ISSN 0975-2366
https://doi.org/10.31838/ijpr/2018.10.04.047

Research Article

OPTIMIZED SEGMENTATION OF BRAIN IMAGES USING SHUFFLED FROG LEAPING ALGORITHM – TABU SEARCH FRAMEWORK

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Received: 20.05.18, Revised: 17.08.18, Accepted: 29.09.18

ABSTRACT
Magnetic Resonance Imaging (MRI) technology allows us for obtaining digital images of brain. The real challenge is to accurately detect the tumor area in the brain, which is composed of the tumor and any edema. It comes to isolate a specific area among the other brain anatomical structures. Image segmentation is one of the most important operations in the field of medical image analysis. Thresholding is basically used because it provides high-speed operation and ease of implementation. This paper contains a new optimized method called Hybrid Shuffled Frog leaping Algorithm –Tabu search(SFLA-TS) method , a robust and fast algorithm, to detect the tumor part in MRI Brain images effectively. This method overcomes the limitations of local optimality of Shuffled Frog leaping Algorithm –Expected Maximization (SFLA-EM) method. In this proposed work hybrid SFLA with TS is used to improve the solution.

Keywords: *Magnetic Resonance Imaging (MRI), Tumor detection, Shuffled Frog Leaping Algorithm (SFLA) and Tabu search (TS).*

INTRODUCTION
The domain of medical imaging earns its importance by the increase in the need of automated and efficient diagnosis in a short time. Computer and information technologies are very used in medical image processing, classification and recognition. Magnetic Resonance Imaging (MRI) is widely used to visualize soft tissues of brain and help medical experts to diagnose possible abnormality in brain structure. Brain image segmentation is one of the critical and challenging tasks and much effort has been invested by researchers and developers to automate this task [1]. MRI is employed as a valuable tool within the clinical atmosphere as a result of its characteristics comparable to high abstraction resolution and distinction. imaging area unit visually examined by radiologists to analyze traditional slices from defective ones and so to find tumors within the defective slices. the massive volume of imaging to be analyzed and therefore the shortage of radiologists build such readings price expensive and infrequently inaccurate. therefore there's an enormous would like for automatic systems for analysis and classification of such pictures. Segmentation of a medical image helps to reveal necessary abnormality (if exists) that additional helps in image analysis and classification. Image segmentation divides a picture into regions such pixels among square measurea|a district|a locality|a vicinity|a part|a section} are solid with similar properties supported some predefined condition. All regions area unit reciprocally exclusive and aggregation of all the regions offers original image. Segmentation ways area unit challenged for magnetic resonance imagingpictures because the tumors or any pathological space to be divided have non-rigid complex body part, unknown noise, poor image distinction, complicated form that varies in size and position among magnetic resonance imaging pictures [2, 3].Image segmentation [4] is an essential step for many image analysis tasks. The goal of image segmentation is to partition an image into homogenous regions and accurately locate the contour of the regions. Effective image segmentation is very important in various medical image analysis tasks and it helps clinicians and researchers with visualization, image-guided surgery, radiotherapy, and surgical planning. Magnetic resonance imaging (MRI) is especially used in medical image segmentation because of its high contrast. Accurate segmentation of brain tissue is not a simple task [5], because of the presence of noise, and intensity non-uniformity among other effects. The Expectation and Maximization (EM) algorithm is a class of algorithm for finding the maximum likelihood in an iterative manner. The EM algorithm performs alternating steps of Expectation (E) and Maximization (M) iteratively until the results converge. An expectation of the likelihood is computed on the E-step by including the latent variables, and the maximum likelihood of the parameters is performed on the M-step based on the last E-step by maximizing the expected likelihood. Based on the parameters found on the M-step, another E-step starts, and the process

is repeated until convergence is met. The EM algorithm can be used in wide areas, including medical image processing, and image interpolation [6].Thresholding could be a basic task in image process and pattern recognition because it represents a basic step for image understanding in various applications. Thresholding could be a wide used methodology for image segmentation attributable to its simplicity. Thresholding is a vital a part of image segmentation as a result of it separates the grey levels of these pixels that belong to the objects from the grey levels of these pixels that belong to the background. Hence, it plays a significant role in separating objects from the background. In planned methodology, the threshold value was considered from the set of means obtained after the EM algorithm and is selected as the mean of the brightest cluster consisting of gray matter and cerebrospinal fluid. Usually, Thresholding techniques supported constant models suffer from some serious downside reminiscent of (i) they're supported the mathematician assumptio n for modeling the category distributions within the image, which often does not hold in real images; (ii) they often lead to biased estimates of the statistical parameters of the object and background classes; and (iii) their effectiveness is strongly reduced when the prior probabilities of object and background classes are unbalanced or when the two classes overlap significantly. Many optimization problems in practice require large space and more computational time in nonlinear framework. Shuffled Frog Leaping Algorithm (SFLA) is a new meta-heuristic that mimics the principle of a group of frogs evolution that searches discrete locations containing as much food as available. SFLA combines the advantages of PSO which inspires its principle from the herding behavior of animals like fish floquant and from GA which is a research technique developed with such characteristics as great capability in global search and easy implementation. Extensive effort has been directed towards the design of good heuristics, in other words algorithm efficient with respect to computing time and storage space. Tabu Search (TS) is proposed to solve combinatorial optimization problem and is an adaptive procedure which overcomes the limitations of local optimality [7]. In this work, hybrid SFLA-TS is proposed to improve the solution. Section 2 briefly details the literatures related to this work, section 3 explains the methods in detail, section 4 represents and discussed the obtained results and finally section 5 concludes the work.

Literature Review

Bazi et al [8] planned a completely unique constant and international image bar graph thresholding methodology is bestowed. it's sup ported the estimation of the applied math parameters of "object" and "background" categories by the expectation–maximization (EM) rule, below the belief that these 2 categories follow a generalized Gaussian(GG) distribution. The adoption of such a applied math model as an alternate to the a lot of common Gaussian model was intended by its engaging capability to approximate a broad kind of applied math behaviors with a little range of parameters. Since the standard of the answer provided by the unvarying EM rule was powerfully littered with initial conditions, a sturdy initialisation strategy supported genetic algorithms (GAs) was planned. Experimental results obtained on simulated and real images confirm the effectiveness of the proposed method. Ladgham et al [9] presented a novel optimal algorithm for MRI brain tumor recognition. Newly developed meta-heuristic MSFLA (Modified Shuffled Frog Leaping Algorithm) was proposed to obtain the MRI brain tumor recognition, otherwise, a suitable choice of the fitness function ensures faster time of research with greater chance of convergence to the optimal value. The calculation of the used fitness function was linked to the image. The image was scanned to calculate this function and it was assists to quickly discover the adequate area modeling the tumor. Computer simulation results illustrate the effectiveness of the developed algorithm. Kwon et al [10] used in medical image segmentation because it produces complete division even under poor contrast. However, over-segmentation is its most significant limitation. There- fore, this article proposed a combination of watershed transformation and the EM algorithm to segment MR brain images efficiently. The EM algorithm was used to form clusters and converted into a binary image. A Sobel operator was applied on the binary image generates the initial gradient image. Morphological reconstruction was applied to find the foreground and background markers. The final gradient image was obtained using the minima imposition technique on the initial gradient magnitude along with markers. In addition, watershed segmentation was applied on the final gradient magnitude generates effective gray matter and cerebrospinal fluid segmentation. The results were compared with simple marker controlled watershed segmentation, watershed segmentation combined with Otsu multilevel thresholding, and local binary fitting energy model for validation. Ladgham et al [11] proposed a new meta-heuristic algorithm for MR brain image segmentation, named MSFLA, based on the technique of SFLA. In this new paradigm, there is no need to filter the original image. The new fitness function proposed in our algorithm helps to evaluate quickly the particle frogs to arrange them in descending order. The proposed approach has been compared with other meta-heuristics such as3D-Otsu thresholding with SFLAand

Genetic Algorithm (GA) and also with the algorithm of segmentation using the Rician Classifier (RiCE). Experimental results show that the proposed MSFLA achieved a better segmentation quality and execution time than the latest methods.Shen et al [7] developed a hybrid Particle Swarm Optimization (PSO) and Tabu Search (HPSOTS) approach for gene selection for tumor classification. The incorporation of TS as a local improvement procedure enables the algorithm HPSOTS to overleap local optima and show satisfactory performance. The proposed approach is applied to three different microarray data sets. Moreover, we compare the performance of HPSOTS on these datasets to that of stepwise selection, the pure TS and PSO algorithm. It has been demonstrated that the HPSOTS is a useful tool for gene selection and mining high dimension data.

Methodology

In this work Hybrid SFLA-TS is proposed to achieve better solution.

Shuffled Frog Leaping Algorithm (SFLA)

SFLA may be a recent meta-heuristic rule is meant to see Associate in Nursing best resolution by reproducing the principle of a gaggle of frogs evolution obtain distinct areas containing a lot of food accessible. Its principle relies on the evolution of memes carried by interactive people and a world exchange of data among the population. The population consists of a collection of frogs [13] having constant PSO structure however with completely different adaptabilities. Every frog of the set is a possible resolution to the improvement drawback and is partitioned off into subsets spoken as memeplexes. every memeplexes is {different |totally completely different| completely different} to the opposite and is taken into account different cultures of frogs, every owns a neighborhood search within the search space. Generally, the SFLA algorithmic program is applied to found the optimum answer. In which, every frog features a completely different answer from alternatives frogs within the same memplexes or frogs in other memplexes of the complete population. This answer is customizable by dominant the fitness perform and its ability to adapt [14]. So, good selection of the fitness perform makes the determination of the most effective answer with quicker run time process and with higher threshold price. this is often what we tend to try and notice for each PSO and SFLA during this work.Let m-memplexes of the SFLA algorithm building a population of frogs (solutions). Let each m-memplexes contains n crops of frogs. The entire number of frogs randomly initialize is equal to F=n x m. The partitioning of F frogs into m memelexes is done according to their fitness values. Those frogs happiness to every mememplexes area unit thought of to perform an area search. Frogs of every memplex have their own strategy to explore the setting in numerous directions. The sharing of data between totally different memplexes takes place during a shuffling method all when a predefined variety of iteration memetic. This method of evolution towards the actual interval should be with none prejudice. Memetic evolution and shuffling area unit performed instead till reaching the convergence criterion or otherwise till a stopping criterion.

Tabu Search (TS)

TS was fictitious by Glover (1986) and has been wont to solve a large vary of onerous optimisation issues. TS is AN unvaried procedure designed for the answer of optimisation issues. TS starts with a random solution and evaluate the fitness function for the given solution. Then all potential neighbors of the given resolution area unit generated and evaluated [7]. A neighbor could be a resolution which might be reached from this resolution by an easy, basic transformation. If the simplest of those neighbors isn't in Tabu list then choose it to be the new current resolution. The Tabu list keeps track of antecedently explored solutions and prohibits TS from revisiting them once more. Thus, if the simplest neighbor resolution is worse than this style, TS can go uphill. during this means, native minima will be overcome. Any reversal of these solutions or moves is then for bad move and is classified as Tabu. Some aspiration criteria which allow overriding of Tabu status can be introduced if that moves is still found to lead to a better fitness with respect to the fitness of the current optimum. If no a lot of neighbors area unit gift (all area unit Tabu), or once throughout a pre-determined range of iterations no enhancements area unit found, the rule stops. Otherwise, the rule continues the TS procedures.

Hybrid Shuffled Frog Leaping Algorithm – Tabu Search (SFLA – TS)

EM algorithmic rule within the method of statistics linguistic communication has wide selection of applications, it's circuitously maximizing or doing analog to the sophisticated posterior distribution, however supported the observation information adding some "potential data" to alter calculation and complete a serial of straight forward maximizing or simulation. The characteristics of EM algorithmic rule is easy and stable, particularly every iteration will guarantee the index chance operate of observation information is monotonous while not decrease, which might guarantee the chance operate converge to a neighborhood most worth purpose. however this alg orithmic rulehas some pitfalls: initial of all, EM algorithmic rule is extremely sensitive to the setting of initial worth, unhealthy parameter initial worths area unit straightforward to

form the algorithmic rule convergence value to succeed in some native optimization points; second, the convergence speed of EM algorithmic rule is slow. Therefore, the coaching of model usually adopts the "offline" technique, that is, when coaching model being qualified then doing application; this is often against the important time method. The SFLA in spite of its advantages like being a good convergent property and being effective in optimization solving, post some generations, the diversity of the population is reduced greatly and may result in convergence that is premature to local optimum. TS could be a meta-heuristic that guides native| an area |a neighborhood} heuristic search procedure to explore the answer house on the far side local optimality. It imitates human memory, starts from Associate in Nursing initial possible answer, chooses a series of specific search direction (neighborhood space) as a temptation, and uses tabu list storage the realm simply has searched to avoid detour search. At constant time, it forgives some condition of the realm of the tabu list to make sure the variety of the search, so it makes the particular objective operate worth moving perpetually . thus it's sturdy native search ability. TS algorithmic rule solely search during a selected adjacent neighborhood house. Speed, therefore, could be amassive advantage, however it's simply at bay into native optimisation. TS could be a sensible initial answer may result a decent convergence. TS could be a meta-heuristic that guides native|an area|a neighborhood} heuristic search procedure to explore the answer area on the far side local optimality. It imitates human memory, starts from AN initial possible answer, chooses a series of specific search direction (neighborhood space) as a temptation, and uses tabu list storage the realm simply has searched to avoid detour search. At a similar time, it forgives some condition of the realm of the tabu list to confirm the variety of the search, therefore it makes the particularobjective perform worth moving perpetually . thus it's robust native search ability.

The flowchart for SFLA is shown in figure 1.

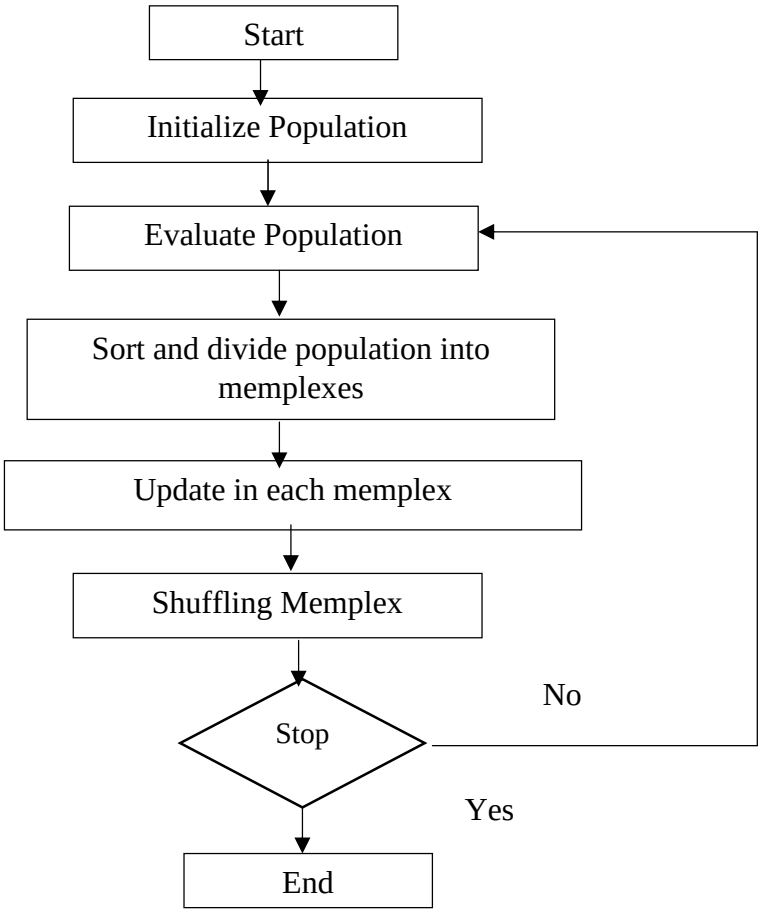

Figure 1 Flowchart for SFLA

TS formula solely search in an exceedingly selected adjacent neighborhood area. Speed, therefore, could be a massive advantage, however it's simply cornered in to native optimisation. TS could be

a smart initial answer may result a decent convergence.

The option to adopt SFLA is adopted for initializing variables of the categories of distribution and this feature depends on the traits of the technique of improvement mentioned earlier. because of the initial values of the variables within the categories that impact significantly the estimates that's goth by the EM protocol at eachthres holding and convergence outcomes, it becomes necessary to use an accurate and resilient method for data format which may explore the area of the answer accurately.

The effectiveness of exploration of the area of the {answer} in SFLA has been amalgamated with the likelihood of shaping ancriteria that's on the idea of the performs of fitness that implement the up taken notions by the EM protocol that is that the function that's increasing log probability and conjoint ly by the protocol of the edge choice that is that the likelihood of minimizing the errors calculable

Steps of SFLA are given below [15, 16].

Step 1: Initial population of F frogs, in which individual frogs are equivalent to the GA chromosomes, is created randomly.

Step 2: All frogs are sorted in descending order based on their fitness values and divided into m memplexes, each memplex containing n frogs; the frog that is placed first moves to the first memplex, the second one moves to the second memplex, the nth one to the nth memplex, and the (p+1)th returns to the first memplex, etc.

Step 3: Within each memplex, the frogs having the best and the worst fitness are identified. The frog with the best fitness in the whole population is identified. During the evolution of memplexes, worst frogs jump to reach the best ones.

Step 4: After a defined number of memplex evolution stages, all frogs of memplexes are collected and sorted in descending order again based on their fitness. Step 2 divides frogs into different memplexes again, and then step 3 is achieved.

Step 5: If a predefined solution or a fixed iteration number is reached, the algorithm stops.

Steps for proposed SFLA – TS

1. Initial population of individuals is created arbitrarily,
2. Excellence of chromosomes is tested as per pre-defined fitness function that permits retaining best memeplex after discarding the worst (better the fitness, greater the likelihood of being chosen). This selection procedure is significant for the subsequent stage that is focused on reproduction of the population.
3. After every 10 iterations of SFLA, Tabu Search is initiated to improve the overall solution.
4. Select an initial $x \in X$ and let $x^* := x$. Set the iteration counter $k = 0$ and begin with T empty.
5. If $S(x) - T$ is empty, go to Step 7.

Otherwise, set $k := k+1$ and select $s_k \in S(x) - T$ such that $s_k(x) = \text{OPTIMUM}(s(x) : s \in S(X) - T)$. --------(1)

6. Let $x := s_k(X)$. If $c(x) < c(x^*)$, where x^* denotes the best solution currently found, let $x^* := x$.
7. If a chosen number of iterations has elapsed either in total or since x^* was last improved, or if $S(x) = \varnothing$ upon reaching this step directly from Step 5, stop and move to step 8. Otherwise, updated T (as identified) and return to Step 5.
8. Best results obtained and stop.

Measures used for Performance evaluation

As defined in[17]

a) **Total Correct Fraction: It is used to calculate the efficiency of identifying the tumor part**

Total Correct Fraction = T_t/T_{tot} --------(2)

Where

T_t indicates selected tumor pixels

T_{tot} indicates total tumor pixels

b) **Sensitivity**, which indicates the fraction of positives correctly classified as such, computed as:

$$Sensitivity = \frac{TP}{TP + FN}$$

--------(3)

Where, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

c) **Specificity**, which indicates the fraction of negatives correctly classified as such, defined as:

$$Sensitivity = \frac{TN}{TN + FP}$$

----------(4)

d) **The dice coefficient D** is one of a number of measures of the extent of spatial overlap between two binary images. It is commonly used in performance measures of segmentation and gives more weighting to instances where the two images agree. Its values range between 0 (no overlap) and 1 (expected image).

$$D = \frac{2TP}{2TP + FP + FN}$$

--------(5)

e)Volume error : is used to calculate the

Volume error = T_s/T_a ----------(6)

Where

T_s indicates total wrong pixels selected

T_a indicates actual number of tumor pixels

Mean Volume Error = $(\sum V)/N$ -----(7)

Where

Vi is the volume error of each image

N is the Total Number of images

Results And Performance Analysis

The proposed work is implemented with MATLAB. We carried two different series of tests for performance analysis by taking fifteen sample MRI brain images and by taking 250 MRI brain images from standard database of brain images.

A) Performance analysis for sample images:

Table 1 and figure 2 to 6 shows the total correct fraction, Sensitivity and specificity for SFLA-TS and Expert, Dice co-efficient and volume error respectively. Figure 7 shows the best fitness for the proposed method.

Table 1 Results for Total Correct Fraction, Sensitivity and specificity for SFLA-TS and Expert, Dice co-efficient and volume error

	Total Correct Fraction	Sensitivity-Expert	Sensitivity-SFLA-TS	Specificity-Expert	Specificity-SFLA - TS	Dice Coefficient	Volume error
Image 1	0.8648	0.933	0.9767	0.9306	0.9627	88.6	19.23
Image 2	0.8686	0.9334	0.9765	0.9316	0.9617	89.27	18.26
Image 3	0.8836	0.9336	0.9797	0.9351	0.9642	89.52	17.82
Image 4	0.8997	0.9345	0.9776	0.9353	0.9688	89.92	17.47
Image 5	0.9249	0.9353	0.98	0.9355	0.9678	90.73	16.18
Image 6	0.9352	0.9406	0.9824	0.9358	0.9704	90.61	15.88
Image 7	0.939	0.9416	0.9826	0.9362	0.9718	91.71	15.75
Image 8	0.9423	0.9447	0.9804	0.9363	0.9713	93.28	14.09
Image 9	0.9524	0.9468	0.9804	0.9366	0.9748	93.72	13.62
Image 10	0.9504	0.9487	0.9832	0.9381	0.9773	93.65	12.23
Image 11	0.9593	0.9489	0.9841	0.9386	0.9773	94.45	12.17
Image 12	0.9626	0.9498	0.983	0.9393	0.977	94.53	11.95
Image 13	0.9648	0.9553	0.9882	0.9396	0.9794	94.72	11.41
Image 14	0.9654	0.9581	0.9892	0.9435	0.9804	94.78	11.34
Image 15	0.9789	0.9592	0.9912	0.944	0.9853	95.17	11.1

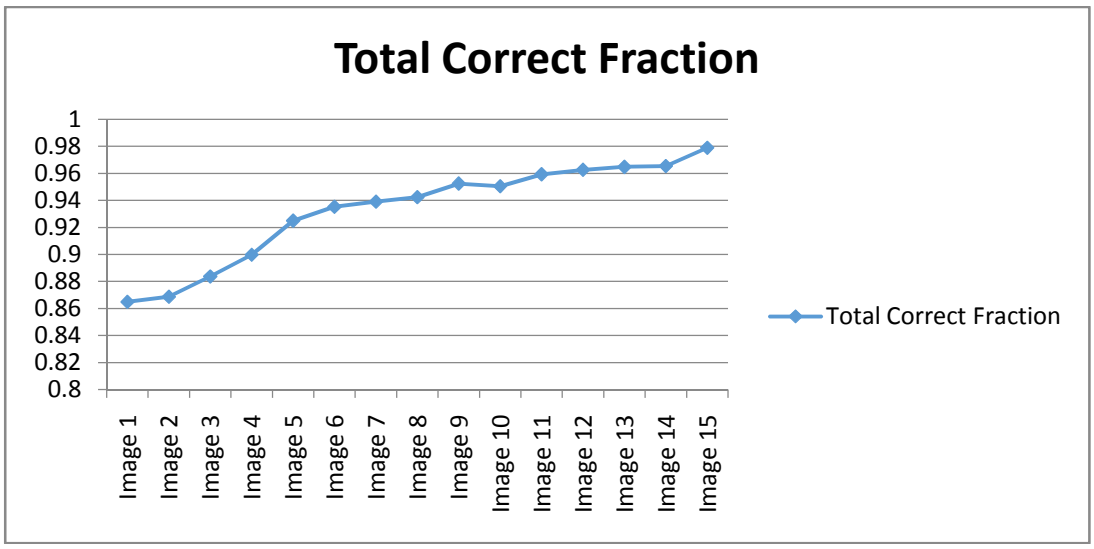

Figure 2 Total Correct Fraction for SFLA-TS and

It is observed from table 1 and figure 2 that the average of 93.28% of tumor pixels are extracted correctly by the proposed SFLA-TS algorithm.

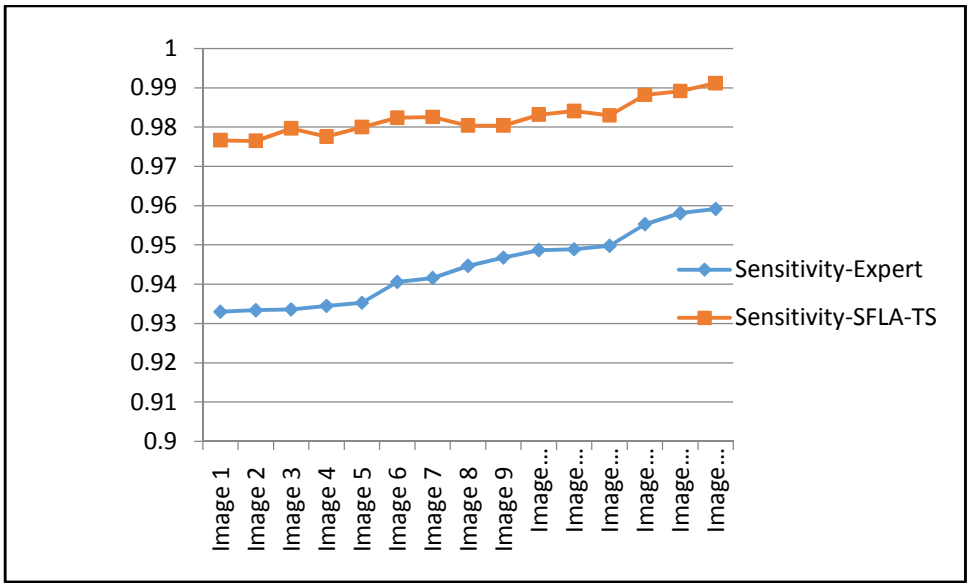

Figure 3 Sensitivity for proposed SFLA-TS and Expert

It is observed from table 1 and figure 3 that the sensitivity for proposed SFLA-TS performs better by 4.58% than Expert for image 1. Similarly for image 15, the sensitivity of SFLA-TS performs better by 3.28% than Expert.

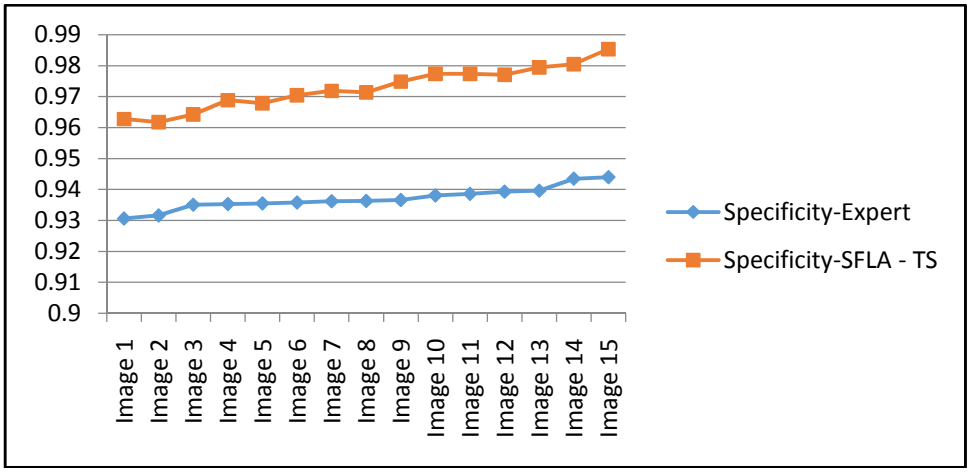

Figure 4 Specificity for proposed SFLA-TS and Expert

It is observed from table 1 and figure 4 that the Specificity for proposed SFLA-TS performs better by 3.39% than Expert for image 1. Similarly for image 15, the Specificity of SFLA-TS performs better by 4.28% than Expert.

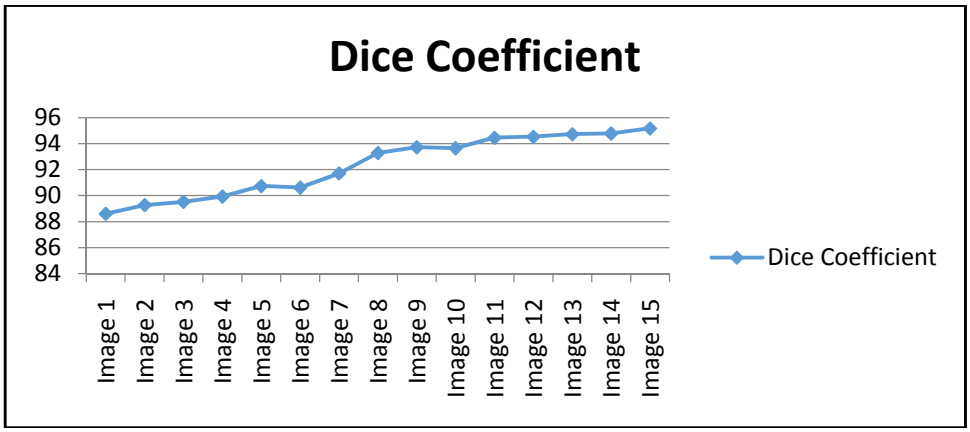

Figure 5 Dice Co-efficient for proposed SFLA-TS

It is observed from table 1 and figure 5 that the dice coefficients for the individual tumor sub-regions are relatively higher for all the 15 images. The average dice co-efficient obtained for proposed method is 92.31%.

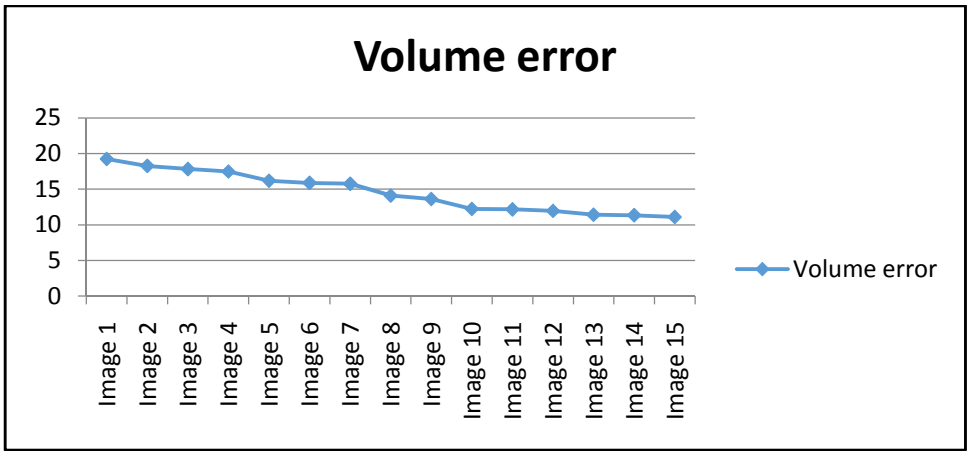

Figure 6 Volume Error for proposed SFLA-TS

It is observed from table 1 and figure 6 that the average volume error obtained is 14.57% for proposed method.

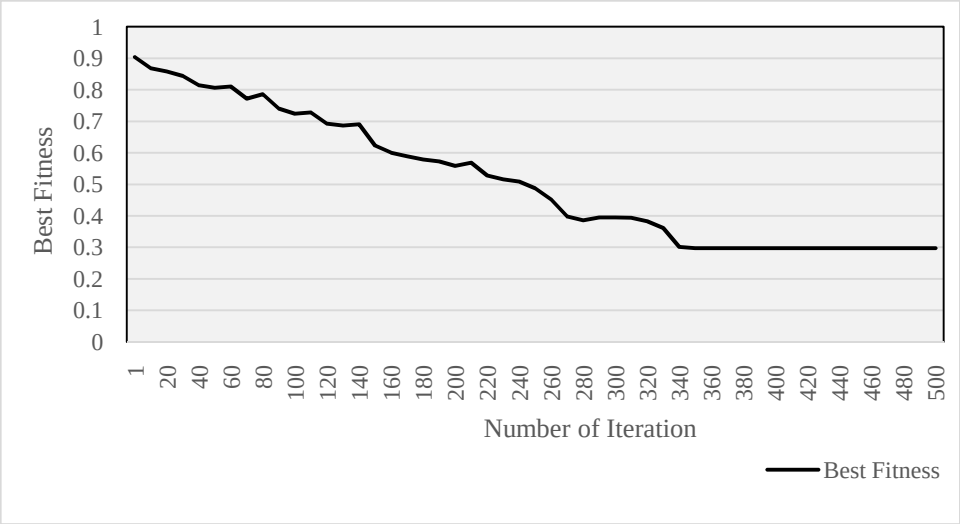

Figure 7 Best Fitness for proposed SFLA-TS

It is observed from figure 7 that the best fitness for proposed SFLA-TS converges at iteration number 350.

B) Preformance analysis of 250 standard database images:

It is observed form Table 2 and 3 that SFLA-TS method shows better improvement compared to Expert method.

Table 2 : Average of Specificity of SFLA- TS method over expert method

No.of Images	Specificity of Expert	Specificity of SFLA-TS	% improvement of Specificity of SFLA-TS method over expert method
50	0.941312	0.97311	3.59
100	0.937442	0.968231	3.28
150	0.937915	0.968444	3.25
200	0.937953	0.968372	3.24
250	0.938315	0.968659	3.23

Table 3 . Average of Sensitivity of SFLA-TS method over expert method

No.of Images	Sensitivety of Expert	Sensitivety of SFLA-TS	% improvement of Sensitiviety of SFLA-TS method over expert method
50	0.950706	0.979122	2.99
100	0.947257	0.973637	2.78
150	0.947895	0.974043	2.76
200	0.948014	0.973432	2.68
250	0.948426	0.973501	2.64

Conclusion

Image segmentation plays a very important role in understanding and interpretation of medical images. It makes processing disease tasks simpler and more efficient. It is the transaction stage between image processing and image analysis. Segmentation of medical images, especially MRI, has received a huge amount of interest by researchers who have proposed hundreds of approaches, especially in recent decades. Image thresholding is a tool widely used in image segmentation. SFLA is a new meta-heuristic that mimics the principle of a group of frogs evolution that searches discrete locations containing as much food as available. Results show that the average of 93.28% of tumor pixels are extracted correctly by the proposed SFLA-TS algorithm. The specificity and sensitivity is good for proposed method. At iteration number 350, convergence occurred when best fitness is calculated for proposed method.

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