A Threshold-based Brain Tumour Segmentation from MR Images using Multi-Objective Particle Swarm Optimization

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Abstract

The Pareto optimal solution is unique in single objective Particle Swarm Optimization (SO-PSO) problems as the emphasis is on the variable space of the decision. A multi-objective-based optimization technique called Multi-Objective Particle Swarm Optimization (MO-PSO) is introduced in this paper for image segmentation. The multi-objective Particle Swarm Optimization (MO-PSO) technique extends the principle of optimization by facilitating simultaneous optimization of single objectives. It is used in solving various image processing problems like image segmentation, image enhancement, etc. This technique is used to detect the tumour of the human brain on MR images. To get the threshold, the suggested algorithm uses two fitness(objective) functions- Image entropy and Image variance. These two objective functions are distinct from each other and are simultaneously optimized to create a sequence of pareto-optimal solutions. The global best (G_{best}) obtained from MO-PSO is treated as threshold. The MO-PSO technique tested on various MRI images provides its efficiency with experimental findings. In terms of "best, worst, mean, median, standard deviation" parameters, the MO-PSO technique is also contrasted with the existing Single-objective PSO (SO-PSO) technique. Experimental results show that Multi Objective-PSO is 28% advanced than SO-PSO for 'best' parameter with reference to image entropy function and 92% accuracy than Single Objective-PSO with reference to image variance function.

Keywords: Multi-objective optimization; PSO; Median filter; Threshold; Image segmentation.

1- Introduction

Image segmentation is important step in the image processing. It is the process of dividing the image into number of picture elements (generally, called "pixels"). The goal of image segmentation is to gradually change or modify the portrayal of an image, which is important and simple to analyze [1]. The image segmentation's output contains either a lot of forms removed from the picture or a lot of segments that will cover the total image. In a region of image, each pixel is comparative as for certain qualities like intensity, color, or texture [2]. Therefore, many tests and studies have been conducted to develop strategies and methods related to image segmentation. These strategies are classified into different classifications, including threshold-based and clustered-based segmentations. Image thresholding is an important tool in image segmentation, which separates the object distinct from background. This is done by based the on the different gray levels.

Basically, there are two types of thresholding techniques exits, one binary thresholding and another one is multi-thresholding [3][4]. In thresholding methods, it is very difficult to find optimum threshold value suitable for the separation of the target image. One of the best solutions for the above-mentioned problem is Particle Swarm Optimization (PSO) algorithm. PSO is recursive method that optimizes (minimize or maximizes) given problem. It is used in solving various image processing problems like image segmentation, image enhancement, etc. [5]

Brain is typical organ, which contains billion number of neurons. It is comprised of huge cells, and each cell performs some function. Magnetic Resonance Imaging (MRI) is a tool, which gives a high-quality image of various parts of the human body. But when dealing with one of the sensitive organs of the human body i.e. Brain, a care should be taken. A Brain tumor is nothing, but abnormal cells grew inside the brain. Basically, there are two types of tumors exists. One is benign (Non-cancerous) and

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another one is malignant (cancerous). Also, there is another classification exists, tumor that starts inside the brain – primary brain tumor, whereas a tumor which starts in another part of the human body and spreading into brain- secondary brain tumor (also called metastatic) [6].

The main objective of this paper is to segment the lesion from MRI image using Multi-objective Particle Swarm Optimization (MOPSO) algorithm. First, the MRI image is pre-processed, then skull-stripping is performed. Skull-stripping is the process of removing extra-meningeal tissue from the head image to find the boundaries of head and brain. Then the tumor segmentation is done by MOPSO algorithm using two fitness functions called – image entropy and image variance.

The organization of the paper as follows- section 2 gives the related work done by different authors and section 3 about acquisition of the MR images. Section 4 explains the proposed MO-PSO technique and section 5 shows the results of various MRI images. And finally, the conclusion of the paper is given in section 6.

2- Literature Survey

In reference [7], a gray-scale image is segmented using 2-D entropy maximization was proposed. Reference [8] used a technique called variance minimization for image segmentation. And it also introduced local statistics in the formulation of energy function. Reference [9] proposed a method for multilevel threshold selection for image segmentation. In this paper, a multi threshold value was computed by hill-clustering technique, linear minimax approximation algorithm and then golden search minimization algorithms.

Reference [10] proposed a method to implement image segmentation using two entropy functions. Entropy region and entropy layout functions were considered. Reference [11] gives a method called skull stripping to remove the non-cerebral tissue in T1-weighted MRI image. Reference [12] proposed multi-objective particle swarm optimization (MOPSO) for image segmentation using multi-threshold technique. Reference [13] gives a clustered- based MOPSO algorithm to separate the tumour part from MRI images. Here two fitness functions-KFECSB and AWGLAC are used to produce the non-dominated solutions.

Reference [15] proposed a method in which the leader party, self-adaptive criteria, and disruptive operator for balancing convergence and diversity are included. They used an elitist learning technique as the perturbation operator with a Gaussian mutation. Reference [16] proposed a technique to classify the tumors using brain emotional learning. Reference [17] used thresholding, segmentation, and morphological operations to identify the accurate location of brain tumour.

3- MR Images Acquisition

Different kinds of slices of brain of patients are taken for testing the proposed method. Some of the patients are presently taking chemotherapy and some of them are cured. Different types of lesions exist, from vascular lesions to tumors. Using centricity DICOM viewer, the MRI images are taken. Axial T2 view images were considered for our experiments. These images provide the pathology of the disease. Experiments were performed on 1.5-T MRI imaging device. Thickness of slice is 5 mm and resolution are 256 x 256. The gap between two slices is 1.5mm.

4- Proposed Technique

The proposed method contains several steps to segment the tumor from MRI images.

1. **Preprocessing:** In this step, the input MRI image is resized into 256 x 256 size image. Then convert the RGB image into gray-scale image. To remove the noise present in the input image a digital filter is used, called Median filter. It is most popularly used filter for removing the noise in the image. In each image, median filter is applied on pixel by pixel, each pixel is replaced with the median(middle) of neighboring pixels.

2. Skull stripping: In this process, by using Otsu thresholding and morphological operations skull stripping was done. This process is used to remove extra-meningeal tissue from head image.

3. Threshold based Optimization: Next step in the proposed algorithm is finding the threshold value using one of the optimization techniques called Multi-objective Particle Swarm Optimization (MOPSO).

In single objective PSO (SO-PSO) algorithm, the model contains 'n' number of particles. They communicate with other particles by using gradients (search directions) directly or indirectly. By using single objective (fitness) function, the global threshold (global minima or global maxima) has been calculated.

The SO-PSO was originally introduced by Kennedy and Eberhart, inspired by the social actions of flocking birds and fish schooling, for problems of optimization. Any individual considered to be a potential solution to the problem of optimization of a given swarm will benefit from the previous experiences of all other individuals in the same population [13]. Every particle, through the search process in the solution space, the speed and location will be changed according to their own flying experiences and from the others in the swarm as well.

Consider Mp is the swarm size, any particle that contains the elements N, with a position vector Xi and velocity vector Vi, its own best location, p^{best} find so far, and communicates with neighboring particles via the best location so far, g^{best} has been found in the neighborhood. The optimality of the position is measured using one or more fitness functions described in the relationship to the issue of optimization. Each particle is moved according to the below equations at qth iteration in the search space.

$$Vq + 1 = wVq + c1 * r1 * [\boldsymbol{p}^{best}q - Xq] + c2 * r2 * [\boldsymbol{g}^{best}q - Xq]$$
(1)

$$Xq + 1 = Xq + Vq + 1$$
(2)

Where w is inertia weight,
  r1 and r2 are the random variables,
  c1 and c2- acceleration coefficients.

But most of the real-world problems contain simultaneous optimization of one or more objective functions. In general, these objective functions belong to different groups and conflicting and competing. The MOO (multi-objective optimization) techniques have such conflicting and competing objective functions which gives optimal solutions set instead of single solution. With respect to all objectives, no solution is better than the other. These optimal solution set is known as Non-dominated solution set. Also called Pareto-solution set.
The MOO has 'n' number of objectives and 'm' number of equality and inequality constants. Mathematically,

Minimize/Maximize

$$F_i(x) = [\, f_1(x), f_2(x), \ldots \ldots, f_N(x)]$$
(3)

Subject to

r^j(x)= 0; j=1, 2, ...J
s^k(x)≤ 0; k=1, 2, ...K
(4)

where F$_i$(x)- fitness function,
  x- decision vector,
  J- Equality constant,
  K- Inequality constant.
In MOO, multiple fitness functions need to be handled at the same time. Pareto improvement is the process of moving from one solution to other that can make at least one objective function to return a best value and with no other objective function becoming worst. When no further pareto improvements can be happened, those candidate solutions are said to be "Pareto optimal solutions". Still, all of the elements of an ideal pareto set

may not be desirable, and although it provides certain space and time constraints, the pareto set may be infinite.[14]
Threshold based image segmentation is one of the popular methods used to extract tumour from MRI images. To segment tumour part from MRI images, two fitness functions are used here: Image entropy and Image variance.

Entropy is the actual ratio of randomness that can be utilized to describe the shape of a gray-scale image. It gives the average information of image can be resolved around from the histogram of the image. Mathematically, the entropy is defined as

$$E = -\sum_L q_l \, log_2 \, q_l$$
(5)

Where L represents number of gray levels,
  q$_l$ is the probability related to with gray level 'l'.

Another fitness function is variance of the image. It is used to discover how every pixel varies from its neighboring pixel (or centre pixel) and is utilized in characterize into various regions. Mean of the image is nothing but, the average of total pixels of given image. With M X N image size, mean is defined mathematically,

$$\bar{d} = \frac{1}{MN} \sum_m \sum_n d_{mn}$$
(6)

The simplified notation of equation (4) is

$$\bar{d} = \frac{1}{K} \sum_K d_k$$
(7)

The variance is

$$\sigma^2 = \frac{1}{K} \sum_K (d_k - \bar{d})^2$$
$$= \frac{1}{K} \sum_K d_k{}^2 - \bar{d}^2$$
(8)

These are the two objective functions need to be optimized. Image entropy function must be maximized, and image variance function must be minimized.

After finding the threshold using above method, the object and backgrounds are separated as follows,

- Pixel intensity is above the obtained threshold => taken as object (1).
- Pixel intensity is below the obtained threshold => taken as background (0).

4-1-   Algorithm:

1. Convert the input RGB image to gray-scale image.

2. Apply median filter to remove the noise.

3. Perform skull stripping process to remove skull from input MRI image.

4. Find the threshold value using MOPSO technique.
   i)   Initialize the PSO parameters like c1, c2, inertia weight, initial position and velocity.

   ii)   Initialize repository.
   iii)   Evaluate the fitness for all particles using two functions- entropy and variance.
   iv)   Find the particle $_{best}$ and global $_{best}$.
   v)   If the total number of iterations is not satisfied DO FOR each particle:

   - Update velocities and positions
   - Perform mutation
   - Evaluate fitness for all particles
   - Find particle $_{best}$ and global $_{best.}$

5. Update repository.

6. Display the tumor part from input MRI image.

The flowchart of the proposed method is shown in figure 1.
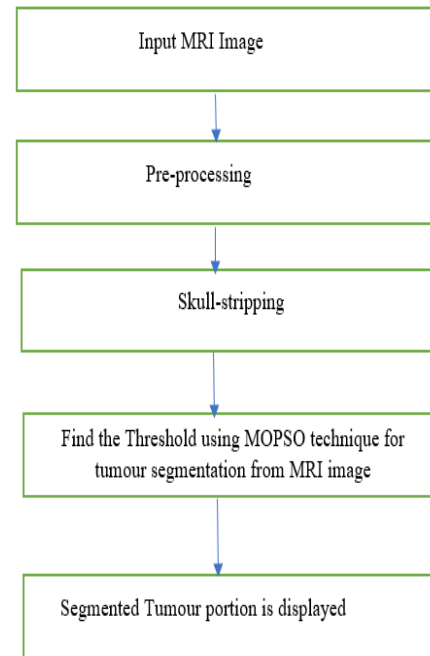
Fig. 1 Flowchart of proposed algorithm

5- Results

We have taken different slices of the human brain and single patient's MRI images are analyzed. The MRI images are taken from different datasets of the same patient at different times and in different view-focuses. These are taken from Kaggle dataset, using the link htttp://www. kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection/.

In this, 240 datasets are considered. Among them, 100 datasets are related to malignant and 140 are related to benign type of tumor. The extensive simulation has been done to validate the significance of the proposed algorithm. These MRI images are T1-weigthed type, which are widely considered in medical diagnosis of tumor.

The experiments are done in MATLAB on PC. The MOPSO parameters are set as follows:
Acceleration constants: c1=2, c2=2,
Minimum and maximum weights:
    w^{min}=0.1, w^{max}=0.9
Number of iterations= 100,
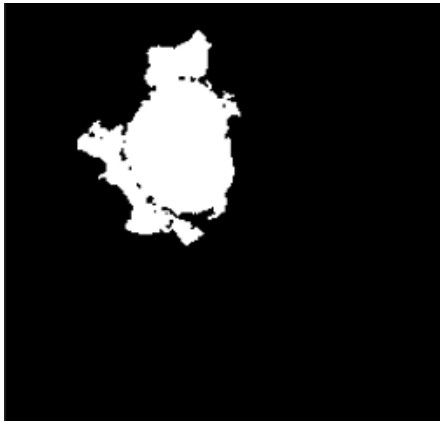Number of particles in population= 100.

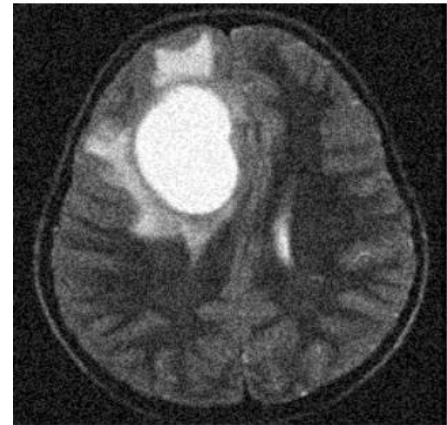Fig. 2 a) Input MRI image from dataset 1
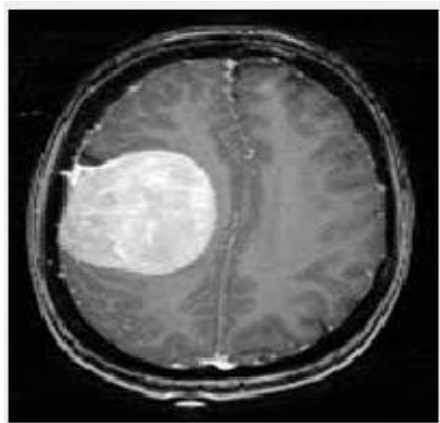

Fig. 2 b) Segmented output image

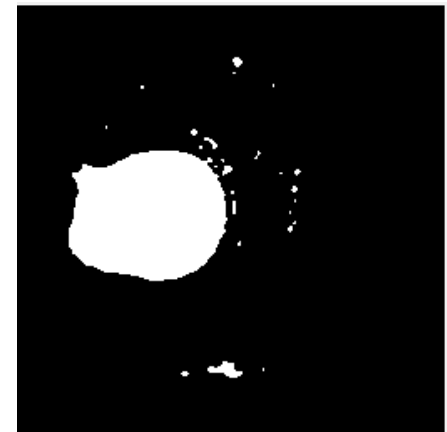Fig. 3 a) Input MRI image from dataset 2

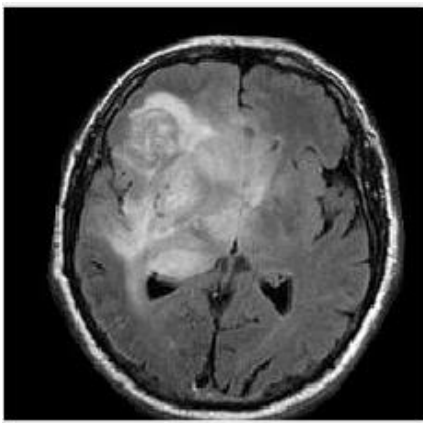
Fig. 3 b) Segmented output image

Fig. 4 a) Input MRI image from dataset 3
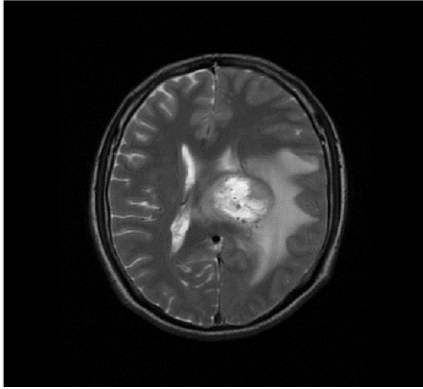

Fig. 4 b) Segmented output image

Fig. 5 a) Input MRI image from dataset 4
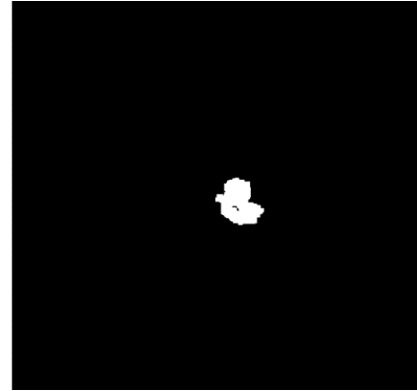

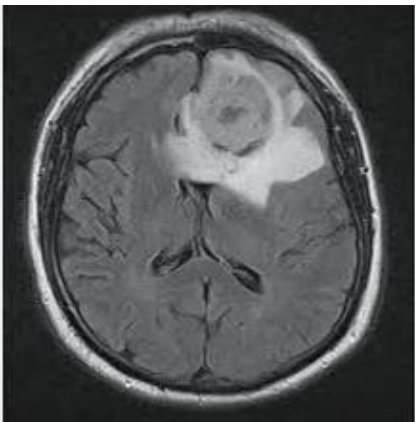Fig. 5 b) Segmented output image

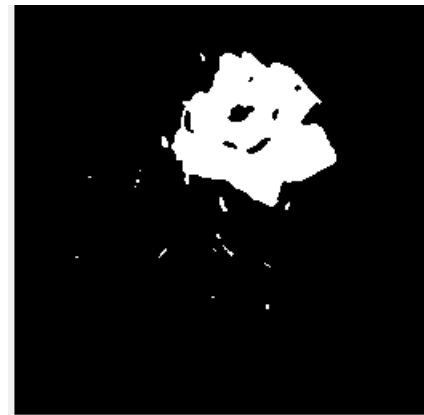Fig. 6 a) Input MRI image from dataset 5

Fig. 6 b) Segmented output image

Table I gives the summary of experiments done on MOPSO algorithm. It gives the executed time, best fitness, and threshold of given input MR images.

Figures 2 (a), 3(a), 4 (a), 5 (a), 6 (a) represents the input MRI images and figures 2 (b), 3 (b), 4 (b), 5 (b), 6 (b) represents their outputs which contain tumors and threshold values are 138,151,144,133,198,135, 128 respectively.

Table I. Summary of Experimental Results

Input	Time	Best fitness	Threshold
Image 1	16.98 sec	1.009	138
Image 2	18.44 sec	1.004	151
Image 3	16.63 sec	1.008	144
Image 4	17.52 sec	1.006	133
Image 5	18.13 sec	1.004	198
Image 6	16.92 sec	1.007	128

Table II and table III gives the analysis of PSO and MOPSO algorithms with and without preprocessing step.

In the following table II, with reference to entropy and variance functions the performance measures like "best, worst, mean, median, standard deviation" are compared for both PSO and MOPSO techniques before preprocessing step.

Table II.PSO and MOPSO algorithms Analysis without Preprocessing

Parameter	With reference to Entropy		With reference to Variance	
	PSO	MOPSO	PSO	MOPSO
Best	0.823	0.62	7.82	0.92
Worst	0.00223	0.00219	5333	3394
Mean	0.423	0.391	2244	1549
Median	0.4357	0.412	2196	1449
Standard deviation	0.052	0.062	429	349

By considering entropy function, it is observed that MOPSO is 24% advanced than PSO for 'best' parameter, mean is 7.5% improved than PSO, and median is 5.4% is better than MOPSO.

Table III.PSO and MOPSO algorithms Analysis with Preprocessing

Parameter	With reference to Entropy		With reference to Variance	
	PSO	MOPSO	PSO	MOPSO
Best	0.8432	0.6051	7.923	0.592
Worst	0.00312	0.00219	5449	3459
Mean	0.4556	0.4123	2139	1297
Median	0.4559	0.4294	2096	1304
Standard deviation	0.0637	0.0874	495	307

By considering entropy function, it is observed that MOPSO is 28% advanced than PSO for 'best' parameter, mean is 9.5% improved than PSO, and median is 6% is better than MOPSO. The analysis is shown graphically in following figure 7.
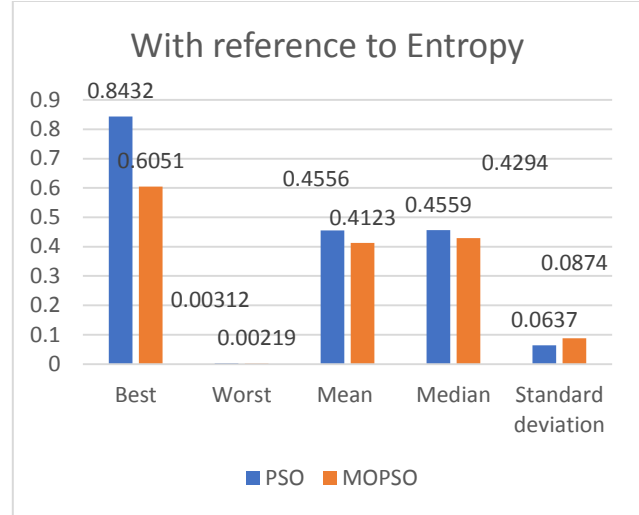

Fig. 7 Analysis of PSO and MOPSO algorithms with reference to Entropy function

These are the following observations from figure 8- for best measure the MOPSO is 92% advanced than PSO, the mean for MOPSO is 39% better than PSO algorithm. Median of MOPSO is 38% advance than PSO with reference to variance function.

From the above analysis, MO-PSO is performed well in lesion segmentation of brain MR images.
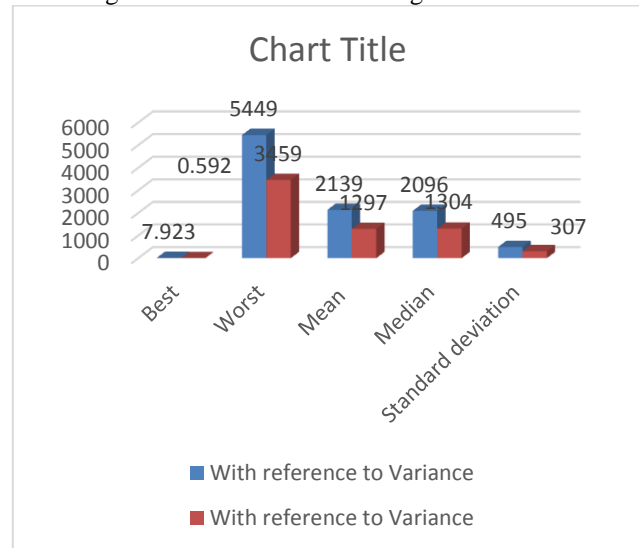

Fig. 8 Analysis of PSO and MOPSO algorithms with reference to Variance function

6- Conclusions

In this paper, MOPSO algorithm has been described to segment the lesion from MRI images. The goal of Multiobjective optimization (MOO) technique is to optimize at least two fitness (quantitative) functions simultaneously. Image entropy and variance functions are used in this work. Entropy is maximized and variance is minimized to get the optimal threshold value. This value is used to segment the lesion from MRI image. The exploratory outcomes give fulfilled and great image segmentations. Also, this technique is better when compared to single objective PSO technique.

Future Scope

In future, we will extract the texture features of segmented tumor and given to the machine learning algorithms to evaluate the performance of the classifier. Finally, the user will know the type of tumour whether it is Benign or Malignant.

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