Segmentation of MR Brain Images Using Particle Swarm Optimization (PSO) and Differential Evolution (DE)

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Abstract— **Magnetic resonance imaging (MRI) is a powerful tool for clinical diagnosis because it allows to distinguish different tissues and allows multiple modalities (T1, T2, ...) each having particular properties. In this work, the segmentation of MR Brain images is considered as an optimization problem and solved using evolutionary algorithms: particle swarm optimization (PSO) and differential evolution (DE),. The process of segmentation is done with multilevel fuzzy thresholding. The performances of three approaches were compared using the fidelity criterion: the peak-to-signal-noise (PSNR) ratio. The methods adopted provide good results in terms of accuracy and robustness. However, the PSO is the most efficient.**

Keywords-component; Optimization, Segmentation, Particle swarm optimization, Differential Evolution Algorithm, MR images.

I. INTRODUCTION

In last decades, biomedical and medical image processing have become one of the most challenging fields of image processing and pattern recognition. Brain segmentation consists of separating the different tissues: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and probably abnormal (tumor) tissue.

The aim of segmentation of MR Brain images is to: Study anatomical structure, Identify region of interest: locate tumor, …, others abnormalities, measure tissue size (to follow the evolution of tumor) and help in treatment planning prior to radiation therapy(radiation dose calculation).

However, the segmentation of MR Brain images has remained a challenge in image segmentation. And this is due to partial volume effects, motion (patient movement, blood circulation and respiration), the existence of image noise, the presence of smoothly varying intensity in-homogeneity, the fact that different anatomical structures may share the same tissue contrast and large amounts of data to be processed. For these and others many approaches have been studied, including Methods based edge [1][2][3], methods based region [4][5], Methods based on thresholding [6][7], methods based artificial neural networks [8], data fusion methods [9], Markov random field methods [10] and hybrid Methods [11][12][13][14].

Thresholding is one of the oldest methods for image segmentation. Segmentation is done by grouping all pixels with intensity between two such thresholds into on class. Sezgin and Sankur [15] have developed classification of thresholding algorithms based on the type of information used, and they measure their performance comparatively using a set of objective segmentation quality metrics. They distinguish six categories, namely, thresholding algorithms based on the exploitation of: 1. histogram shape information, 2. Measurement space clustering, 3. histogram entropy information, 4. image attribute information, 5. spatial information, and 6. local characteristics [16].

In recent years there has been a growing interest in evolutionary algorithms for diverse fields of science and engineering. The differential evolution algorithm (DE), is relatively novel optimization technique to solve numerical optimization problems. The algorithm has successfully been applied to several sorts of problems as it has claimed a wider acceptance and popularity following its simplicity, robustness, and good convergence properties [17]. Particle Swarm Optimization (PSO) has the distinction of being one of the simplest heuristic algorithms in terms of complexity of equations.

In this work, we use multilevel fuzzy thresholding to segment human MR Brain images. And we consider the segmentation as an optimization problem, so we aim to evaluate the segmentation of human brain tissues using some evolutionary algorithms: particle swarm optimization (PSO) and differential evolution (DE).

The organization of the paper is as follows: in section 2 the fuzzy c-partition entropy technique of thresholding is reviewed. A description of proposed segmentation algorithms is presented in section 3. Section 4 illustrates the obtained experimental results and discussions and section 5 concludes this work.

II. FUZZY C-PARTITION ENTROPY TECHNIQUE [18]

In the fuzzy c-partition entropy approach proposed in ref [19][20], an image is modeled by c fuzzy sets which have

[1] www.bic.mni.mcgill.ca/brainweb.

membership functions and there is no sharp boundary between these sets.

A. The Bi-level Thresholding

An image is modeled by two fuzzy sets dark and bright, whose membership functions are defined as follows:

$$\mu d = \begin{cases} 1 & x \le a, \\ \dfrac{x-c}{a-c} & a<x<c, \\ 0 & x \ge c. \end{cases} \quad (1)$$

$$\mu b = \begin{cases} 0 & x \le a, \\ \dfrac{x-a}{c-a} & a<x<c, \\ 1 & x \ge c. \end{cases} \quad (2)$$

Where x is the independent variable and a and c are parameters determining the shape of the above two membership functions.

The images have 256 gray levels ranging from 0 to 255. Then, an exhaustive search is used to find the pair aopt and copt which forms a fuzzy 2-partition that has the maximum entropy as follows:

For a = 0 to 254
For c = (a+1) to 255

1. For given a and c. new membership functions μd(i) and μb(i) are computed, for i =0, ..., 255.
2. Probabilities of the two fuzzy events dark and bright are defined as:

$$P(dark) = \sum_{i=0}^{255} \mu d(i) P(i) \quad (3)$$

$$P(bright) = \sum_{i=0}^{255} \mu b(i) P(i) \quad (4)$$

where P(i)is the probability of the occurrence of the gray level i=0 ,...,255.

3. The entropy of this fuzzy 2-partition is given by:

$$H = -P(dark)\,.\,\log(P(dark)) - P(bright)\cdot\log(P(bright)) \quad (5)$$

4. The selected threshold value Topt which is the mid-point of aopt and copt has to satisfy the following criterion function:

$$H(T_{opt}) = \max_{t=0,\dots,255}\left(H(t)\right) \quad (6)$$

Where $$T_{opt} = \frac{a_{opt} + c_{opt}}{2} \quad (7)$$

End For c
End For a

B. The Multi-level Thresholding

The 3-level thresholding is used to demonstrate how multiple thresholding can be conducted. Consider the following 3-fuzzy sets A1, A2, and A3, whose membership functions are defined as follows:

$$\mu_{A1} = \begin{cases} 1 & x \le a1, \\ \dfrac{x-c1}{a1-c1} & a1<x<c1, \\ 0 & x \ge c1. \end{cases} \quad (8)$$

$$\mu_{A2} = \begin{cases} 0 & x \le a1, \\ \dfrac{x-a1}{c1-a1} & a1 < x < c1, \\ 1 & c1 \le x \le a2, \\ \dfrac{x-c2}{a2-c2} & a2 < x < c2, \\ 0 & x \ge c2. \end{cases} \quad (9)$$

$$\mu_{A3} = \begin{cases} 0 & x \le a2, \\ \dfrac{x-c2}{a2-c2} & a2<x<c2, \\ 1 & x \ge c2. \end{cases} \quad (10)$$

Where x is the independent variable, a1, c1, a2 and c2 are parameters, and 0≤a1<c1<a2<c2≤255.

Similar to bi-level thresholding, 3-level thresholding is also used to find a fuzzy partition in the fuzzy 3-partition space, such that the entropy is maximized. But at this time, we need to find two pairs of a's and c's. Because the search space is too large, the PSO algorithm is used to solve it.

A fuzzy c-partition can be determined by 2(c-1) parameters using the proposed approach. The problem becomes to find the best combinations of these parameters. It can be considered as a combinatorial optimization problem. The size of search space increases very rapidly when the number of parameters increases as given away in table 1 below.

TABLE I. THE SIZE OF SEARCH SPACE FOR FINDING FUZZY PARAMETERS
TABLE TYPE STYLES

Number of class	Number of fuzzy parameters	Size of search space
2	2	32640
3	4	$2.7\text{x}10^{6}$
4	6	$1.7\text{x}10^{8}$

III. PROPOSED APPROACHES

Segmentation of brain images can separate different brain structures and detect possible pathologies, namely brain tumors. A good segmentation helps the doctor for making a final decision before his surgery. The main applications of the segmentation are morphometry, functional mapping and surface or volume visualization. Morphometry is the quantitative measurement of the positions, shapes and sizes of brain structures. It requires prior segmentation of these structures, and can identify, understand and follow the progression of diseases such as Alzheimer's or different tumors

The next figure shows the implementation of the proposed approach with its various stages:

A. Acquisition:

MR Brain images are obtained by a Magnetic resonance imaging (MRI). Examination performed on a machine of high field 1.5 T according to the sequences:

-Axial and Sagittal Tl

-Axial T2 * Flair and diffusion.

-Coronal T2.

[1]www.bic.mni.mcgill.ca/brainweb/.

-Examination with and without gadolinium injection.

These MRI images are of different sections (axial, sagittal, and coronal) of healthy and pathological subjects and they are grouped into several sections.

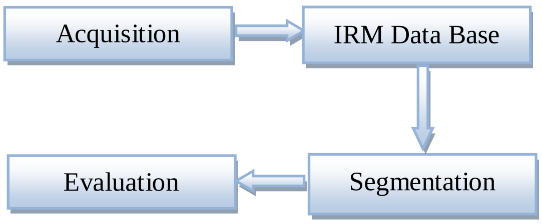


Figure.1. Diagram of the various steps of the analysis system MRI images.

B. *IRM DataBase:*

Brainweb[1] provides a simulated brain database, including a set of realistic MRI data volumes produced by an MRI simulator. These data are available for viewing in three orthogonal views (transversal, sagittal, and coronal). Also, these data enable us to evaluate the performance of the proposed approaches. To done tests under realistic conditions, one volume was generated with a thickness of one mm and a level of noise of 3%. The parameter of heterogeneity is fixed to 20%.

C. *Segmentation*

Normally MR Brain image can be classified in three classes: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF). The background region can be called as fourth region of the brain. Each region has a certain gray level, for the T1 modality, the WM region has the gray level which tend to white one, the CSF region has the gray level which tend to black one and the grey level of GM region is between the both. The multi-level thresholding devise the image in many region using thresholds. So, we will use thresholding for extracting each tissue a part using the algorithms as follows:

1. The three-level threholding

```
For all pixels of MR Bain image
  If the gray level of pixel <Threshold_1
     The pixel belong to WM region
     Else if the gray level of pixel < Threshold_2
            The pixel belong to GM region
        Else
            The pixel belong to CSL
        End if
  End if
End for
```

2. The four-level threholding

```
For all pixels of MR Bain image
  If the gray level of pixel < Threshold_1
     The pixel belong to WM region
  Else if the gray level of pixel < Threshold_2
        The pixel belong to GM region
      Else if the gray level of pixel < Threshold_3
           The pixel belong to CSL
          Else The pixel belong to Background region
          End if
       End if
   End if
End for
```

Fuzzy thresholding and PSO and DE are used to segment human MR Brain images. The fitness function represent the entropy of the fuzzy c-partition H. The fuzzy c-partition based on evolutionary algorithms (PSO and DE) is shown as follows:

The Fuzzy c-partition based evolutionary algorithms:

It consists of the flowing steps;

1. Initialisation of parameters: c: number of thresholds, ...
2. Input the MR Brain image
3. Calculate its histogram
4. Compute the probability of the occurrence of each grey-level
5. Use one of the evolutionary algorithms (PSO or DE) to Generate the thresholds values
6. Generate the fuzzy partition.

To improve the quality of the segmentation, we opted for the use of a median filter (3x3). Because it eliminates the pulse noise and preserves discontinuities, in contrast to linear filters which blurring the image and result in the loss of information at the edges.

D. *Evaluation :*

Peak signal to noise ratio (PSNR) is used to compare the performance of the three techniques adopted for segmentation of MR brain images. The PSNR give the similarity of an image against a reference image based on the mean square error (MSE) of each pixel:

$$PSNR = 20\log_{10}\left(\frac{255}{RMSE}\right) \qquad (11)$$

Where, RMSE is the root mean-squared error, defines as:

$$RMSE = \sqrt{\frac{1}{MN}\sum^{M}\sum^{N}\left[I(i,j)-\hat{I}(i,j)\right]^2} \qquad (12)$$

Here I and Î are the original and thresholded images of size MxN, respectively.

IV. Experimental Results

The T1-weighted MR axial brain images with different slices shown in Figure 2 are considered as test images for segmentation. In this work, we have use the three and four level thresholding based PSO and DE algorithms to separate the different tissues of MR brain images: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and the background

The numerical results obtained using algorithms PSO and DE with c= 3 and 4 are presented in Table 2. The performances of the approaches were compared using the fidelity criterion: the peak-to-signal-noise (PSNR) ratio.

The various fuzzy thresholds obtained are used to segment the brain image. The segmented images with the obtained

[1]www.bic.mni.mcgill.ca/brainweb/.

optimal multilevel fuzzy thresholding for the third and fourth levels are shown in Figure 2.

As is apparent, from Figure 3, DE thresholding has lowest average PSNR of 30.8717 with the biggest standard deviation of 1.4343. The fuzzy c-partition entropy using PSO and DE algorithms perform equally well in terms of the processing time and the quality of image segmentation. From Figure 2, MR Brain images have been well classified in three classes: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) using the two adopted methods.

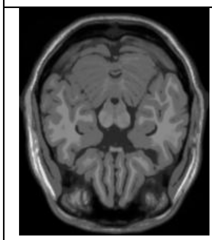
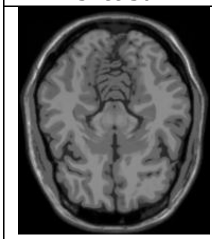
The representation of the PSNR values obtained using different algorithms for 3 and 4 level thresholding are also shown in Figure 4 and figure 5 respectively.

V. Conclusion

In this work, two approaches (PSO, DE) were proposed to segmenting the MRI Brain images, based on the concept of fuzzy thresholding, which can be very useful for medical images segmentation. T1-weighted axial MR Brain images with different slices are employed as test images. The use of PSO and DE algorithms reduce greatly the time complexity. The experimental results have shown the effectiveness and usefulness of the proposed algorithms for MR Brain images segmentation. As a perspective of this work, use these algorithms to distinguish the normal and abnormal tissues.

TABLE II. . Experimental results using PSO and DE algorithms for the test images

Original Image	Number of Classes	PSO		DE	
		Optimal Thresholds	PSNR(dB)	Optimal Thresholds	PSNR(dB)
Slice 50	3 4	33, 96 14, 65,101	30,8068 32,8160	28, 94, 23, 75, 101	31,3184 31,3184
Slice 60	3 4	33,105 25,92,117	29,4385 32,5678	34,104 24,102,117	29,7423 30,2775
Slice 70	3 4	34, 110 23,104,126	29,6182 30,6489	38,109 23,105122	29,6182 30,4223
Slice 80	3 4	32, 108 13,75,123,	29,7423 34,1514	29,107 22,105,121	30,1374 30,5721
Slice 90	3 4	23,113 14, 81, 136	30,3493 33,8172	23,112 22,88,135	30,4223 33,2172
Slice 100	3 4	11,113 1,62,128	31,0551 33,3596	12,115 12,81,135	30,8880 34,9086
Slice 110	3 4	2,105 1,65,129	32,9457 33,9811	12,109 13,84,133	31,8983 35,3433
Slice 120	3 4	1,88 1,52,114	35,1205 32,9457	15,104 1,67,124	33,6592 34,1514
		M	31,9190	M	30,8717
		σ	1,4329	σ	1,4343

Original Image	PSO		DE	
	c=3	c=4	c=3	c=4
 Slice 50				
 Slice 60				

[1]www.bic.mni.mcgill.ca/brainweb/.

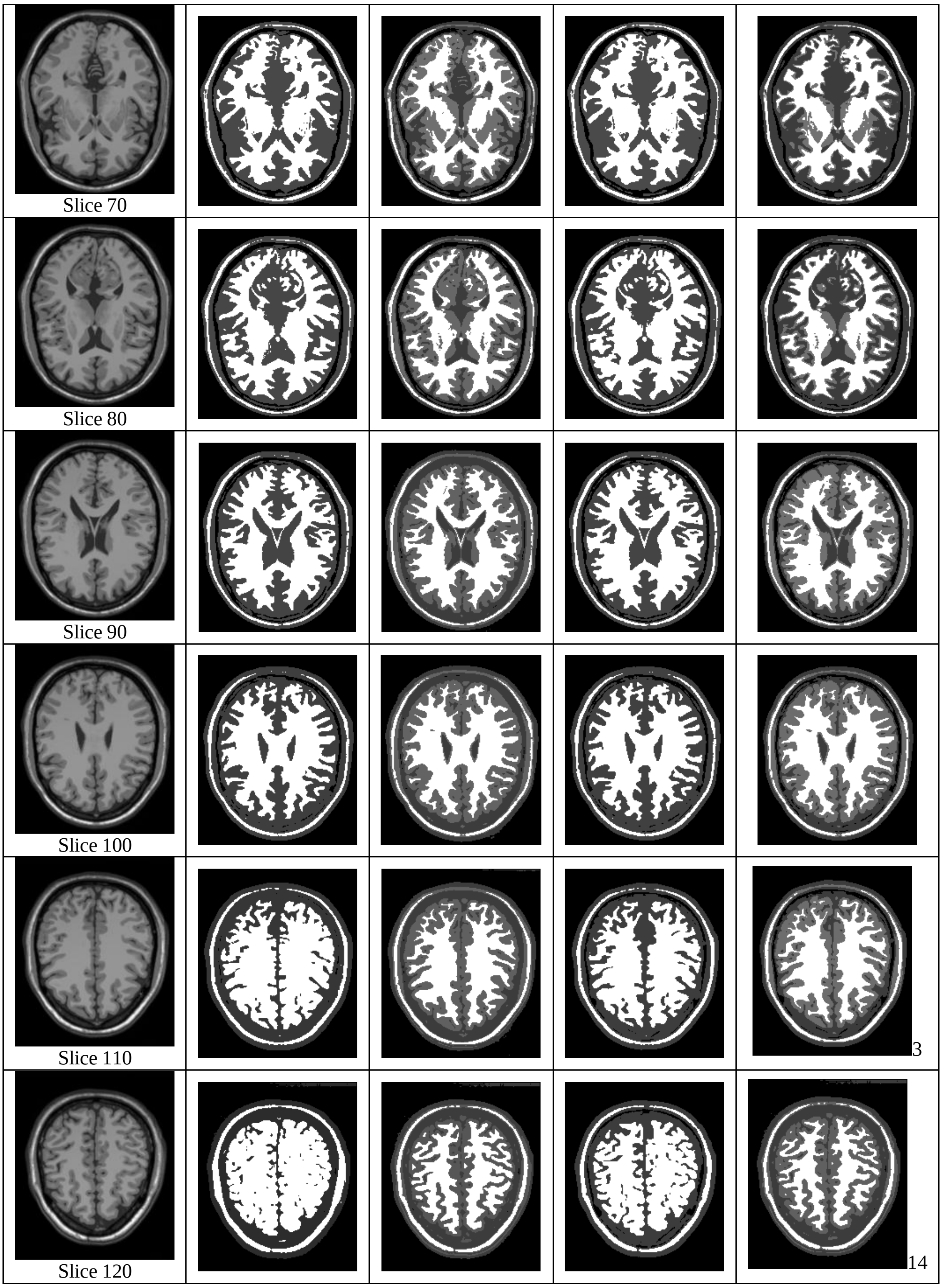


Figure.2. Examples of the test Data set and corresponding results for the algorithms:PSO and DE for c=3,4.

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[1]www.bic.mni.mcgill.ca/brainweb/.

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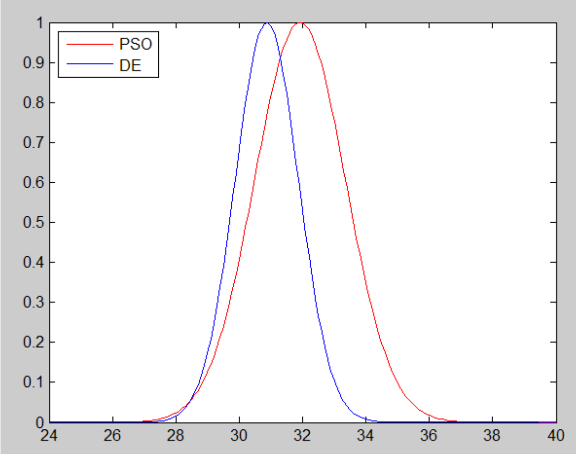

Figure.3. : PSNR Distribution for the three approaches (PSO and DE).

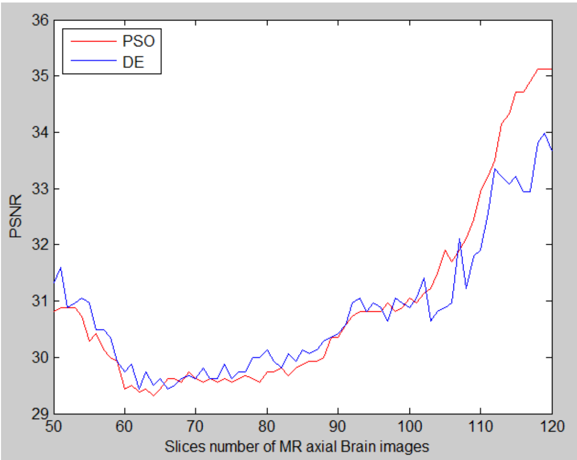

Figure.4. PSNR value for different MR slices images using the adopted approachs PSO and DE for c=3

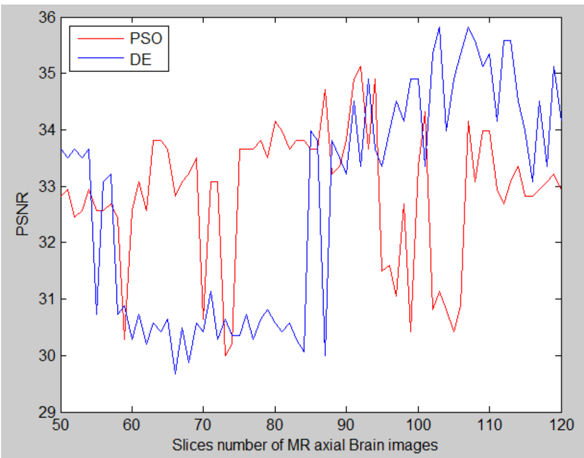

Figure.5. PSNR value for different MR slices images using the adopted approachs PSO and DE for c=4

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