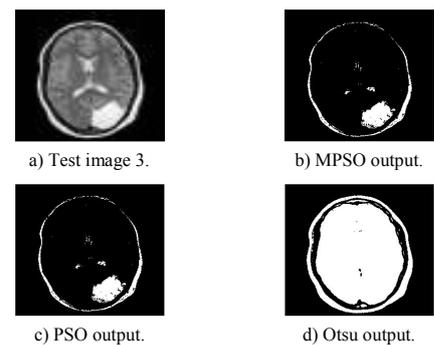


Figure 6. Simulated segmentation output for test image 3.

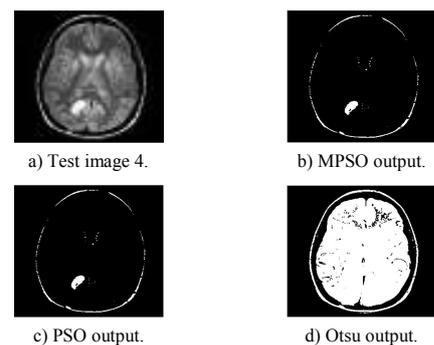


Figure 7. Simulated segmentation output for test image 4.

Figure 4-b shows the segmentation performed by the MPSO method with an obtained optimal threshold value of $T=184.142$, Figure 4-c shows the segmentation performed by the PSO method with a threshold value of $T=182.531$. Figure 4-d shows the segmentation performed by Otsu segmentation method with a threshold value of $T=74.2902$.

Figure 5-b shows the segmentation performed by the MPSO method with an obtained optimal threshold value of $T=193.7421$

Figure 5-c shows the segmentation performed by the PSO method with a threshold value of $T=190.301$. Figure 5-d shows the segmentation performed by Otsu segmentation method with a threshold value of $T=82.3216$.

Figure 6-b shows the segmentation performed by the MPSO method with an obtained optimal threshold value of $T=222$. Figure 6-c shows the segmentation performed by the PSO method with a threshold value of $T=220.483$. Figure 6-d shows the segmentation performed by Otsu segmentation method with a threshold value of $T=72.282$.

Figure 7-b shows the segmentation performed by the proposed MPSO method with an obtained optimal threshold value of $T=225.3562$ and Figure 7-c shows the segmentation performed by the PSO method with a threshold value of $T=225.536$. Figure 7-d shows the segmentation performed by Otsu segmentation method with a threshold value of $T=60.2353$.

Figure 8-a shows the segmentation performed by the exhaustive search method with a threshold value of $T=184.142$. Figure 8-b shows the segmentation performed by the exhaustive search method with a threshold value of $T=193.7421$. Figure 8-c shows the segmentation performed by the exhaustive search method with a threshold value of $T=22.6239$. Figure 8-d shows the segmentation performed by the exhaustive search method with a threshold value of $T=225.3562$.

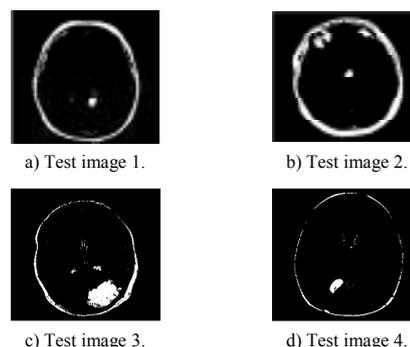


Figure 8. Simulated segmentation output for exhaustive search method for test images.

From Figures 4-b, c, d, 5-b, c, d, 6-b, c, d, 7-b, c, d and 8 it is inferred that the segmentation of the tumor is more precisely segmented by the proposed MPSO method when compared with that of PSO, Otsu segmentation method and exhaustive method.

The membership function corresponding to proposed MPSO and the PSO for test images are shown in Figures 9, 10, 11, 12, 13, 14, 15 and 16.

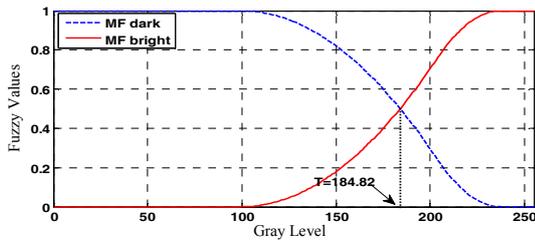


Figure 9. MF for image1 using MPSO with a=99, b=203, c=238 and maximal fuzzy entropy H=7.4158.

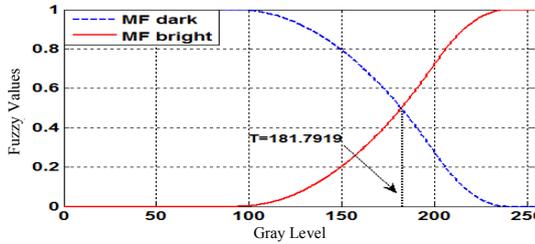


Figure 10. MF for image1 using PSO with a=99, b=203, c=238 and maximal fuzzy entropy H=7.4158.

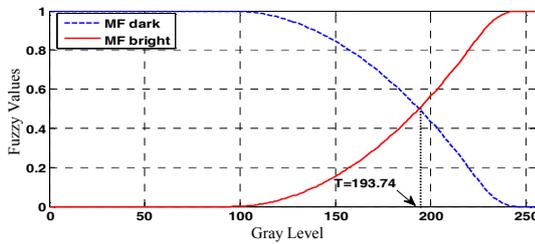


Figure 11. MF for image 2 using MPSO with a=95, b=225, c=245 and maximal fuzzy entropy H=6.9207.

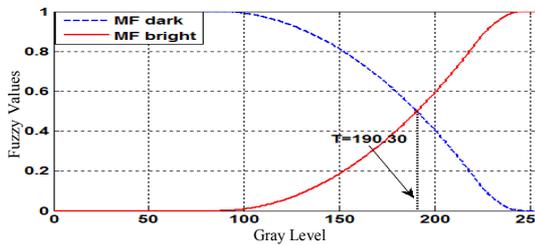


Figure 12. MF for image 2 using PSO with a= 95, b= 225, c= 245 and maximal fuzzy entropy H= 6.9207.

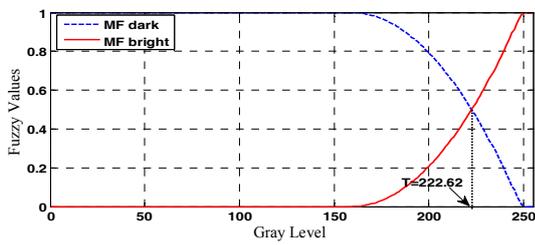


Figure 13. MF for image 3 using MPSO with a=159, b=247, c=251 and maximal fuzzy entropy H=8.8191.

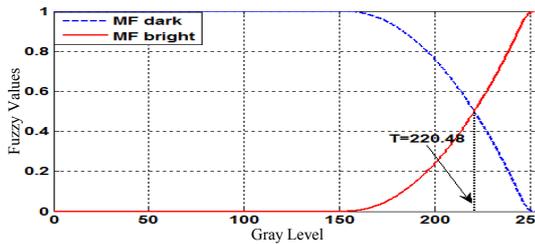


Figure 14. MF for image 3 using PSO with a=159, b=247, c=251 and maximal fuzzy entropy H=8.8191.

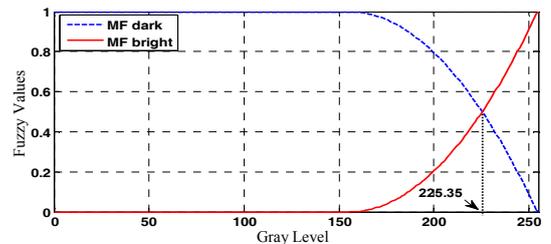


Figure 15. MF for image 4 using MPSO with a=155, b=254, c=255 and maximal fuzzy entropy H=6.9698.

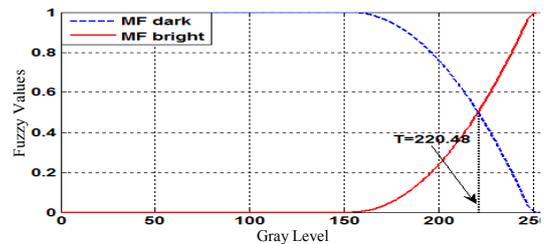


Figure 16. MF for image 4 using PSO with a=155, b=254, c=255 and maximal fuzzy entropy H=6.9698.

Table 3 shows the comparison of the results for the test images with Otsu, Exhaustive, PSO and proposed MPSO method. Among the proposed methods MPSO method gives the same threshold as that of exhaustive search method with minimum computational time which is around 95 times lesser than that of exhaustive search method.

Table 3. Comparison of results for the test image parameters.

Test Image	Method	Fuzzy MF Parameters	Threshold(T)	Entropy(H)	Time(sec)
		(a, b, c)			
Image 1 (225×225)	Otsu	NA	74.290	4.877	0.327
	Exhaustive	(99, 203, 238)	184.142	7.416	353.68
	PSO	(93, 201, 239)	182.531	7.121	1.98
	MPSO	(99, 203, 238)	184.142	7.416	2.08
Image 2 (630×612)	Otsu	NA	82.322	4.935	0.51
	Exhaustive	(95, 225, 245)	193.742	6.921	358.09
	PSO	(86, 222, 246)	190.301	6.398	3.46
	MPSO	(95, 225, 245)	193.742	6.921	4.76
Image 3 (300×300)	Otsu	NA	72.282	5.995	0.41
	Exhaustive	(159, 247, 251)	222.624	8.819	354.28
	PSO	(152, 245, 252)	220.483	7.992	2.94
	MPSO	(159, 247, 251)	222.624	8.819	3.02
Image 4 (500×383)	Otsu	NA	60.235	5.670	0.42
	Exhaustive	(155, 254, 255)	225.356	7.713	355.22
	PSO	(149, 252, 254)	222.536	7.026	2.78
	MPSO	(155, 254, 255)	225.356	7.713	3.94

In all the test images, the MPSO method produced the same entropy as that of exhaustive search method and is well known that exhaustive search method provides the global best solution in the entire search space and the computational time required in finding the best value is very high. Hence, it is evident that the proposed MPSO method finds the global best fuzzy MF parameters in minimum computational time.

Due to the randomness of the proposed MPSO method and to show the frequency of convergence to the near optimal solutions, convergence test is carried out. Hence, the randomness check for the proposed MPSO method is carried out for 25 trial runs with the parameter settings given in Table 2. The convergence results for proposed MPSO are summarized in Table 4.

Table 4. Convergence results with test images for 25 trial runs.

Test Image	Fuzzy Membership Function Parameters									Fuzzy Entropy (H)			
	a			b			c			6.5-6.8	6.9-7.2	7.3-7.6	7.7-8.0
	90-115	116-141	142-167	162-192	193-223	224-254	211-225	226-240	241-255				
Image 1 (225×225)	23	2	0	1	23	1	0	24	1	0	2	23	0
Image 2 (630×612)	24	1	0	0	3	22	0	1	24	1	24	0	0
Image 3 (300×300)	0	2	23	0	2	23	0	2	23	0	0	0	25
Image 4 (500×383)	0	1	24	0	1	24	0	1	24	0	0	2	23

7. Conclusions

A bi-level thresholding method for MR brain image segmentation based on maximum fuzzy entropy using evolutionary algorithms such as PSO and MPSO was explained in this paper. To obtain the best fuzzy MF parameters MPSO was introduced, which leads to effective exploration and exploitation. The results show that the proposed method obtains satisfactory performances in the segmentation experiments conducted for different test images. To ensure the optimized fuzzy parameters are global optimum, the results are compared with conventional search method (enumerative search method). The proposed method is capable of finding the global optimal fuzzy membership parameters as that of the conventional search method with minimum computational time. To validate the consistency and robustness of the proposed method, convergence test were carried out. From the convergence tests, the results showed that more than 95% of the output remains consistent. Therefore, it is concluded that fuzzy entropy based MR brain tumor segmentation using evolutionary algorithm methods are the effective method for bi-level segmentation.

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