HYBRID SHUFFLED FROG LEAPING ALGORITHM WITH
PROBABILITY DISPERSAL METHOD FOR TUMOR DETECTION
IN 3D MRI BRAINTUMOR IMAGES

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ABSTRACT

In the medical image study, the brain tumor classification using MRIs is difficult due to the brain's complicated structure and the high variance in tumor tissues' position. So, the requirement for useful and specific tumor identification methods is developing for medical recognition and regular medical applications. The conventional brain tumor identification performs anatomical knowledge of irregular tissues in the brain, helping the doctor design approach. The research proposes several techniques for brain tumor identification. This work aims to present brain tumor identification methods based on evolutional intelligence and segmentation. Unusual areas in the brain are identified by using the Expectation-Maximization (EM) algorithm. For segmenting the 3D brain MRI data, this work presents a novel hybrid optimization meta-heuristic called the Shuffled Frog Leaping Algorithm (SFLA) with probability dispersal (i.e., SFLA - Stochastic Diffusion Search (SDS)). The efficacy of the suggested 3D SFLA probability dispersal EM in enhancing the performance of the 3D SFLA tabu EM has been proven by empirical outcomes.

Keywords: Medical Imaging, Magnetic Resonance Imaging (MRI), Image Segmentation, Expectation Maximization (EM), Shuffled Frog Leaping Algorithm (SFLA) and Stochastic Diffusion Search(SDS).

1 INTRODUCTION

A brain tumor is a mass of tissue such as a tumor or cancer depends on the slow addition of irregular and atypical cells and unusual tissue proliferation, causing damage to the vital system and increased pressure inside the skull. A brain tumor can be both benign (not cancerous) and malignant (cancerous). The most common brain tumors are glioma and low-stage meningioma, which is a type of malignancy. A homogeneous form of a benign brain tumor that no longer contains most of the cancer cells or has been removed entirely by surgery can be monitored radio logically. If a malignant mental tumor is present, it carries a cancerous cell phone treated with chemotherapy and radiotherapy. MRI is primarily a clinical imaging method [1] that provides useful records of the analysis. It is mainly used by surgical radiologists who plan and visualize the frame's function and the frame's internal structure. Magnetic resonance imaging plays a vital role in detecting most cancers.
and tissue abnormalities with affected tissues' dimensions and area. Further evaluation is offered using MRI rather than CT images. It makes it especially useful in diseases of the cardiovascular system and the nervous system (mind).

The development of image processing into unique areas of interest has been connected with the latest clinical imaging techniques, as more acquisition models and larger images are being produced. It makes it insufficient to see the photos have received without image processing software. Thus, image processing packages have a important influence on the method of analysis by serving the physician investigate all volumetric information to make a treatment verdict and wait for disease consequences.

In just a few decades, there has been a variety of research involving the topic of segmentation of mental tumors because it is essential to understand the points obtained with MRI to predict and monitor treatment effectiveness [2].

The subdivision of mental tumors from magnetic resonance imaging presents an intrinsic and challenging task in assessing and planning solutions. Image segmentation is a vivid neighborhood in the clinical picture and consists of extracting one or more regions of the image that make up a hobby site on the Internet. Numerous algorithms have been developed in the literature to find intellectual neoplasms and methods that in most cases depend on thresholds, techniques that rely specifically on regions, deformable techniques, separation strategies and deep understanding. Distorted models are the most popular of the various strategies used to remove intellectual tumors through the use of MRI. It is represented with the help of curves (2D) or surfaces (3-D) specified in Fig [3] which rotate through the influence of two forces, internal or close specific within the curve to keep calm at some moments. From the deformation model, at the same time, external forces are calculated from photographic facts to pass the angle towards the boundary of the desired object. He distinguishes between two primary classes, parametric distorted or snake fashions and distorted geometric patterns in deformed techniques. The benefit of these patterns is their ability to topological seizures at some point in the curve diffusion.

The holistic rule-based method uses a set of optimization rules [4] to optimize the segmentation outcomes. Initially, brain tissue is improved by some methods and an optimization algorithm is applied. The most commonly applied algorithms are nature-inspired or meta-heuristic techniques due to their simplicity and flexibility. Several sets of descriptive properties have been proposed for entirely rule-based segmentation techniques. In the hybrid strategies, additional tactics for the tumor area class of brain MRI are incorporated. This work presents a 3-D EM approach to SFLA potential dispersion (SFLA-SDS hybrid) that optimizes the 3D MRI category. The final part of the investigation is prepared in the following sections. The second section analyzes related works in the literature. Section 3 explains the different
methods used in creation. Section IV analyzes the experimental results, and Section 5 concludes with panels.

2 RELATED WORKS

The 3D brain tumor segmentation is a medical need for mental tumor analysis and radiotherapy planning. It is a difficult challenge because of the difference in genre. Several techniques, along with a set of Particle Clustering Optimization (PSO) rules, the size, location, and shape of the tumors have formed a topological association of slides that convert 2D images into 3D MRI images that no longer afford good results and depend on the number of segments introduced and the positions and shape of the MRI images. Gtifa et al. [5] proposed a practical approach to 3D mental tumor segmentation known as modified PSO. Moreover, the segmentation results are compared to the Darwinian PSO (DPSO) process and Fractional-Order DPSO (FODPSO).

Experimental effects showed that the technique achieved 97.6% 3D segmentation.

When compared to DPSO and FODPSO techniques with 78.1% and 70.21% for the case of the T1 - C method, there is an additional accuracy rate.

Badura [6] presented new flexible swarm intelligence optimization method has been provided to different segment systems into 3D or 2D images. Merchants in a self-regulating colony discover their host, use stigma to communicate, and mark areas of interest that lead to element extraction. In this work, detailed specifications of a bacterial colony segmentation technique (BCS) in terms of individual and social behavior are defined. The approach has been demonstrated and evaluated through various experiments, including synthetic information, tomography, and ultrasound research. The results and observations obtained in terms of parameter settings and the approach's potential utility are discussed in the various segmentation tasks.

Mehmood et al., [7] developed intelligent computer-assisted diagnostic device specializing in magnetic resonance imaging of the human mind. These panels provided the ability to detect brain tumors, their fragmentation and the 3D display device, and offered good medical deals regardless of the geographical area and the degree of knowledge of scientific experts in this research. Malignant and benign based primarily on the BoW version of the Resistant Supporting Vector Machine
The BoW function extraction technology is further amplified by the powerful accelerated features (SURF) that incorporate a selection factor of interest factor. Finally, 3D visualization of the brain and tumor was implemented using a set of volume rules that are used to represent clinical events. The efficacy of the proposed system was constructed on a dataset collected from 30 patients and implemented with an accuracy of 99%.

Sumathi et al., [8] a unique set of rules has been provided that has evolved and relied entirely on entropy-based morphological reconstructions and Kapoor's cuckoo search optimization filters. The former is used to locate and stage tumor boundaries, while the latter is used to eliminate unnecessary pixels within the cropped footage. The proposed method produces up to 97% accuracy in determining the tumor site's exact topographic region. If we need less computing time (about 3ms, combined) for this method. Therefore, the proposed method can assist radiologists in quickly determining the exact topographic area of tumor areas, even assuming versions of excessive depth and serious limitations.

To arrive at and develop a completely unique dependency framework for prominently perceptions of tumor regions and division of tissue systems, particularly within the human brain, Narayanan et al. He proposed a completely unique set of synthesis rules [9]. Combined with two optimization technologies, PSO and Bacteria Foraging Optimization (BFO), the algorithm enables the unique function of bacteria worldwide for the BFO. It supports the modified Fuzzy C-mean (MFCM) set by moving the improved block heads finally; the MFCM divides tissue regions and identifies the tumor component, minimizing the reaction and problem encountered with the help of a radiologist while reading the affected man or woman.

Krishna et al., [10] A version of the local radial linear function neural network (LLRBFNN) that relies primarily on PSO to classify and find mental tumors into malignant (precancerous) and benign (non-cancerous) tumors is provided. In these paints, the wavelets are reshaped to improve Magnetic resonance image segmentation and post-extraction performance. Machine learning techniques, the SVM device, and the least-squares mean (LMS) classifier were also examined to validate the proposed PSO-based LLRBFNN model. Whiteboards follow steps that involve extracting features that are viable functions for research work. In a second step, the characteristics are entered into the rating company's PSO-based LLRBFNN model. In a third step, the instrument was implemented to determine the LMS-based SVM and LLRBFNN approach to the category responsibilities and compare the results.

Sahu et al. [11] presented a hybrid version of LLRBFNN that mainly relies on ant-colony optimization - mimetic annealing (ACO-SA) to detect mental tumor tissue and its type of blurred images. Blurring the blurry images affected by the
software becomes a complex and challenging task. The local ambiguous C (FLICM) segmentation algorithm was taken into account from the start. The algorithm's characteristic value was modified for a better final segmentation result to eliminate the MRI noise. Images are split using a modified FLICM algorithm. Capacitances are extracted with gray matrix matching feature extraction (GLCM) technology, and fed as input to the fully ACO-based LLRBFNN model due to the elegance of the malignant and benign neoplasms of the MRI. The proposed model is altered compared to PSO-LLRBFNN and the Adaptive Particle Swarm optimization (APSO) - LLRBFNN improved, and evaluation effects are provided. The proposed algorithm fully based on ACO-SA LLRBFNN to indicate superior effects over conventional techniques was identified.

3 METHODOLOGY

Automated 3D segmentation of a brain tumor can store clinicians' time and provide an accurate, repeatable solution for further tumor evaluation and follow-up. The Expectation-Maximization (EM) algorithm [12] is used to define the predictable parameters with the highest or maximum likelihood later in arithmetical copy when facts are "incomplete" or absent. The parameter is frequently estimated in two steps. It contains steps, the first one being step E, which calculates the expected price of the logarithmic probability property, and in step M the parameters to maximize the value of M based on the observed rate in step E. Then to discover the distribution of the underlying variables in the next step E. In the 3-d SFLA tabu EM, This hybrid algorithm maintains the framework of the SFLA rule set. However, it uses the Community Structure approach of Tabu Search (TS) and avoids the neighborhood that was already explored within the solution area to move it. Towards a significant response within the evolution of local memory. The SFLA, SDS, and 3-D SFLA by chance EM (SFLA-SDS) methods are discussed in these panels.

Shuffled Frog Leaping Algorithm (SFLA)

The SFLA implementation mechanism aims to end the problem-solving process by simulating the cooperation and data-sharing performance of frog flocks by frog in the wild. Each frog is described as a problem option. The entire frog organization is divided into unique subgroups by compiling a meme to simulate frog crowd behavior, and each subset is known as a meme institution. Each frog within a meme establishment strives to get close to the target and determine the area from food assets—meanwhile, every frog was encouraged by other frogs, which is known by tradition here. Each meme organization has its lifestyle, which affects different people and develops with the memes foundation [13].

While making each evolutionary step of the meme set, discover frogs with good neighborhood and worst area. The frog with the worst zone organizes its region
by implementing the neighborhood zone replacement and adopting the gear shift release trigger similar to the PSO. After the positive times of meme development for a meme enterprise, the various meme companies' frog reorganizes the entire organization and understands the exchange and exchange of information between the meme's organizations so that the pre-defined cases of population development are done using the algorithm. The rule set conveys facts according to ethnic grouping and instead implements neighborhood evolution and reintegration. It efficiently combines the exchange of international events and the search for neighborhood development. It's incredibly high overall computational performance and global search ability to solve optimization problems. The mathematical version of SFLA (Equation (1 to 3)) can be briefly presented here.

\[
\begin{align*}
M_{in} f (x) &= \{ f_1 (x), f_2 (x), \ldots, f_k (x) \} \quad (1) \\
\text{s.t. } g_i &\leq 0 \quad (i = 1, 2, \ldots, m) \quad (2) \\
h_j (x) &= 0 \quad (j = 1, 2, \ldots, p) \quad (3)
\end{align*}
\]

Basic flow of SFLA can be described as follows:

Step 1: Configure the algorithm parameters, along with group P length, number of meme M deals, meme G development times, a maximum permissible distance of frog Dmax, and full population generation range MaxIter.

Step 2: Randomly initialize population.

Step 3: Arrange the sequence of the frog population, which is divided into several memegroups according to grouping operators.

Step 4: Execute local location on updating operators in every meme group.

Step 5: Frogs leap between different groups and remix to form new populations.

Step 6: Check whether the ending condition is satisfied. If yes, output the solution; otherwise, jump to Step 3 and repeat.

**Stochastic Diffusion Search (SDS) Algorithm**

SDS is a global multi-agent research and improvement foundations that rely entirely on simple retail interaction. A hyperbolic description of the SDS level is provided in the form of a social metaphor describing the movements through which the SDS identifies sources. SDS provided a new generation perspective to solve the problems of sample recognition and exact shape matching. SDS, as an international multi-agent research and development group, is mainly based on population in
custom account mode which appropriately uses agent interaction [14]. The SDS algorithm starts searching or optimizing by configuring the population (for example, miners, within the mining game metaphor). In any SDS research, each agent maintains a hypothesis, h, that identifies a potential solution to the problem. In a mining analogy, you determine the dealers' guess a hill. After initialization, two stages are followed:

- Test Phase (e.g. testing gold availability)
- Diffusion Phase (e.g. congregation and exchanging of information)

The SDS algorithm:

*Initializing agents (*)
While (stopping condition is not met)
  Testing hypotheses ()
  Diffusion hypotheses ()
End

In the test segment, SDS examines whether or not predictive analysis is successful using a partial hypothesis evaluation that returns the logical cost. Subsequently, under iteration, depending on the appropriate recruitment approach used, the hypotheses of compliance are disseminated to the majority of the population. Therefore, statistics regarding solutions suitable for capacity are sent at some point over the service provider's network. In the validation stage, each agent plays a partial characteristic evaluation, pFE, which are some of the agent's guessing functions; $pFE = f(h)$. In mining recreation, the assessment of micro-characteristics involves extracting a randomly defined area on the hill, described by the agent's speculation (rather than excavating all of the regions on this hill). In the broadcast segment, each agent recruits another factor to interact and connect to the hypothesis ability. In the metaphor of mining recreation, diffusion ends with the discourse of the hill hypothesis.

**Proposed 3D SFLA Probability Dispersal EM (i.e. Hybrid SFLA-SDS Algorithm)**

SFLA is an evolutionary set of rules similar to the PSO algorithm and the memetic algorithm used to search for a universal answer, that is, in real number problems. Each SFLA frog represents a solution [15], and each frog is sent to a different memeplex. Each memeplex represents a small portion of the response area. A separate live search is performed on each memeplex. After a rigorous and rapid number of memeplex evolutionary steps, a shuffle is performed where frogs can exchange messages between memeplexes and aggregate towards a global response.
Traditionally, SFLA allows for quick searches; however, similar to other optimization algorithms, you can get stuck with nearby optimizations, which can also protect you from finding a more reliable solution globally. To avoid such pitfalls, he mixed it with SDS, used as an alternative to the SFLA update equation, i.e., the SDS does careful research and avoids falling to a close front while still adapting to the evolutionary memeplex of SFLA. For this algorithm, each memeplex will independently evolve to perform local searches in different areas of the response area. Flow chart of the proposed method is shown in Figure 1.

![Figure 1 Flowchart for Hybrid SFLA-SDS Algorithm](image-url)
4 RESULTS AND DISCUSSION

In this stage, the professional strategies of 3D SFLA dispensability EM and 3D SFLA tabu EM are used. Experiments were performed using 250 images. Total correct fraction means common sensitivity, common specificity, common cube coefficient, and common volume errors, as shown in Figures 2 to 6. Table 1 shows a summary of the results.

| Techniques                      | 3DSFLA TABU EM | 3DSFLA Probability Dispersal EM |
|---------------------------------|----------------|---------------------------------|
| Average Total Correct Fraction  | 0.957358       | 0.969295                        |
| Average Sensitivity             | 0.971577       | 0.981855                        |
| Average Specificity             | 0.964429       | 0.975928                        |
| Average Dice Coefficient        | 95.16225       | 96.42342                        |
| Average Volume Error            | 11.69856       | 11.51542                        |

Table 1 Summary of Results

![Figure 2 Average Total Correct Fraction for 3D SFLA Probability Dispersal EM](image)

From figure 2, it can be seen that the dispersion potential of 3D SFLA probability dispersal EM has a higher global average fraction resolution with the help of 1.24% compared to the SFLA 3D tabu EM.
From figure 3, it can be found that SFLA 3-D randomized dispersion MS has a higher mean sensitivity of up to 1.05% compared to SFLA 3-D tabu EM.

Figure 4 shows that 3D SFLA probability dispersal EM has a better average specificity of 1.18% compared to the 3D SFLA tabu EM.
Figure 5 Average Dice Coefficient for 3D SFLA Probability Dispersal EM

Figure 5 shows that the SFLA 3D probability EM has the best average dice coefficient across 1.32% compared to the SFLA 3D tabu EM.

Figure 6 Average Volume Error for 3D SFLA Probability Dispersal EM

From figure 6, it is possible to determine that 3D SFLA probability EM has a lower mean extension error across 1.98% compared to 3D SFLA tabu EM.

5 CONCLUSION

The Automated segmentation of brain tumors from 3D MRI images is essential to identify, informant, and handle the disease. For this purpose, parametric representations are typically considered online, i.e., together with an affiliated segmentation maximizing an a posteriori likelihood population frequency using EM. In this work, the hybrid SFLA-SDS is recommended for the brain tumor 3D image...
segmentation method. The SFLA connects with local search and global knowledge interchange. The most qualified particular leaps out of the local. Then, with the shuffle approach, it can convey an international exchange of local information. Through SDS, every agent can obtain the whole of the search space and carry with it information about the total of its target design. SFLA-SDS connects the benefits of the SFLA, specifically the interchange of data between particular parts of the group (frogs), and executes a local search using an SDS to assess the process results. The suggested work results show that the 3D SFLA probability dispersal EM has a more extensive average total exact section by 1.24% associated with 3D SFLA tabu EM. The 3D SFLA probability dispersal EM has a lower average volume error by 1.58% compared to 3D SFLA tabu EM.

REFERENCES

1. Sonavane and P Sonar, 2016, “Classification and segmentation of brain tumor using Adaboost classifier”, pp. 396-403, IEEE.
2. A. M Hasan, 2018, “A hybrid approach of using particle swarm optimization and volumetric active contour without edge for segmenting brain tumors in MRI scan”, page no.292-300.
3. M. Raihani, Bouattane A, 2019, “Towards Reinforced Brain Tumor Segmentation on MRI Images Based on Temperature Changes on Pathologic Area”. IJBM.
4. Mahesh, K. M, Renjit, J. A, 2018, “Evolutionary intelligence for brain tumor recognition from MRI images: a critical study and review”, page no.19-30.
5. Gtifa, W and A Sakly, 2019, “3D brain tumor segmentation in MRI images based on a modified PSO technique”, (IJIST).
6. P Badura, 2018, “Virtual bacterium colony in 3D image segmentation”, pp.152-166.
7. M, Shoaib, Mehmood, I, 2018, “An efficient computerized decision support system for the analysis and 3D visualization of brain tumor”, pp.1-26.
8. P, Venkatesulu and S Arjunan, 2018, “Extracting tumor in MR brain and breast image with Kapur’s entropy based Cuckoo Search Optimization and morphological reconstruction filters”, pp.918-930.
9. A, Narayanan and Thiyagarajan, 2019, “Multi-channeled MR brain image segmentation: A novel double optimization approach combined with clustering technique for tumor identification and tissue segmentation”, pp.350-381.
10. S, Krishna and Mishra, 2018, “Detection and classification of brain tumor from MRI medical image using wavelet transform and PSO based LLRBFNN algorithm”, IJCSE, 6(1).
11. Kalla, H and S Ayane, 2019, “Detection and Classification of Brain tumor tissues from Noisy MR Images using hybrid ACO-SA based LLRBFNN
model and modified FLIFCM algorithm”, ICACCP, pp. 1-6, IEEE.

12. G. Aswathy, GlanDevadhas, 2015, “Quick detection of brain tumor using a combination of EM and level set method”, pp.74-82.

13. Peng, X, Li, K, 2016, “An efficient hybrid algorithm based on hs and sfla”, IJPRAI 30(05), pp.1659012.

14. Blackwell, T M, al-Rifaie, 2011, “An investigation into the merger of stochastic diffusion search and particle swarm optimization”, pp.37-44.

15. Yang, C. H, Yang, C, 2008, “A combination of shuffled frog-leaping algorithm and genetic algorithm for gene selection”