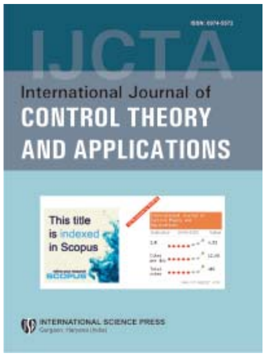

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Segmentation of MRI Brain Images: A Comparative Analysis

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Abstract: The medical image segmentation is a complex and stimulating task due to the distinct features of the images. The segmentation for Magnetic Resonance Imaging (MRI) of brain is a difficult task due to the high quality of images, anatomical structures of the brain and complexity of tumors. In the field of medical imaging several researchers have made many algorithms in the field of tumor segmentation. This research work is comparing the previously proposed hybrid algorithm Electromagnetic Level Set Methods (ELSM) algorithm with other segmentation algorithms. The ELSM algorithm has been compared with the common clustering algorithm fuzzy c means (FCM) and with the Particle Swarm Optimization (PSO) optimization algorithm is also been considered for the comparison and the results are discussed. The comparison criteria used in this work are computation time, memory occupied by the resultant images and the counting the white pixel of the predicted region. Using these three selected features, the accuracy of the dataset collected has been evaluated and the results are discussed, from these the novel hybrid ELSM algorithm produces higher efficiency. We compare these results with the PSO and the FCM algorithms, which are widely, used technique in the medical image analysis. The future work is measuring the size of the predicted tumor region, which provides more accuracy to the algorithms.

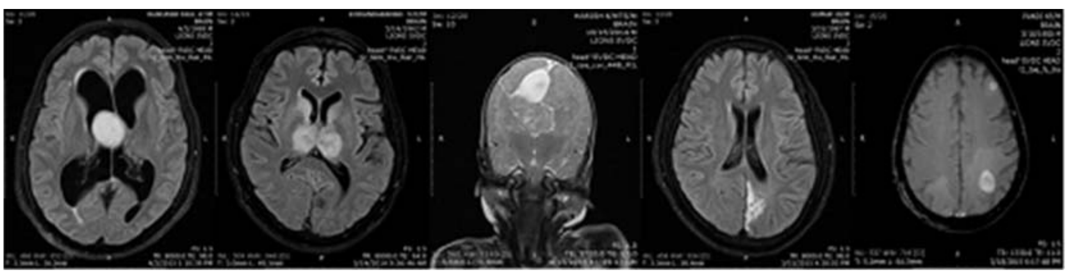
Keywords: *Magnetic Resonance Imaging (MRI), ELSM, PSO an FCM.*

1. INTRODUCTION

In medical image study, image segmentation plays predominant role. Medical images are one of the main concerns in image processing where the competence and correctness are necessary at extremely high level. Three-dimensional (3-D) processing and visualization of medical images is a promptly growing area of research MRI data. In biomedical applications image segmentation plays a major role. Radiologists use the segmentation techniques to segment input medical images into meaningful region to detect the tumor. Physical segmentation of image by the radiologists is a tedious and extended procedure [18]. The brain is an extremely dedicated organ and it serves as the determination for the brain tumors which affects whole body so segmentation of the affected region from Magnetic Resonance Imaging (MRI) are significant in medical image analysis and in finding the behavior of the diseases. The segmentation is a significant tool in medical image dispensation and it has many applications, in discovery of tumors, measuring tumor volume, surgical planning and preparation, discovering coronary edges, categorization of blood cells [16].

Brain tumor is identified with magnetic resonance imaging (MRI), shows that there is a tumor in the brain. It uses magnetic fields to produce detailed images of the body and to measure the tumor's size. The MRI T1-weighted and T2- weighted images are the most commonly used techniques in MRI imaging. The MRI brain tumor segmentation provides useful information for surgical planning and further medical diagnosis. The large variance and complexity of tumor characteristics such as size, location, intensity and shape in MRI images is a difficult task. So the manual tracing and delineating of segmentation of brain tumor is in practice [20]. Brain tumor anatomy, vascular supply and cellular structure are the detailed information provided by the MRI. Brain tumors are abnormal and uncontrolled growth of cells [17]. The manual segmentation of brain tumors in MR images is a challenging and time-consuming task. The segmentation that provides objective, reproducible segments from the brain which is capable of producing results are closes to the manual results [14].

The ultimate aim of brain tumor imaging is extracting the patient clinical information and their diagnostic features. The multidimensional 3D image data, monitors the tumor detected area and leading to the knowledge for clinical staging, diagnosis and the treatment for the diseases. The main objective of image segmentation is to partition an image into meaningful exclusion regions such that each region is relatively contiguous and pixels with in the region are homogeneous with respect to their intensity values. The segmented tumor region is non-rigid and complex in shape, varies in position, size and show significant changes from patient to patient [4]. The image segmentation is essential in medical diagnosis, computer vision and in many emerging fields. Numerous approaches for image segmentation exists among these image clustering, region growing, optimization techniques and thresholding plays major role [7].



(*a*) Img_01 (*b*) Img_02 (*c*) Img_03 (*c*) Img_04 (*c*) Img_05

Figure 1: Input abnormal MRI brain images

The main aim of this research work is comparing segmentation algorithms with our proposed method to the MR brain dataset. The comparison of the MR images is based on the three criteria, time, storage and the pixel count of the segmented images. The research work carried out by the various segmentation algorithms like the optimization algorithm, clustering algorithm with our previously developed novel segmentation ELSM (Electromagnetic Level Set Methods). Figure 1 shows the input abnormal input MR image data set. The figure 1(*a*)-1(*e*) shows the MR image of different patients. The dataset collections are the real world image and it has been categorized as normal and abnormal image. The rest of the paper is organized as follows. Section II discusses the Particle Swarm Optimization algorithm and its results for the MR dataset and Section III deliberates the Fuzzy C Means algorithm and its evaluation results. In Section IV, our proposed approach ELSM algorithm has been discussed and shows the results. The performance analysis of the three algorithms is discussed and summarized in Section V. Section VI concludes this research work.

2. PARTICLE SWARM OPTIMIZATION ALGORITHM

2.1. Introduction

The Particle Swarm Optimization is a population based optimization techniques which simulates the social behavior of bird. By randomly initializing algorithm the solution of PSO successfully leads to the global optimum [22].The PSO is a new algorithm for searching inspired by social behavior of birds proposed kennedy and Eberhart in the year 1995 to solve problems with the continuous variables. The algorithm is exceeds by an iterative procedure based on the intelligence and processes of movements of birds in the evolutionary system[5]. The PSO algorithm follows the behavior of bird, while searching for the food, the birds get scattered or they move together in finding the food. In general, the birds search for the food from one place to another, the bird can smell the food when it is nearer to the food.

An MR Brain Images Classifier System via Particle Swarm Optimization and Kernel Support Vector Machine proposes a novel hybrid system for the MR brain abnormal images. In the proposed methods they first uses the digital wavelet transform to extract features then uses the principal component analysis and the construct a kernel support vector machine using particle swarm optimization to reduce the feature space. The authors worked on around 90 images and the results shows that PSO is better than KVSM [21]. Faycal Hamdaoui and et.al. proposes a algorithm based on the stochastic optimization strategies for the MRI brain images segmentation based on PSO. The proposed algorithm presents an improved PSO, particularly for the segmentation, to arrange the particle in space in descending order it uses the fitness function. The quality of image after segmentation is measured by its run time [5]. The multi-elitist strategy is been introduced with the concepts of PSO and proposes a new PSO algorithm in the research work titled as Spatial Information Based Image Segmentation Using a Modified Particle Swarm Optimization Algorithm [2]. An important feature of the proposed algorithm is finding the optimal number of clusters automatically in which clusters should not be noted in previously. The results of the proposed model are compared with the formal FCM algorithm and the analysis is performed.

2.2. PSO Algorithm

The PSO algorithm consists of '*n*' swarm particles and the position and intensity of each particle stands the best potential solution of the particle. The best potential solution can be achieved with the help *g*best and *p*best of the algorithm [11]. The traditional PSO algorithm equations are described below

$$v_{id}^{k+1} = v_{id}^{k+1} + c_1 r_1^k (p\text{best}_{id}^k - x_{id}^k) + c_2 r_2^k (g\text{best}_{id}^k - x_{id}^k) \quad (1)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (2)$$

v_{id}^{k+1} and x_{id}^{k+1} represents the speed of the particle "I" and its "*k*" times and the *d*-dimension quantity of its position, $g\text{best}_{id}^k$ is the optimist position of the *d*-dimension quantity of the swarm and $p\text{best}_{id}^k$ stands the *d*-dimension quantity of the individual "I" at its most optimist position at its "*k*" times. The speeding figures are represented by c_1 and c_2 and the r_1, r_2 indicates the random fiction with the random numbers in between 0 and 1. The pseudo code for the PSO algorithm is follows:

The pseudo code for the PSO algorithm is follows:

Step 1: Initialization

1. Set the constant parameters.
2. Randomizing X and V the vector position and the velocity of particles in the search space.
3. Set Pbest = X the current position to the best potential position.
4. Set Gbest = arg{min *f* (X)}

Step 2. Termination Check.

1. Stop the process when the termination criterion is satisfied.
2. Else go to step 3.

Step 3. For $i = 1$ to n(number of iteration)

Do

1. In the range space update the equation (1) and (2) for the velocity and position.
2. Evaluate fitness function for each and every particle in the space.
3. The global fitness value and best potential position should be save if it is better than the previous values.

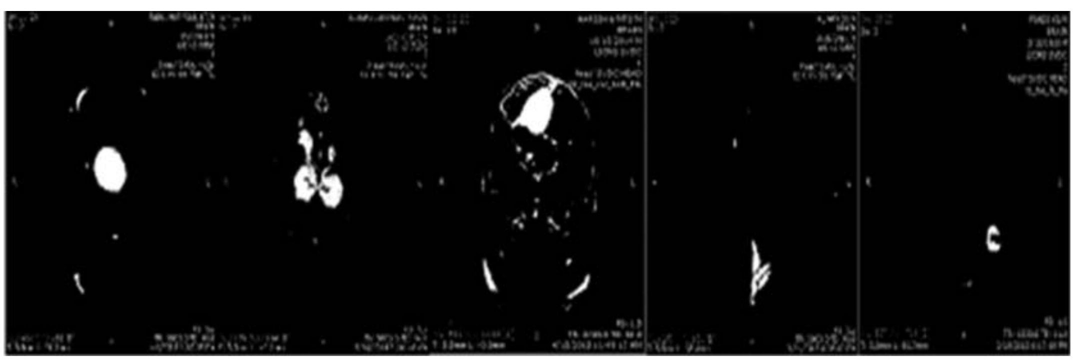
End for

$$\text{Update the Gbest} = \arg\{\min f(\text{Pbest})\}$$

Step 4. Goto Step 2 [12].

2.3. Results and Discussion

The PSO algorithm is implemented for the sample MR image brain dataset. Before, evaluating the algorithm, the dataset are converted from DICOM (Digital Imaging and Communication in Medicine) images into standard image file formats. The converted images are preprocessed and follow the pseudo code of the PSO algorithm and follow the methodology proposed in the previous research work [11]. The figure 2 shows the resultant image of MR brain for the PSO algorithm. The figure 2(*a*)-2(*e*) shows the images of the PSO algorithm implementation for the same input MRI dataset. The segmentation is carried out the based on the values of n. By increasing the value of *n* various segmentation results are obtained. The results, when $n = 2$ are more accurate than the other values. On increasing the values of n the results obtained are distinct by manually selecting the best resultant is an important task. For the input dataset taken the cluster values of the image has been as $n = 2$.The segmentation is based on the pixels intensity values. Time, space and number of pixels of the PSO resultant images are discussed and compared in the summary and discussion section.



(*a*) Img_01 (*b*) Img_02 (*c*) Img_03 (*c*) Img_04 (*c*) Img_05

Figure 2: Results of PSO algorithm

3. FUZZY C MEANS ALGORITHM

3.1. Introduction

The Fuzzy C-Means algorithm was introduced by Ruspini and further been extended by Bezdek and Dunn. The concept is been first introduced to cluster analysis, image processing, pattern recognition and further it has been introduced by more research problem. Although the FCM is the extension of the classical k means algorithm it has more advantages in practice. The FCM clustering algorithm has the advantage of robustness for ambiguity and produces more information than any other methods. Image segmentation, pattern recognition, data mining, image clustering and wireless sensor networks [9]. Segmentation plays an important feature of medical image processing, where clustering approach in biomedical application particularly for brain tumor detection from abnormal MR images. The fuzzy clustering algorithm proves to be more superior over the other clustering approaches in the segmentation of images and proves it efficiency. The major drawback of the algorithm is it acquires more computation time for produces the cluster center values [18].

Modified Fuzzy C Means and Ensemble based Framework for Min Cost Localization and Power Constraints in Three-Dimensional Ocean Sensor Networks is the research work carried by Vasim Babu and Ramprasad. They proposed a new hybrid algorithm for cluster based design in the ocean sensor networks based on the FCM algorithm. The technique for the MFCM is based on the modified FCM with the selection of clusters depending on the parameters like coverage, link quality and residual energy. The model is designed and implemented on localization system and it requires only sensor nodes in additional to previous system [1]. Sai Krishna and et al. carried their research work in Comparative Study of Fuzzy C Means and K Means Algorithm for Requirements Clustering [7]. They proposes a novel fuzzy and nonlinear type of energy to images, the segmentation combines two region, they physical dimension of the image and contextual data is merged with the fuzziness of the energy level which is derived from the level set process. The outcome depicts that the sum of clusters derived through this FCMCA, is acceptable on noise image segmentation process [7]. To detect the multi-tumor in irregular Magnetic Resonance Image (MRI) the authors derives an innovative approach based on support vector machine and the FCM. The proposed methodology AAFFCM is a hybrid approach for color base segmentation technique which uses the *k*-means clustering system to predict the multi tumor object in MR brain images. The SVM algorithm is uses to classify the brain MRI images and the results produce more accuracy and efficiency than the traditional algorithms [16].

3.2. The FCM algorithm

Fuzzy C-Means (FCM) is a method of clustering where it can identify two or more clusters which contains one group of data belongs to one clusters or more clusters. The traditional FCM equation is described in equation (3)

$$J_m = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \, || X_i - C_j ||^2 \qquad (3)$$

The above equation is the objective weighting function of the FCM clustering algorithm where m is real number greater than the value of 1.||*|| is an norm representing similarity between the cluster center and the measured data. Euclidean distance between the i^{th} centroids and j^{th} data joint is represented by u_{ij} and weighting function is m£(1, ∞). The pseudo code for the FCM algorithm is explained as with the following steps:

Step 1. Set U = [u_{ij}] matrix, U(0)

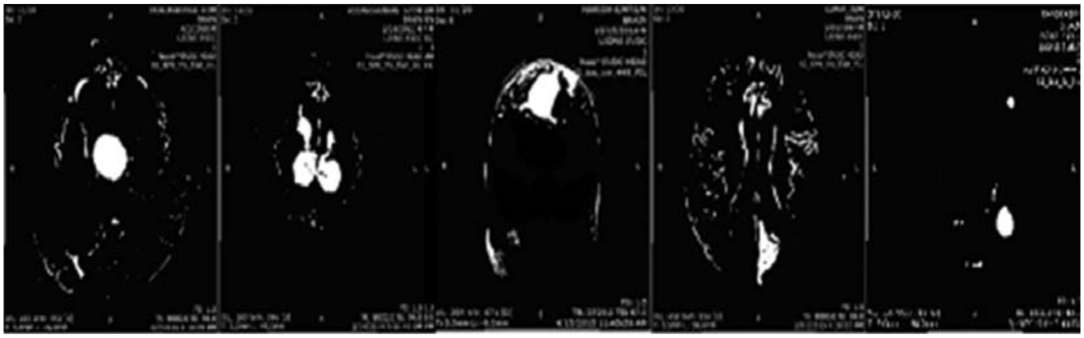
Step 2. In the step K: calculate the centers vectors C(k) = [cj] with U(k)

Step 3. Update U(k), U(k + 1)

Step 4. If ||U(k + 1) − U(k)|| < ε then STOP; otherwise return to step 2 [15,19].

3.3. Results and Discussion

The FCM is algorithm is evaluated for the sample dataset of MR images as shown in figure 1. The images are preprocessed with the Gaussian filter in order to remove the white noise in the image. Before performing the segmentation it is necessary to preprocess the image is required for better accuracy and finding the efficiency of algorithms. The preprocessed images are evaluated with the FCM clustering algorithm. The FCM algorithm is been evaluated as in the pseudo code by clustering the images based on the intensity values. The images are clustered with its values and the results are shown in the figure 4, which depicts the segmentation results of the FCM algorithm. The figure 3(a)-3(e) shows the images of the PSO algorithm implementation for the same input MRI dataset. In the dataset taken, the cluster center values are n = 2, by increasing the center the resultant images are not maintaining its accuracy and efficiency. The cluster center results are taken and validate with the histogram values of the image before and after segmentation in order to qualitatively check the images accuracy. The time, space and the number of pixels in the resultant images are discussed in the section V.



(*a*) Img_01 (*b*) Img_02 (*c*) Img_03 (*c*) Img_04 (*c*) Img_05

Figure 3: Results of FCM algorithm.

4. ELECTROMAGNETIC LEVEL SET METHODS – ELSM

4.1. Introduction

Electromagnetism-like algorithm (EMO) is a global optimization algorithm which undergoes the concept of electromagnetism law of physics, it's a population based methods. EMO is relatively new meta- heuristic algorithm introduced first by Birbil and Fang in the year 2003 [10]. The level set methods are originated basically for numerical technique for shape and tracking interface and in future is has start applied in image segmentation. In this method, contours or surfaces are represented by higher dimensional function as the zero level set called a level set function. The curves and surface of the level set methods are numerical computed based on fixed Cartesian grid without interference of the parameterizes these objects [8]. The main disadvantage of EM algorithm is the normal distribution of intensities in the brain image, especially for the noisy images [3]. The EMO algorithm and the level set methods both techniques have several drawbacks over the MR brain images in finding the tumor affected region on the images. To overcome the disadvantages and we develop a new algorithm based on the traditional EMO and level set methods.

An Empirical Study on the Effect of Mating Restriction on the Search Ability of EMO Algorithms is an research work carried out by Hisao Ishibuchi and Youhei Shibata. The authors show the experimental results of EMO algorithm on many test problems with the improvement of mating restrictions. They also included various algorithms performance with matting restriction and their experimental results [6]. Tadahiko Murata and Ryota Itai authors use the non-dominated solutions for the vehicle routing problem. They examined to apply EMO ways one is applying EMO to each problem individually. The other one is initial solutions of EMO algorithm with the problem. The initializing EMO algorithm in the beginning gives better results [13]. An energy level set function is proposed to partition of an image based on intensity clustering property, is performed by minimizing the proposed energy functional. The proposed energy function of the bias filed is naturally ensured to explicitly smoothing term of the bias field. The new method is more robust that the piecewise smooth model. The application of MRI brain images of the proposed function is demonstrated and the results are superior accuracy, efficiency and robustness than the traditional method [8].

4.2 ELSM Algorithm

The ELSM (Electromagnetic level set methods) algorithm we proposed is consists of three steps: one is clustering the image based on the intensity values by the EMO attraction and repulsion mechanism and finding the best fit cluster value n from the equations (4) and (5).The second step is segmenting the image with iterative level set method and the number of level value k from the equation (7) and the last step is empirically choosing the min and max values of *n* and *k*.

$$q^i = \exp\left[\sum_{k=1}^{m} f(x^{1-k}) - f(x^{\text{best}}) + f(x^{\text{last}})\right]^n \tag{4}$$

$$\mathrm{F}^k = \sum_{j \neq i}^{m} \left\{ \frac{x^i q^i q^j - x^i q^i q^j}{\left(x^i \pm x^j\right)^2} \right\} f(x^i) > f(x^j) \tag{5}$$

$$\frac{\partial\phi(x(t),t)}{\partial t} = 0 \tag{6}$$

$$x_t = \mathrm{F}(x(t)^k,$$

where...

$$k = \frac{\nabla\phi}{\|\nabla\phi\|} \tag{7}$$

The population is randomly generated in the search space in the algorithm. After calculating the function of each particle in the image , the point with the best function value will be stored in best particle. The new particle is been calculated by considering the last position, best position and current position in the image. The initial ∅ at $t = 0$, it would be possible to know ∅ at any time t with motion equation with the applying chain rule give us the equation (6). Ongoing through number derivations the value of *xt* will be denoted as in the equation (7) where k denotes the level value. The pseudo code for the ELSM algorithm is:

Step 1. Randomly initializing the search space for the clustering of image

1. Set the q^i value for the image
2. Evaluate various n values ($n = 2,3,..$)

Step 2. Initializing the level set functions

1. Set the $t = 0$
2. Update the motion function
3. increment the k values($k = 1,2,3,\ldots$)

Step 3. Ealuating min and max terms

1. Incrementing n and k values
2. Until the result satisfied repeat from step 1.

4.3. Results and Discussion

The proposed novel ELSM algorithm is executed for the input MR brain image dataset. The converted DICOM images are evaluated with the ELSM algorithm. The segmentation is based on the intensity values and the algorithm consists of three steps. After preprocessing with the linear Weiner filter the input dataset is evaluated with pseudo code of the algorithm. The first step is intensity based cluster of images with the modified EMO algorithm where the segmentation values starts from $n = 2,3,\ldots$and so on. The second step is extracting the affected region of segmented resultant with the level set function. The various levels of k combined with the clustering values of n yields several resultant images. By empirically, on selecting among the resultant image using the minimum and maximum techniques to the images and finding the tumor affected results. In the first step the EMO algorithms attraction and repulsion mechanism has been used. The various levels of iteration on the level set methods for the region growing techniques is carried out in the second step. The last step in the ELSM algorithm is by the selecting the combination of n and k using the maximum and minimum techniques. The various combination of max and min based on the prediction the resultant images are selected manually. Figure 4 shows the results of ELSM algorithm and in the next section the performance evaluation, accuracy and validation of all the algorithms are carried out. The figure 4(a)-4(e) shows the images of the PSO algorithm implementation for the same input MRI dataset.

(a) Img_01 (b) Img_02 (c) Img_03 (c) Img_04 (c) Img_05

Figure 4: Results of ELSM algorithm

5. SUMMARY AND RESULTS DISCUSSION

The comparative study of three distinct algorithms for the same MRI brain image dataset is the main aim of this research work. The accuracy and efficiency of algorithms are measured by three criteria, one is the computational time of all the algorithms and second one is storage capacity of the resultant images obtained. The last criteria, is the accuracy finding the number of black and white pixels in the resultant image. The white pixels are the tumor affected region in the resultant images. The abnormal input dataset are real world images collected from Swami Vivekananda Diagnostic Center scan center in Chennai. The 5mm Dataset in our experiments on MR images from 5 different patients with tumor. Each volume contains 24 slices in axial plain with 5mm slice thickness. The image engaged in the dataset is around 3.0 mm thickness of T2-flair image type. The resultant images are compared to validate the efficiency and accuracy of the algorithms and conclude the best algorithm. The validation is based on time, space and the pixel count of the image.

Table 1
Pixel variation of three algorithms

MRI Dataset	*PSO*			*FCM*			*ELSM*		
	T	*B*	*W*	*T*	*B*	*W*	*T*	*B*	*W*
Img_01	19558	18703	855	19558	18517	1041	19558	18723	835
Img_02	19404	18709	695	19404	18237	1167	19404	18967	437
Img_03	19685	18859	826	19685	18656	1029	19685	19018	667
Img_04	19375	18713	662	19375	18673	702	19375	18781	594
Img_05	19250	19011	239	19250	18525	725	19250	19029	229

The three algorithms PSO, FCM and ELSM discussed in above section, clustering the input MRI abnormal brain images and segmenting the resultant images. The algorithms are clustered and segmented based on the intensity values of the images. The comparison of the method is carried with the all the algorithms cluster value as $n = 2$. Based on these conditions the images are segmented and find the prediction of abnormal tissue in the brain. The table 1 shows the pixel variation of the resultant images from the three algorithms. The T represents total number of pixel volume of the segmented image and B indicates the number of black pixels in the images. The W shows the count of total number of white pixels of the resultant images. The white pixels in the image represent the tumor affected region of the MRI brain input image. The resultant images of three algorithms are compared based on the white pixels and values are indicated in the table 1. On observing, the results empirically, the ELSM algorithm resultant image provides more accuracy and efficiency. The PSO and FCM algorithms segmentation results include artifacts and other details as shown in the figure (2) and (3). The minimum the white pixel area in the image yields more accurate results. From the table 1, it has been noted that the ELSM algorithms white pixels values represents in the column (W) gives more accuracy. The figure 5 shows the graph of the white pixel values of the MRI dataset. From the graph it is clearly indicates that the ELSM algorithm contributes more precision.

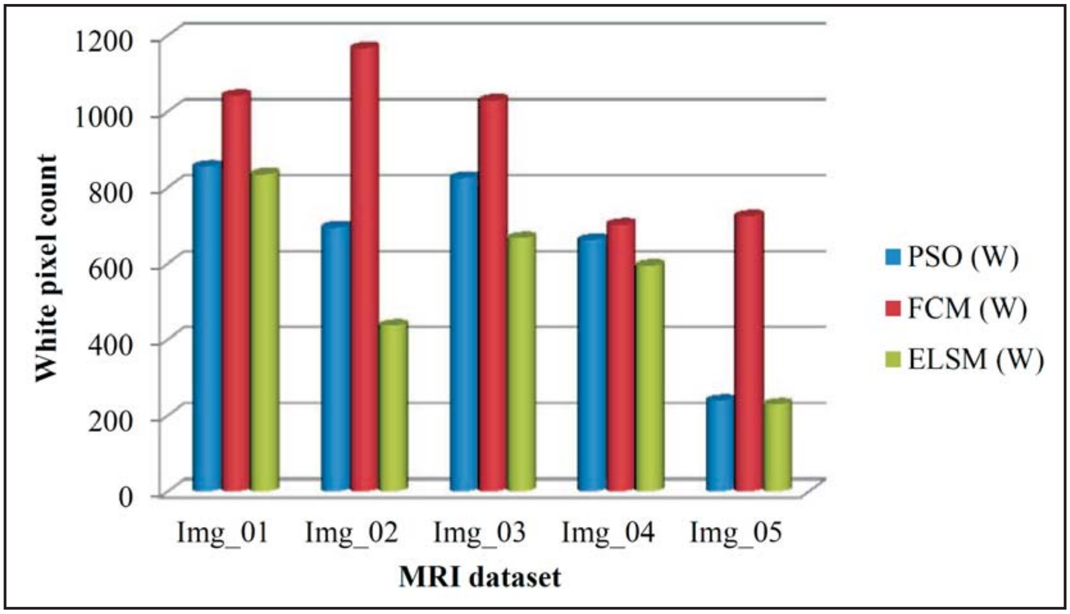


Figure 5: White pixel difference for the MRI dataset

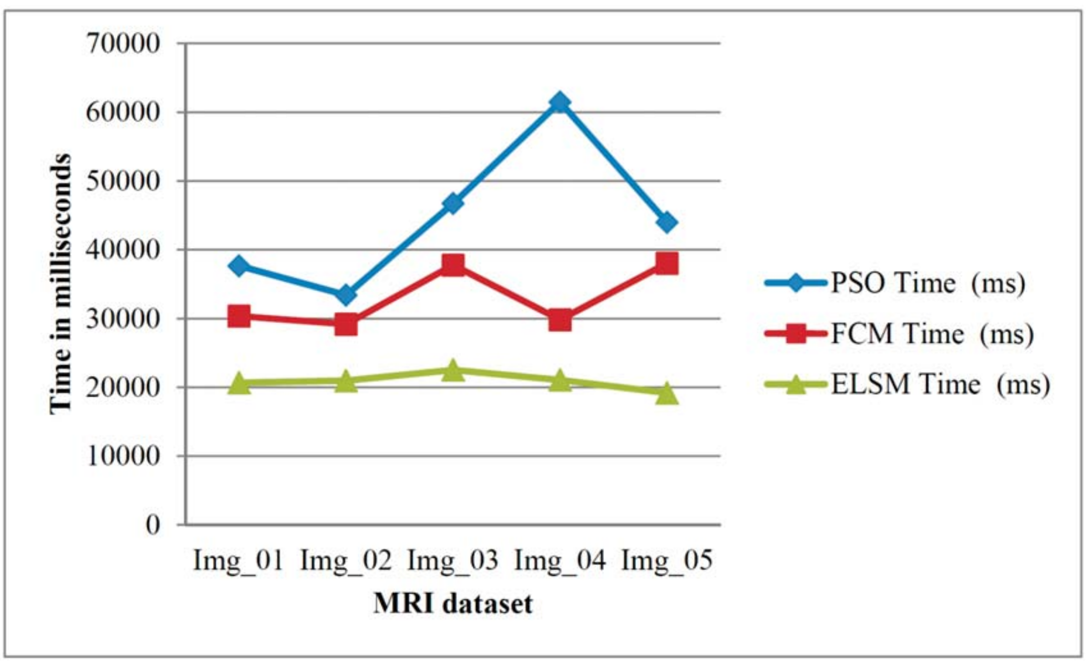


Figure 6: Computation time of three algorithms

Table 2
Computational time and memory of three algorithms

MRI Dataset	PSO		FCM		ELSM	
	Time (ms)	Size (kb)	Time (ms)	Size (kb)	Time (Ms)	Size (kb)
Img_01	37651	4.41	30357	7.05	20656	2.73
Img_02	33394	4.14	29187	6.00	20954	2.98
Img_03	46713	7.20	37767	6.17	22538	3.91
Img_04	61473	4.17	29827	7.69	21078	3.04
Img_05	43984	4.01	38048	5.16	19186	1.87

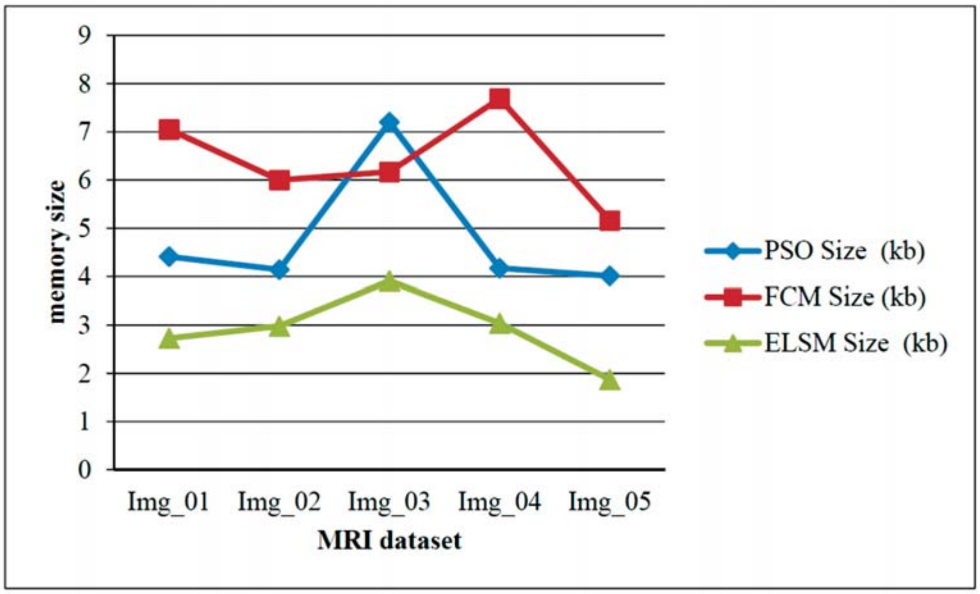


Figure 7: Memory occupation of three algorithms

The table 2 shows the time and memory occupied by the resultant images of the PSO, FCM and ELSM algorithms. The time column in the table 2 represents the computational time of each algorithm in milliseconds as Ms. and the size indicates in kb the memory occupied by the resultant images from the algorithms. From this table 2 it clearly shows that our proposed ELSM algorithm is finds more effective. In terms of robustness, time occupied and the computational cost of storing the image from the ELSM algorithms proves more efficiency than the other two traditional methods. The figure 6 shows the graph of performance evaluation of the computational time of the three algorithms. The figure 7 represents of the graph of memory capacity of the resultant images. From the figure 6 and figure 7 shows the time to compute the ELSM is very less when comparative to the PSO and FCM algorithms. The memory occupied by the PSO and FCM is relatively high and ELSM algorithm occupies lesser on the selected MRI brain dataset.

On finding the efficiency of an algorithm, the implementation time and memory size occupied by the images are not only the consideration. The comparison and the accuracy of the images for the abnormal MRI brain images are also based on the number of pixels. In the MRI brain image predicting the white region present in the image is the objective of the research work. Identifying the white pixels from the images includes lots of works and it is achieved by means of various algorithms. The algorithm undergoes preprocessing, clustering and segmentation techniques and finds the suspect able region. The accuracy of three algorithms PSO, FCM and ELSM for the MRI brain image dataset lies on number of white pixels predicts by each algorithm.

6. CONCLUSION

The MRI brain tumor segmentation is an important technique in medical diagnosis. In this research work, comparing and analyzing our proposed novel hybrid ELSM algorithm results with the existing algorithm results are carried out for the same dataset. The comparison is based on three criteria computation time taken by the algorithm, memory storage of the resultant images and counting the number of pixels in the tumor predicted region. The ELSM algorithm has been compared with the prominent PSO and FCM image segmentation algorithms in medical domain. Experimental results demonstrate the features selected by our methods are more effective and provides quality information in predicting the tumor affected region. By means of time, memory and counting the number of white pixels in the predicted region our proposed ELSM algorithm is better than the other methods. The proposed method ELSM algorithm results are more accurate by empirically and technically. The results observed from the algorithms are very close with the delineations by the doctors; hence the ELSM algorithm is more effective in MRI brain tumor segmentation. In the future, the proposed method is applied to multi-tissue segmentation, and measuring the size of the predicted region will be added to achieve more accurate results and to assists the medical domain.

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