A Novel Approach to Find Tumor in MRI Brain Images using Image Segmentation Techniques

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Abstract : Segmentation is one of the most important task in image processing. It classifies the pixels into two or more groups depend on their intensity value. The quality of the segmentation is based on the method applied to select the algorithm. The objective of the research work is to finding the tumor affected region by extending and modifying the Electromagnetic optimization algorithm with the level set function combined with the active contours. The new hybrid ELSM algorithm is composed of three stages: preprocessing stage and the second stage is evaluating the modified EMO algorithm for segmenting the images and the last stage is to implementing the boundary detection technique to enhance the tumor affected region separately. The first stage is converting DICOM images into standard image file formats and preprocessing with the liner filter to remove noise and adjusting contrast levels of images. The second stage is implementing modified EMO algorithm for segmenting the images with the attraction and repulsion mechanism for the intensity value of the images with the cluster value of n and the last stage is detecting boundary region of the segmented images and its been evaluated with the modified level set functions and with the of level values k to obtain the best optimal images for the MR brain tumor problems. The images are collected and the ELSM algorithm been evaluated and the results are discussed. The ELSM algorithm best resultant images are obtained by analyzing the n and k values of the new hybrid algorithm using maximum and minimum techniques.

Keywords: Magnetic resonance images, Electromagentic optimization(EMO), level set functions, contours.

1. INTRODUCTION

Images are one of the effective ways to reveal information to the world. Immeasurable techniques are used to process the images and used for decision making. In medical field, radiological images are processed by Computer Aided Diagnosis (CAD) tool to detect the abnormalities occur in the image and for the automated detection and quantitative analysis. Segmentation is one of the techniques which divulge some information to the user. It is the process of partitioning an image into regions that shares related features and characteristics or grouped to interpret the images. Magnetic resonance imaging (MRI) of brain is examined by performing with several coil types, depending on the MRI unit design and the information provided by it. The imaging protocols of the MRI brain should meet few important criteria, the clinical questions should be answered and they must be completely provides all the necessary information. The MRI much be has to be short as possible to reduce the time the patient has to spend in the magnet and must be reproducible. The imaging protocols should be standard one to maintain its continuity over a period of time. Numerous changes in the MRI protocols should be avoided, the operator of the equipment may confuse.

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MRI of the whole brain is generally of 3.0 T imaging slices, this thinner slices is superior in accurate detection of brain structure. In general, MRI studies of the brain should be including two weightings and two imaging planes. Some standard sequences of the MRI brain are shown in Table 1.1FLAIR, FLAIR + Gd, DWI/ADC, SWI, T2, T1 ± Gd.

Table 1

Different types of MRI brain image

FLAIR
• Lesion detection.   • Less sensitive in posterior fossa.   • Usually applied in axial and coronal imaging planes.
FLAIR + Gd
• Indicated for the detection of leptomeningeal disease
PD/T2
• Proton density (first echo) can be used as an alternative to FLAIR   • more sensitive for the detection of posterior fossa lesions   • T2-WI second echo for detection of long T2 lesions.
T2
• Echo sequence provides information about hemoglobin breakdown and calcifications   • Sensitivity effects is proportional to TE and field strength.   • Excellent differentiation of gray and white matter to detect the tumor and cell density.

Brain tumors are the formation of new blood vessels to increase the capacity of brain which is also known as angiogenesis. When brain tumor starts growing it outgrows its blood supply, the blood vessels which are developed in this way is irregular, disorganized, abnormal, and tortuous. The tumor region is enhanced after the injection of a gadolinium-chelate, because the contrast agent leaks out the abnormal blood vessels. These abnormalities in tumor blood vessels can be used in MR perfusion imaging. MR perfusion imaging is helpful in identifying high-grade tumor components and glial tumor. The hyper intense areas on FLAIR or T2-WI always correspond to the true tumor margins and the MR imaging also assist in radiation therapy and surgical planning by outlining the tumor boundaries. Image segmentation has many application in all the fields such as medicine, agriculture, ERP development, toll plaza, industry etc. Methods of processing this images requires segmentation, extraction [9].The medical imaging applications such as diagnosis, study of anatomical structure, treatment planning, quantification of tissue volumes, computer integrated surgery, functional imaging data, identification of tumor in liver, brain etc.

In this paper, a segmentation method called level set method based on EMO algorithm is introduced. The algorithm takes random dataset of MR brain imaging planes. The datasets are preprocessed with linear high resolution weiner filter and improve the contrast of the images. The quality of each pixel is evaluated by the objective function of the EM algorithm using the attraction and repulsion operators. The images generated through EMO is again evolved through level set method, contours and surfaces are represented by zero level set usually called as level set function to segment the tumor affected region. Experimental results shows that the performance evidence of the implementation of this novel approach to the image segmentation process. The rest of the paper is organized as follows. In section 2, the related literature review is explained. Section 3 gives a simple description of the standard EMO algorithm and level set method functions are introduced. Section 4 discusses the experimental results and bias field, histogram of the MR images. Finally the work is concluded in section 5.

2. REVIEW OF LITERATURE

In the recent years, so many researchers have developed a new optimization algorithm and level set methods to solve numerous problem of the real world. Some of these new approaches to images are

discussed here. A new Hybrid Electromagnetism-like Algorithm for capacitated vehicle routing problems is carried out by the researchers Alkın Yurtkuran and Erdal Emel. A modified objective function value is utilitzing the random key procedure for EM algorithm to solve the known capacitated vehicle routing problem. The proposed algorithms computational times are high because of the sorting algorithm which uses RKP [17]. Ana Maria A. C. Rocha and Edite M.G.P. Fernandes carried their research work to propose a new local search procedure based on a population shrinking strategy with the pattern search method to improve efficiency. This new process explores in the search space with smaller number of functions [13]. Hamid A. Jalab carried his research work to present a novel Emag algorithm for content based image retrieval based on electromagnetism optimization technique. The results shows an average precision value and a significant improvement over the traditional CBIR technique [3]. A hybrid electromagnetism-like algorithm for single machine scheduling problem research work discuss about the work in population based meta heuristic to solve continuous problems effectively. The convergence and diversity effects are achieved iteratively to solve the problem. The genetic algorithm is the key random key concept for this hybrid algorithm for single machine problems [1].

The multilevel thresholding with the electromagnetic optimization like algorithm forms a new proposed approach MTHEMO. This study explores the study of the two versions of MTHEMO. One is using the otsu function and the second with the kapur criteria. The efficiency is evaluated by using the STD and PSNR values [12]. Chujian et al. discuss the research work titled as An improved electromagnetism-like mechanism algorithm for constrained optimization [18]. The study proposes an improving EM algorithm with FAD rules and corresponding charge formula are used as constraint handling techniques. The modified algorithm is helpful not only for constrained optimization but also for optimization problems. Ching Hung Lee and Fu-Kai Chaung carried out their research work titled as Fractional-order PID controller optimization via improved Electromagnetism-like algorithm. They propose a new evolutionary algorithm with the improved EM algorithm along with the genetic algorithm technique (IEMGA). It is an evolutionary method and avoids the use of calculus and capable of decreasing the computational complexity [5].

The multiphase level set formulation is generated to avoid the problems of overlap and vacuum; in the set functions of n phase in the piecewise constant case. The proposed model is validating by numerical results in image denoising, segmentation and in Sethian level set method [16]. Level set approaches to image segmentation with intensity inhomogeneity discuss a novel level set method. The inhomogeneous objects are modeled by Gaussian distribution with different variances and means with sliding window which map to original image. This new methodology is been directly applied to 3 and 7T MR images with the bias corrections [19]. Bing Nan Li et al. Discuss about the computed tomography images in the liver tumor segmentation [6]. The liver tumor is estimated by fuzzy clustering, and the probabilistic distribution is enhanced by object function and regulates region competition. The new unified level set model is an good measurement for the liver tumor segmentation of computed tomography images. The tumor in MRI brain image and the results of K-Means algorithm for the quality of cluster algorithm is discussed in the Identification of Calcification in MRI Brain Images by k-Means Algorithm[11]. The author describes the role of clustering and its various applications and techniques in his research work.

Yunjie Chen, Jianwei Zhang and Jim Macione carried their research work titled as An improved level set method for brain MR images segmentation and bias correction. They propose a new region based on active contour model for level set formulation with the bias correction of images. They first define a localized k means clustering objective function for image intensities. The cluster centers in the objective function have multiplicative factor which estimates the bias of the neighborhood intensity of the images [2]. Sukassini and Velmurugan carried their research work in segmentation techniques for the mammogram images[15]. The authors discussed various preprocessing techniques for images including morphological operation which gives very quality and effective images as results. They discuss various results of the different research papers by different authors which have greater impact on our novel

approach. Distance Regularized Level Set Evolution and Its Application to Image Segmentation is been discussed by Chunming Li and et al. A new approach for level set evolution called distance regularized level set evolution (DRLSE). It avoids the induced numerical errors and thus eliminates the need of initialization. Since, it's a numerical implementation; it requires large time steps to reduce the number of iterations. It's an edge base active contour model for image segmentation and it greatly reduces the computational cost [7].

3. METHODOLOGY

This paper proposes a hybrid framework that combines EM-like algorithm and Level Set Methods (ELSM) for solving MR imaging problems of brain. To reduce the time complexity and to obtain efficient quality segmentation the EM algorithm with combined with the level set methods form the new hybrid algorithm ELSM. The purpose of this hybrid framework is to take the advantage of EM with a high diversity population, and level set methods; the combined algorithm works faster. The new combinational algorithm proposed in this paper follows the collective attraction-repulsion mechanism by combining with the level set methods. This new algorithm is composed of two phases: electromagnetism optimization technique and level set methods. The clinical and research applications of MR imaging is relying on segmentation of the affected region in each image to diagnose it. In general this novelistic approach towards the EM like algorithm with the level set methods is to detect the tumor affected region of the brain and it can be applied to other imaging problems. The proposed hybrid ELSM algorithm for the MR brain images is evaluated as follows:

Step 1: Converting the general MRI DICOM(Digital Imaging and Communication in Medicine) in to standard image file formats.

Step 2: Preprocessing the images with adequate linear filters to remove high signal noise and white noise for the images to achieve effective resolution.

Step 3: Implementing the modified Electromagnetic optimization algorithm for the images to highlighting white and contrast of the MR brain image with varying intensities for further detection and segmentation of tumor based on the value of n (2,3,4,5).

Step 4: Initializing the level set methods with the step 3 results and starts segmenting the tumor affected region through the iterative process with the varying levels denoted by the value of k (1,2,….) to detect the tumor affected boundary region separately.

Step 5 : The max and min concepts are used to select the best resultant images and time step of hybrid ELSM algorithm is marked.

A.   Electromagnetism optimization algorithm

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. The members of the population are guided by the objective function values which follows attraction and repulsion mechanism. In this paper, the second module of ELSM algorithm is implementing the EMO algorithm to segment the images. The idea behind the EMO is to move a particle to the space by the force of the rest of the particles in the population. In the brain tumor segmentation is detection of white matter i.e. particles from the image is the main goal of this research work. In this research work EMO is used highlight the different regions of particles in the image. EMO is an nonlinear optimization problem that involves multiple objective function, in mathematical terms it can be formulated as

maximize $f(x)$, $x = (x_1,\ldots\ldots, x_n) \in \mathrm{R}^n$

subject to $x \in \mathrm{X}$ (1)

where $f: R_n \rightarrow R$ is a nonlinear function [12]. The solution of EM algorithm can be viewed as a charged particle in search space and its charges are relates with the objective function values. The electromagnetic force exists between the two particles works as with the force of the one particle with more charge will attract the other and the other one will repulse the former. The charges of the particle is based on the objective function values which determines the attraction or repulsion. There are four phases in the EMO algorithm: initialization of the algorithm, calculation of total force, movement along the force direction and the last one is neighborhood search in finding the local minima [18].

EM (M, LSITER, δ)

M: Population size

LSITER : Maximum number of local search iterations

δ : local search parameters, δ £ [0,1]

Initialize()

while termination condition is not satisfied do

        Local(LSITER, δ)

        F = CalcF()

        Move(F)

end while

The initialization part, the population is randomly generated in the search space as in the other optimization algorithm. Each particle obeys a uniform distribution in the upper bound and as in lower bound. After calculating with the function value of each particle, the point with the best function value is stored in a best particle. The EMO algorithm needs a local search randomly to gather neighborhood information, we need two parameters to achieve this one is LSITER representing the number of iterations and the other one is δ denotes the multiplier of the neighborhood search. The total force determines the detection and step length of movement of each particle. The charge of each point I, which identifies the power of attraction and repulsion of particles, q^i is calculated by the formula (2). According to the EM mechanism the particle with the better objective function values attract each other otherwise repel each other the total force of this particles if formulated in the equation (3).

$$q^i = \exp\left(-n\frac{f(x)-f(x^{best})}{\sum(f(x^k)-f(x^{best}))}\right), \forall i \tag{2}$$

$$F^i = \sum_{j \neq i}^{m} \begin{cases} (x^j - x^i), \dfrac{q^i q^j}{\|x^j - x^i\|^2}, f(x^j) < f(x^i) \\ (x^i - x^j), \dfrac{q^i q^j}{\|x^j - x^i\|^2}, f(x^j) > f(x^i) \end{cases} \tag{3}$$

$$X^i = X^i + \lambda\frac{F^i}{\|F^i\|} \tag{4}$$

The last stage in the EM algorithm is the movement of particles after evaluating the total force of the particles. According to the equation (4) the movement is calculated and the λ is the interval of 0 and 1. Range is a vector which denotes the movement of particle in upper and lower bound which the corresponding direction. The implementation details and the step by procedure of all the four stages are evaluated efficiently. In the an improved electromagnetism-like algorithm for global optimization research paper discuss the criteria and recommended steps of the lsiter, total force and move function [4].

B.   Level set method

The last module in the ELSM algorithm is to detect the boundary region separately for future reference. The boundary detection is performed with the level set methods and active contours. In past years, a large set of researchers worked on geometric active contours that is implemented via level set methods to solve many image segmentation problems and in computer vision. Osher and Sethian are introduced the concept of level set methods[14]. Active contours are introduced by kass, Witkins and Terzopoulos for segmenting objects are regions from images using dynamic curves. In the level set formulation of moving active contours the fronts are denoted by C, represented by the zero level set $C(t) = \{(x, y)| \phi (t, x, y) = 0\}$ of a level set function $\phi(t, x, y)$. The general form of the level set function ϕ evolution equation(5), F is the speed function. The function F depends on the image data and level set equation ϕ in image segmentation [8].

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \tag{5}$$

The main idea behind level set method, in the interface T we wish to analyze and compute subsequent motion under a velocity field. The level set function ϕ has the following properties (6). The velocity depends on time, position and geometry of the interface T. The ϕ vanishes by locating the set $T(t)$ in the interface. The motion is analyzed by converting the ϕ level values into velocity field in the above elementary equation (5). The tumor affected region is separated with the level set functions and the boundary is also detected from the neighborhood particles of the image. By using, with the number of iterations, we can effectively detect the particular region separately.

$$\phi(x, t) > 0 \text{ for } x \notin \Omega$$
$$\phi(x, t) < 0 \text{ for } x \notin \Omega$$
$$\phi(x, t) = 0 \text{ for } x \notin \Omega \tag{6}$$

When the level set methods are implemented as computer program the major issue is having finite grid of mesh points. On each time step our grid of mesh points is going to shrink by one layer of mesh points from boundary. To compute the derivation time step the neighbor points are needed. On the boundary, we may lack in the neighbor points, in the time step to droop way this points we use ghost cells. It is the boundary points of the gird that give mirror value to their neighbor. By using ghost cells it will reduce error over time and it is small and manageable.

C.   ELSM Algorithm

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. The evaluation of two algorithms for the dataset taken and the results are discussed in the later section. The previous research work is detecting the tumor affected region using the optimization technique PSO algorithm. The PSO algorithm produces a quality and effective results so we extended the work based on the optimization techniques. The Detection of Brain Tumor by Particle Swarm Optimization using Image Segmentation[10], segments the image based on the number of level of segments represents by n and thus gives more accurate results. By using the optimization concepts we propose a new hybrid algorithm ELSM approach to detect the brain tumor affected region. The detection of tumor affected region is not separated by the two algorithms discussed above, hence a novelistic approach is been introduced. The ELSM (Electromagnetic Level Set Methods) approach is consists of the three steps: one is finding the best fit cluster value for n by the modifying EMO algorithm. The second step is to finding the correct level for the segmentation of images by changing the levels value of k in the level set methods. The last steps in the ELSM algorithm is taking the min and max value from the step 1 and step 2 based on the n and k values, the resultant image is obtained empirically.

The main objective of the ELSM algorithm is segmenting the images with the values of n and the resultant image is leveled by the boundary detection of the tumor affected region through the number of level based on the k value. The new EM algorithm is been introduced in order to segment the images based on the intensity value of pixels in the image to detect the tumor. The modified EM algorithm is been implemented based on the equation (7) in this the value of q^i is the charge of each point (pixel) in the image and the power of n denotes the cluster value of segmentation. By calculating the neighborhood pixel value the x^{best} and x^{last} values are obtained. The equation (8) F^k represents the total force calculation of the modified ELSM algorithm. The q^i and q^j represents the x and y values of the pixels and x^i represents the intensity values of the particular pixels. By using the equation (7) and (8) with the attraction and repulsion mechanism the little contrast intensity values of the images are obtained by the using the cluster values of n the best resultant image is evaluated for the enhancement of image.

$$q^i = \exp\left[\sum_{k=1}^{m} f(x^{1-k}) - f(x^{best}) + f(x^{last})\right]^n \tag{7}$$

$$F^k = \sum_{j \neq i}^{m} \left\{\frac{x^i q^i q^j - x^i q^i q^j}{\left(x^i \pm x^j\right)^2}\right\} f(x^i) > f(x^j) \tag{8}$$

The level set methods is been modified and the tumor affected region is separated by modified the original. The modified level set method overcomes the disadvantages and solves the tumor detection problem in combining with the modified EM algorithm. On finding the number of level segmentation in detecting the boundary region the value of k are being processed with modified level set methods. The changes in the level set methods are described in the equation (9) with the level values k. The equation 5 has been modified with initial $\varnothing$ at $t = 0$, it would be possible to know $\varnothing$ at any time t with motion equation with the applying chain rule give us the equation (9). Ongoing through number derivations the value of x_t will be denoted as in the equation (10) where k denotes the level value.

$$\frac{\partial \phi(x(t),t)}{\partial t} = 0 \tag{9}$$

$$x^t = F(x(t))^k$$

where $$k = \frac{\nabla \phi}{\|\nabla \phi\|} \tag{10}$$

In general the boundary of the pixels are identified by active contours, its computer generated curves that move within the image to find the object boundaries. The intensity I of the tumor tissue should take a specific value with the physical property. In our hybrid algorithm the modified EM algorithm is partially segments the tumor with the various n values. The segmented region of tumor is estimated with the active contour is slowly varying across the image domain with the various levels of k. The image intensities are approximately same within each class of tissue. We propose a method which divides this small region pixel intensity separately [2]. The level set functions are evaluated and active contours are applied to detect the affected region separately. The general active contour functions are implemented as a last phase of the third module of the ELSM algorithm.

4. EXPERIMENTAL RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed algorithm ELSM, experiments are carried out on a subset of abnormal MR brain images from the real world. The image dataset is collected from Swami Vivekananda Diagnostic Center scan center in chennai. Different patient's data from different age and places are taken and the hybrid algorithm is evaluated. The ELSM algorithm main aim is to detect the tumor affected region separately from the normal tissue of the brain to support the radiologists and to assists the physicians. The algorithm works on by computing the coefficient of joint variation of tissue between grey and white

matter of the brain. The measure of tumor affected area is dependent on the changes in contrast and brightness of the MR images, in the sense of minimizing the intensity overlapping between the tissues. The ELSM algorithm is composed of three phases the first one is preprocessing of the images, the second one is implementing the Electromagnetism optimization algorithm to enhance the grey and white matter of images with different intensities and the last one is the segmenting the tumor with the level set methods with contours of the images.

Generally the detection of brain tumor is analyzed in the axial and coronal planes of the MR brain image. In this paper, we work on several images of axial and coronal plane of the MR images. The research work with 50 MR abnormal images are randomly selected from the dataset, in this work sample image evaluation are discussed. The proposed hybrid ELSM algorithm starts with the conversion of DICOM images into standard image file formats .jpg. Figure 1 shows the sample images of axial plane of a patient. The figure 2(*a*) and 2(*b*) shows the evaluation results of the traditional EMO algorithm and level set methods respectively. Since, the in both the algorithm the tumor affected region is not been separated, therefore we propose a new approach ELSM algorithm to overcome the problems. The first module in the ELSM is to preprocessing the image to remove the white noise of the image. Since the detection of brain tumor is separating the white matter of the brain, eliminating the white noise of the image plays an important role in ELSM algorithm. The dataset collected are sequential in pixels, hence using the linear filter gives best resultant images. The linear filter is selected to remove the linear white noise of the image and to obtain the high resolution image. In the linear filter we choose weiner filter to obtain best optimal resultant images in both space and time complexity. By using the adjusting the image brightness, sharpness are performed in the preprocessing module. Figure 3 shows the results of the preprocessing stage of the ELSM algorithm. The performance difference may not be shown visualized in the preprocessing step but the impact will be replied in the next stage of the ELSM algorithm.
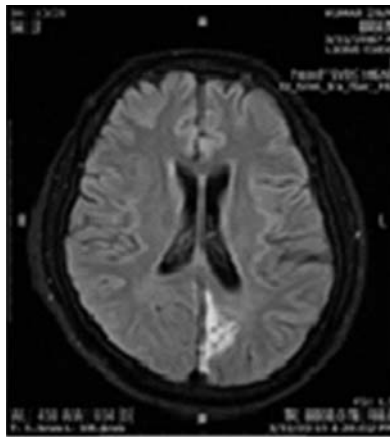

Figure 1: Shows the abnormal MR Data

(a)   (b)
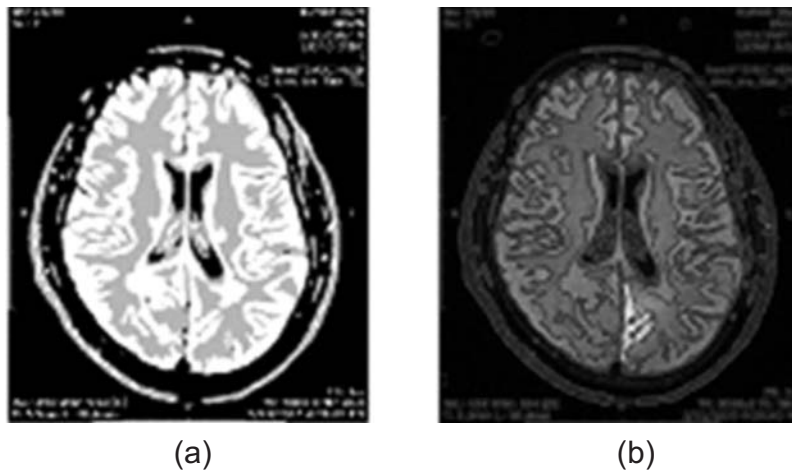
Figure 2: Results of traditional EMO and level set methods

Based on the optimization technique concepts the problem area *i.e.*, the image intensity values and pixels values are optimized to obtain the best optimal image. The second module is implementing the modified EM algorithm to separate the grey and white matter of the image with the varying intensities for assisting in further segmentation of tumor affected region. The segmentation of the images are been carried based on the intensity values of the images. Based on the attraction and repulsion mechanism of EMO algorithm the varying intensities of the image are separated of further segmentation. In this research work all the images are segmented based on the intensity values of the pixels and number of level of segmentation is represented by the cluster values of n ($n = 2, 3, 4, 5$). Based on the intensity of image pixels the variations of partially segmented images are highlighted in the resultant image. Figure 4 shows the second phase of ELSM algorithm based on the values of n. By increasing the value of n the images are changing as per its intensity values.
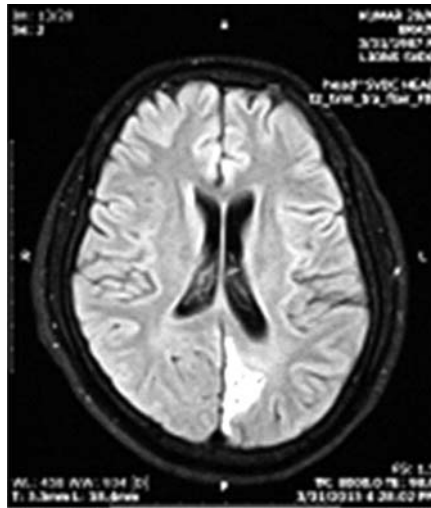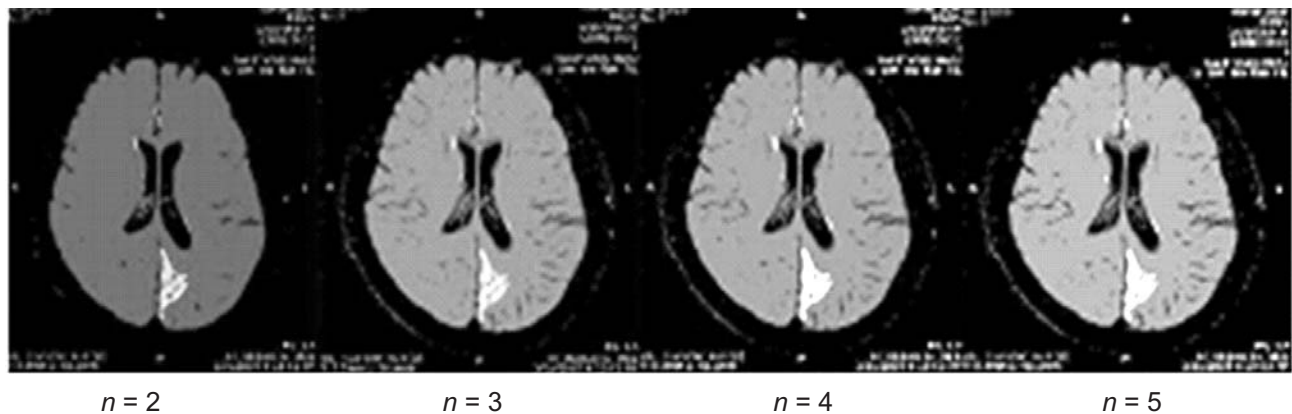

Figure 3: Preprocessing module of ELSM algorithm

n = 2   *n* = 3   *n* = 4   *n* = 5

Figure 4: Shows the second phase of ELSM algorithm based on the values of *n*

The result of the intensity highlighted image is drives through the third phase of ELSM algorithm. In this last phase, the tumor affected region of the segmented images is evaluated through the level set function with the active contours. By carrying the inner and outer layer of the boundary region in the images, iteratively we will reach the tumor affected region separately. The boundary region calculation of the image in the ELSM algorithm is been devised through with the active contours as described in section 3. By using, the active contours with the level set function the affected region of the MR image is been identified in the ELSM algorithm. The various levels of LSM are denoted by the value of *k*. By taking the value of k from 1,2 and 3, the n value results from the second phase is evaluated. Since the range of third step of the ELSM algorithm is basically starts with the value starts from 1.The resultant of image of each *n* values is been evaluated based on the each k value is carried out and the results are shows in the figure 5.

This figure 5 shows the top down approach of our ELSM algorithm based on n and k values. The first stage of the figure shows the preprocessed image and the second stage shows the modified EM algorithm results based on the cluster value of n. The last stage describes the various levels of the boundary detection for the values of k. By manually observing the best fit value for n and k are analyzed.
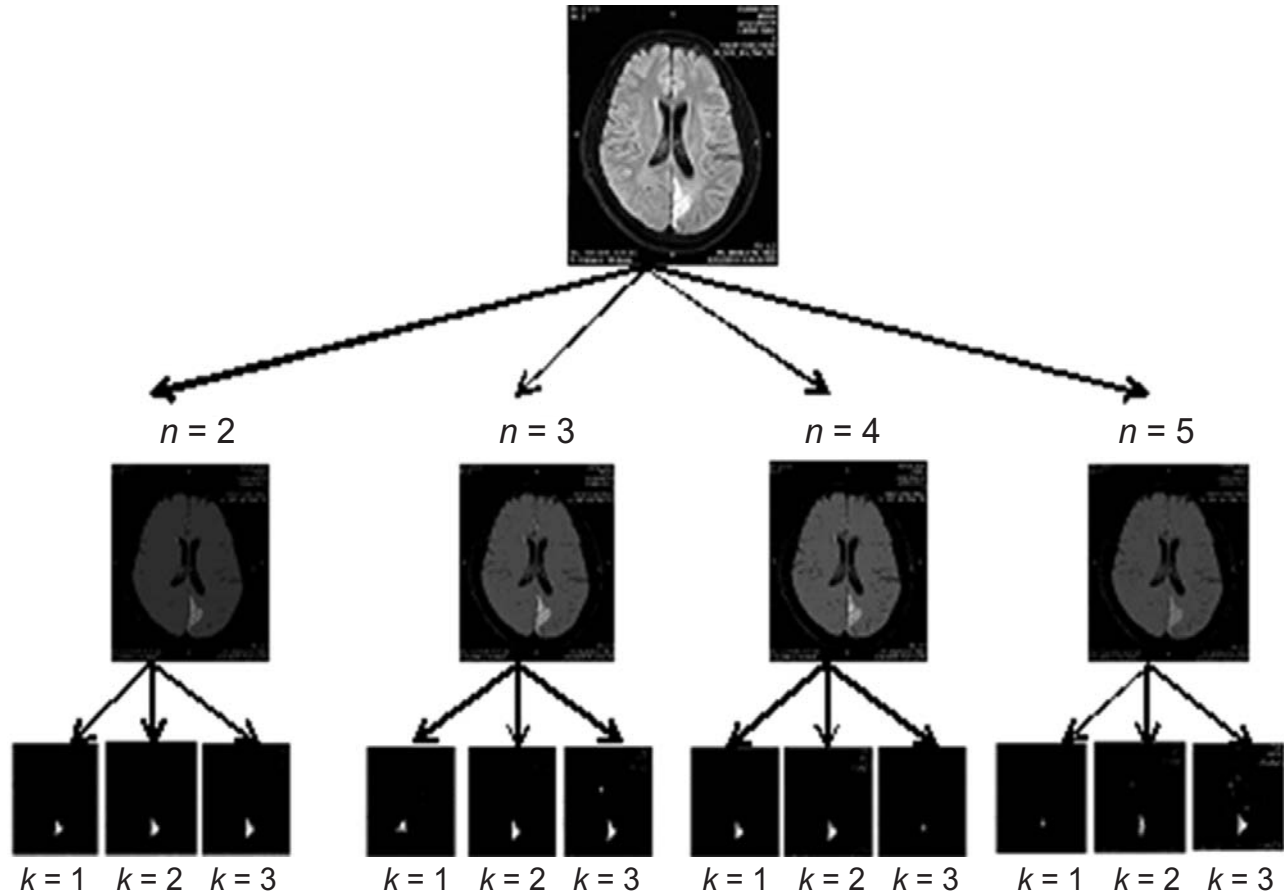

n = 2   *n* = 3   *n* = 4   *n* = 5

k = 1   *k* = 2   *k* = 3   *k* = 1   *k* = 2   *k* = 3   *k* = 1   *k* = 2   *k* = 3   *k* = 1   *k* = 2   *k* = 3

Figure 5: Shows the top down approach ELSM algorithm

Table 2
Observation of ELSM algorithm resutls

Max, min combinations	Values of n and k	Results observed
(min, min)	[2,1]	small in size
(min, max)	[2,3]	feasible solution
(max, min)	[5,1]	small in size
(max, max)	[5,3]	includes artifacts

By changing the values of k the resultant images are observed. Based on the observation from the table 2 the resultant images are analyzed manually. On minimizing both the value of n and k the detected region is small in size. On maximizing both the values of k and n the detected region include the artifacts detail of image. Minimizing the value of n and maximizing the value of k results feasible solution for the image. By minimizing the value of n and maximizing the values of k the best resultant image is obtained by observing the images. Figure 6 shows the tumor affected region when cluster value of $n = 2$ with the changing level value of k 5. The figure 6(a) shows the images partially and 6(b) represents the region with missing some regions and 6(c) detects the entire tumor affected region with the minimum of the n value and the maximum of the k value. The best resultant image is obtained from the value of $n = 2$ and $k = 3$.
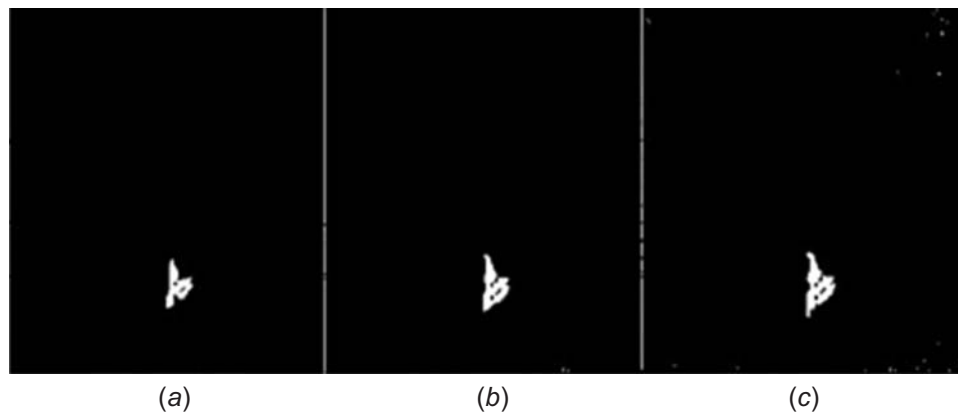
| (a) | (b) | (c) |

Figure 6: Tumor affected region when $n = 2$ with the changing k value
(*a*) **shows the results of the image when $n = 2$ and $k = 1$.** (*b*) **shows the results of the image when $n = 2$ and $k = 2$**
(*c*) **shows the results of the image when $n = 2$ and $k = 3$**

Table 3
Elapsed time of changing the n and k values

Number of clusters (Value of n)	Level Values (Value of k)	Elapsed time in seconds	Space occupied (kb)
2	1	36.0919	7.78
	2	36.6752	7.86
	3	37.2090	8.04
3	1	45.0999	7.41
	2	59.3740	8.85
	3	62.4004	9.97
4	1	95.5818	7.60
	2	101.6191	9.17
	3	71.1677	10.8
5	1	78.9209	7.44
	2	55.3180	9.37
	3	73.7729	11.37

Table 3 shows the elapsed time for the changing n and k values, the value of [2,1] will be small but the best resultant image as in table 2 is [2,3]. The difference between this two min and max value of elapsed time is small, so its negotiable. Its worth noting that our algorithm allows flexible initialization of the level set functions. The initial contour of the image can be inside, outside, or cross object boundaries. The proposed ELSM hybrid algorithm performance tests were implemented using Matlab R2008a on $i5$ processor with 2.2 GHZ, 4GB DDR3 memory, 64-bit, and Windows 7. The figure 7 shows the elapsed time in seconds during the implementation of ELSM algorithm with the number of cluster and level values taken for the dataset. From the figure 7 the x axis represents the cluster values n and the k value number of levels and the space occupies and y axis represents the time taken. From the figure it is observed that the when $x = 3$ the y value is minimized. Figure 8 shows that the space occupied by the resultant images the n and k values are minimized; meantime the space is also reduced. By analysis in the all the criteria the best resultant images is obtained when $n = 2$ and $k = 3$.

In the medical field, to segmentation of tumor or it's the detection of white matter of brain from the given MR images is an important task even in the modern era. By the proposed hybrid ELSM algorithm, both the objectives taken for analysis are achieved in efficient manner. The time complexity and space

complexity are also minimized by this approach. The resultant image is validated with the medical expert and thus provides 90% accuracy. The ELSM algorithm allows the use of relatively large time steps to significantly reduce iteration number in the last phase of the algorithm. The efficiency and accuracy of the ELSM algorithm will find its utility in more application area of the image segmentation.
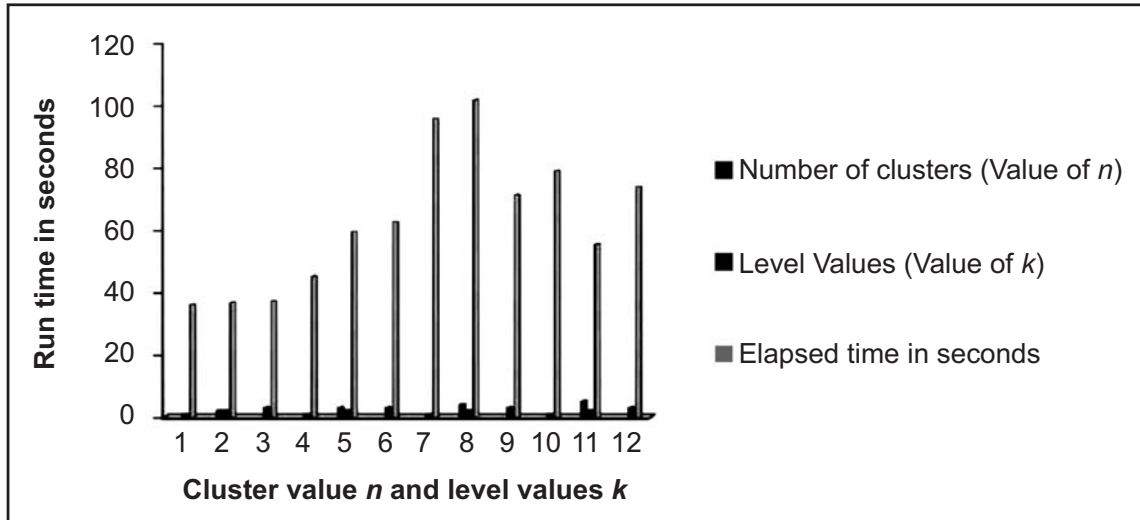

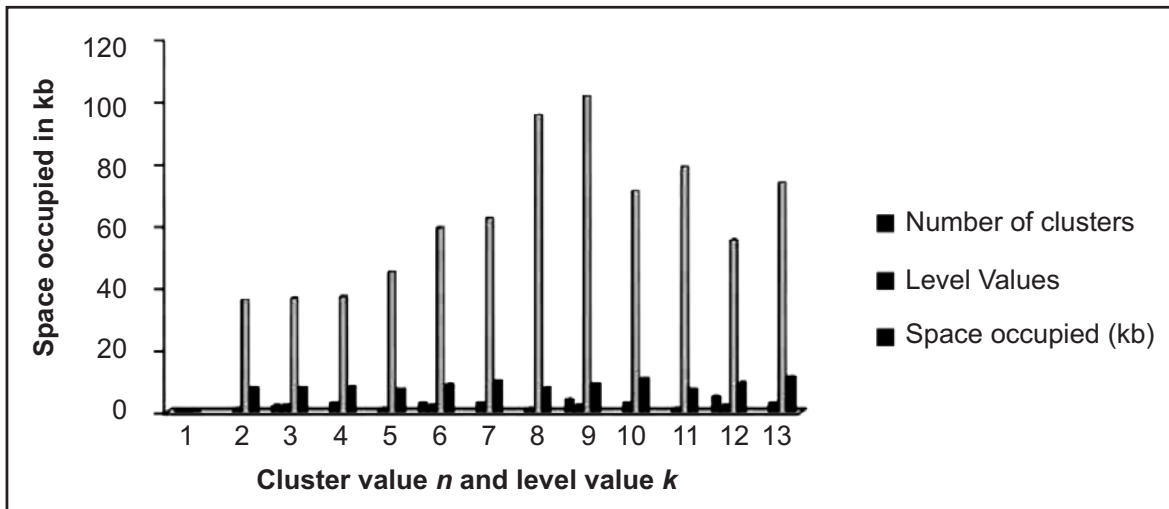**Figure 7: Elapsed time of the dataset**

Figure 8: Space analysis of dataset

5.   CONCLUSION

Finding the tumor affected region in MRI brain images through the image segmentation techniques is a challenging problem due to the great diversity of intensity, shape and texture in the real world. The most important contribution of this study is to propose a new hybrid algorithm with the combination of electromagnetic optimization algorithm and with the level set function. The modified EMO algorithm accompanied with the level set functions will resolve the accuracy and it gives expected results of the data set collected. Hence, the segmentation is carried out in the second phase of ELSM algorithm and the detection of tumor affected region is separated by the level set functions clearly. By using the maximum and minimum observations, the best resultant images are obtained. The real world images are collected and algorithm is evaluated and it modifies the active contours in the third phase of the algorithm. The performance of new hybrid algorithm have advantageous for random initialization, fast convergence, robust segmentation and acquires shorter CPU time. In future, it is planned to measure the area of tumor affected region from the resultant of ELSM algorithm images.

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