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NOVEL BRAIN TUMOR SEGMENTATION USING FUZZY C-MEANS WITH FRACTIONAL ORDER DARWINIAN PARTICLE SWARM OPTIMIZATION

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ABSTRACT: Fractional order derivatives becoming popular and recently finds applications in the field of medical image segmentation. They even extract edge features in the low contrast areas of the images. This motivated us to design a novel brain segmentation approach using Fractional Order PSO. Thus a novel brain tumor segmentation using Fuzzy C-means (FCM) with Fractional Order Darwinian Particle Swam Optimization (FO-DPSO) is implemented in this paper. This segmentation method divides brain tumour segmentation into three stages. In the first phase skull stripping and de-noising steps are used for pre-processing in order to remove the noise and improve the speed of processing. In the second phase fuzzy c-means clustering based segmentation is used with Fractional order particle swarm optimization and in the third phase the proposed method is evaluated. This novel segmentation method can be evaluated in the result analysis and the outputs are compared with state of the art techniques PSO and DPSO in terms of DC (Dice Coefficient), SSIM (Structural Similarity Index) and JSI (Jaccard Similarity Index). The novel segmentation method shows biased performance than the other and reduces the processing time compared to PSO algorithm and DPSO algorithm.

KEYWORDS: Brain Tumour Segmentation, Functional Order Darwinian Particle Swam Optimization (FO-DPSO), fuzzy C-means (FCM).

I. INTRODUCTION

Image segmentation is vital and difficult task as well as an essential foremost step in high level image analysis such as object recognition, medical imaging, satellite imaging and different industrial vision analysis [1]. Segmentation is a procedure of dividing an image into a different number of segments to characterize the pixels of an image effectively in different applications.

There are variety of techniques and algorithms for segmenting an image based on different applications. These techniques can be categorized as threshold based, graph based, and morphology based, boundary based, cluster based, neural network based etc [2]. These techniques have their own pros and cons and thus, one needs to select the method based on the requirements for their application. From above mentioned segmentation techniques, clustering based approach is most popular and efficient technique [3].

MRI is widely used in the medical field to identify and visualize information within the body's internal structure [4]. The better technique will be used to identify the various types of body tissues. An optimization algorithm is a process that compares different solutions iteratively until one is found that is optimal or acceptable. It's used to figure out what the mathematical principles are. Brain tumour segmentation is a major task in medical image

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processing. Physical segmentation of brain tumours for cancer identification from huge amounts of MRI images produced in clinical practice is an arduous and time-eat up task. Brain tumours necessitate automatic image partitioning.

The standard K-Means can be considered as the most popular segmentation clustering technique in the field of pattern recognition [5]. However, this technique uses hard partitioning, in which each data point belongs to exactly one cluster. Fuzzy classifiers are soft classification techniques that deal with vagueness in class definitions and model the gradual spatial transition between land cover classes. To overcome the hard partition of KMeans, Fuzzy C-Means (FCM) was introduced, which is a generalization of the standard crisp K-Means scheme, in which a data point can belong to all clusters with different degrees of membership. Although FCM is an improvement on K-Means, it is known for being very sensitive to its initial cluster configuration and may fall into sub-optimal solutions.

One of the most well-known bio-inspired algorithms used in optimization problems is the particle swarm optimization (PSO), which basically consists on a machine learning technique loosely inspired by birds flocking in search of food. More specifically, it consist a number of particles that collectively move on the search space in search of the global optimum [6]. The Darwinian particle swarm optimization (DPSO) is an evolutionary algorithm that extends the PSO using natural selection, or survival of the fittest, to enhance the ability to escape from local optima. Afterward, a method for controlling the convergence rate of the DPSO using fractional calculus (FC) concepts is proposed in this paper with FCM clustering. Moreover, experimental results show that the FO-DPSO significantly outperforms the previously presented PSO.

II. LITERATURE SURVEY

Dixit et al.[7] described a model to classify the brain as tumorous or non-tumorous by using PSO based segmentation, feature extraction using DWT and SVM classifier with two different kernerl functions to obtain better accuracy. To categorize the type of tumour in MRI brain images Kumar et al.[8] described PSO for features selection and SVM classifier for online MRI data base. By using PSO minimum required features are selected to increases accuracy and decreases the computational time. LAKSHMI et al.[9] sugsted tumour segmentation based on adaptive threshold algorithm and genetic algorithm for feature extraction. Deeep learning CNN classifier is used to compare and results are authenticated based on accuracy, specificity and sensitivity.

Analysis of different literatures of brain tumour segmentation was done by Kumari et al.[10]. Most of the researchers used FCM,K-Means, SVM, deep learning, CNN, KNN etc. for brain tumour segmentation to get better accuracy in minimum time. Almahfud et al.[11] applied FCM to the result of K-Means to categorize the convex shape based upon the edge so that the cluster outcomes are better and lighter computation process. The segmentation accuracy improved by the described method over K-means, FCM and FCM integrated K-Means. Rajinikanth, V et al.[12] proposed a method for segmentation based on TLBO, entropy value, and level set/active contour. The described method is tested on the images using flair, T1C and T2C modalities for CEREBRIX and BRAINIX data sets. This method obtained better values of JI, DC, Precision, Sensitivity, Specificity and Accuracy.

Halder et al.[13] suggested an approach for tumour image extraction using genetic algorithm based FCM. In this article genetic algorithm is used to optimize cluster center compared with K-Means, KFCM and the performance is evaluated in terms of number of false alarms, missed alarms, overall error and accuracy. Enver Küçükkülahli et al.[14] compared K-Means, Llyod, Lloyd with K-Means, GA, PSO and Jaya clustering algorithms for MR image segmentation using the parameters VOI(Variance of Information), RI (Rand Index), GCE (Global Consistency Error). When compared to other algorithms, PSO performs better and takes less time to process. Eman abdel-

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Maksoud et al.[15] combined K-Means and FCM to get benefits of K-means in aspect of minimal computational time and FCM in aspect of accuracy. The suggested segmentation perspective was calculated using some state of the art segmentation algorithms in terms of accuracy, processing time and performance.

III. NOVEL BRAIN TUMOR SEGMENTATION USING FCM WITH FO-DPSO FOR

The method which is proposed here implemented on MRI tumour images of human brain. The Dimensions of images are 256*256. MRI database, Multimodal Brain Tumour Segmentation (BRATS) 2015 is used. MATLABR2019a with a core i7 (2.4 GHZ) is used. Skull stripping and de-noising are used as an initial step in the process of segmentation. After that Fuzzy C-Means clustering method is used with Functional Order DPSO Optimization algorithm. Then the Optimized tumour image is compared with the other two Optimization algorithms PSO and DPSO in terms of various similarity metrics and processing time.

3.1 Pre-Processing

Initially the image is subjected to pre-processing to enhance the quality of the image by skull stripping and denoising. In general background of the image is not having any of the necessary information but the processing time is increased. Therefore by removing the skull which is called skull stripping, the memory required is decreased. By this process time is decreased. After this step median filter is used to remove the noise in the input image by preserving edges. Then the output of pre-processing is the only human brain without any noise. It is a method for improving image data by suppressing unwanted data or enhancing certain image features that are important for further processing. When compared to other brain images, the MRI tumour image has a higher intensity level.This stage consists of skull removal and de-noising. It removes skull, background, and all structures that are not in the interest to increase the speed of processing and also decrease the amount of memory used. We used a median filter to remove noise in the presence of edges and the result is a free noising MRI image.

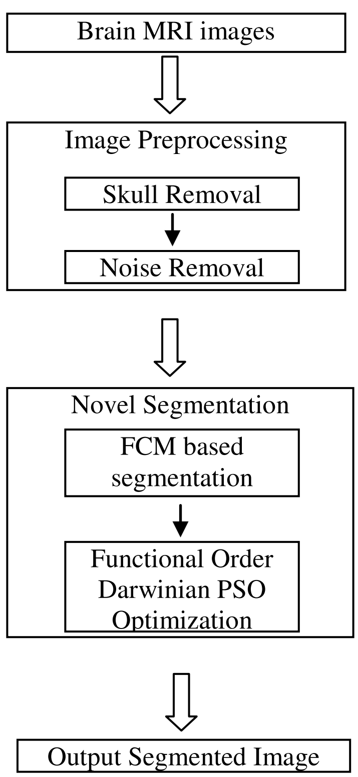

Fig. 1: FRAMEWORK OF BRAIN TUMOR SEGMENTATION USING FCM WITH FO-DPSO

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3.2 Fuzzy C-means Clustering Algorithm

The most popular fuzzy based clustering algorithm for image segmentation is Fuzzy C means clustering. Unlike traditional clustering algorithms, in which each pixel belongs to one cluster only, this algorithm allows each pixel can belongs to more clusters which are ranging from 0 to 1, with the sum of each pixel always equal to one. It first assigns a random value to the cluster centres, and then uses the equation below to calculate the fuzzy membership of each element in each cluster.

$$z_{ij} = \frac{1}{\sum_{k=1}^{n}\left(\frac{|a_i - c_j|}{|a_i - c_k|}\right)^{2/(m-1)}} \text{ --------- (1)}$$

Updates the cluster centres using the following equation and process terminate if the maximum number of iterations is completed or the objective function has been optimized as per specifications

$$c_j = \frac{\sum_{i=1}^{s} z_{ij}^{m} a_j}{\sum_{i=1}^{s} z_{ij}^{m}} \text{ ------ (2)}$$

3.3 Darwinian PSO (DPSO)

By using PSO algorithm with natural selection DPSO technique was developed in which it is having many swarm of assessment solutions. Similar to an ordinary Particle Swarm Optimization algorithm, in DPSO growing swarm performs independently which governs the gathering of swarms outlined to simulate natural selection. Even though there are some resemblances between Genetic Algorithm and Particle Swarm Optimization like random generation of population, objective function calculation, updating of population, and checking for optimality using random techniques; Particle Swarm Optimization is not considered as evolutionary technique because of it does not use crossover and mutation operations.

PSO algorithm is extended by the Darwinian PSO (DPSO) by including natural selection process. The proposed method is to run on several parallel Particle Swarm Optimization algorithms on the same problem at the same time, each with a different swarm, and then apply a basic selection mechanism. When a search is aimed at a specific location, the particular search in that region is simply discarded then it begins the search for other location. In this regard, in every further step move, successful swarms are awarded (particle life is extended or a new offspring is spawned) and stagnant type of swarms are punished (swarm life is reduced or particles removing). By measuring fitness of all the particles, it updates the individual and neighborhood best positions of each particle to evaluate the state of each swarm. When a global solution is detected then a new particle will be created.

3.4 Fractional Order Darwinian PSO (FO-DPSO)

It evaluates each swarm life by determining the fitness function of all the particles and updating each particle's neighborhood and personal best positions. A new particle will be created when a new global solution is discovered. The Functional-Order Optimization algorithm is as abbreviated FO-DPSO, is put to the test with a number of eminent functions, and the association between convergence of the algorithm and functional-order velocity. Further investigational results demonstrate that the FO-DPSO gives significant performance over DPSO. In general, the following are the most improved methods for the standard particle swarm: Changing the weight and constants by developing new methods. Other topologies and intelligent optimizations are introduced into PSO to redefine the position and velocity updation. As a result, an extended version of the DPSO algorithm known as Functional Order DPSO (FODPSO) was presented to control the algorithm's convergence rate by using fractional calculus. Intensity scale and hyper spectral image segmentation have been investigated further using this method.

The Grunwald-Letnikov definition of the fractional differential of a general signal y(t) is given as follows:

$$D^{\alpha}[y(t)] = \lim_{p\to 0}\left[\frac{1}{h^{\alpha}}\sum_{l=0}^{\infty}\frac{(-1)^{l}\Gamma(\alpha+1)y(t-lp)}{\Gamma(l+1)\Gamma(\alpha-l+1)}\right] \text{ ----- (1)}$$

The above expression discrete time implementation is as follows

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$$D^{\alpha}[y(t)] = \frac{1}{h^{\alpha}} \sum_{l=0}^{r} \frac{(-1)^{l} \Gamma(\alpha+1) y(t-lT)}{\Gamma(l+1)\Gamma(\alpha-l+1)} \text{ --- (2)}$$

By using the fractional calculus concept and equation (2), the velocity derivative order can be generalized to a real number α in between 0 and 1that results in a extensive memory effect and a smoother variation . As a result, using the discrete-time fractional differential, the velocity update equation can be rewritten as:

$$v_n^s[t+1] = \sum_{l}^{r} \frac{(-1)^{l} \Gamma(\alpha+1) v_n^s(t+1-lT)}{\Gamma(l+1)\Gamma(\alpha-l+1)} + \sum_{i=1}^{2} \rho_i \, r_i (Y_{in}^s[t] - x_{in}^s[t]) \text{ ----- (3)}$$

By using the first r=4 terms, equation (3) can be rewritten as,

$$v_n^s[t+1] = \alpha v_n^s[t] + \frac{1}{2}\alpha(1-\alpha) v_n^s[t-1] + \frac{1}{6}\alpha(1-\alpha)(2-\alpha) v_n^s[t-2] + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)(3-\alpha) v_n^s[t-3] + \sum_{i=1}^{2} \rho_i \, r_i (Y_{in}^s[t] - x_{in}^s[t] \text{ ----- (4)}$$

The FODPSO algorithm outperforms PSO and DPSO in terms of computational accuracy and convergence speed. In this paper, we present a new method for improving the optimal effect by introducing the fractional-order difference with PSO. The proposed FO-DPSO-based FCM segmentation method is shown below.

IV. RESULTS

We present MRI images of tumour-affected areas of the brain in this paper. Pre-processing is the process of skull stripping and de-noising the collected images. After applying pre-processing step the images are clustered using Fuzzy C-means with Functional order Darwinian Particle Swarm Optimization. Then the outputs are compared with the state of art techniques Particle Swarm Optimization, Darwinian Particle Swarm Optimization and Fo-DPSO in terms of DC (Dice Coefficient), SSIM (Structural Similarity Index) and JSI (Jaccard Similarity Index). After that, the results are validated. From BRATS 2015 dataset for three brain images we have performed the entire procedure. The proposed FO-DPSO method outperforms over the state of art techniques PSO and DPSO by minimizing the cost function. Depending on the number of generations and cost function we plotted a graph for the three Optimization algorithms. By using FO-DPSO Optimization algorithm the processing time is reduced by 50% over PSO and 41.3% over DPSO.

The novel segmentation method used in this work is validated in this section for its visual usefulness through different images acquired by various other techniques. The sample input MRI images applied for segmentation are shown Figure (2).

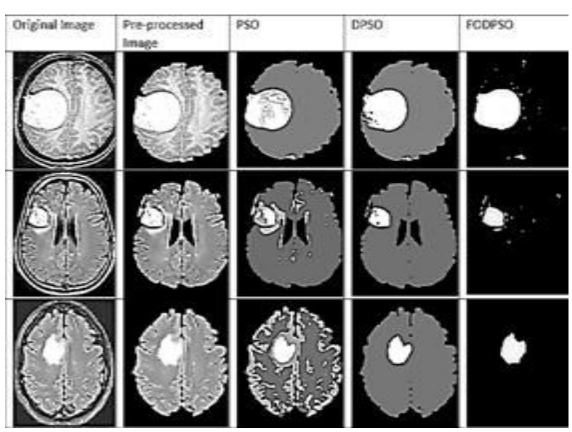

Fig. 2: RESULTS OF OPTIMIZATION SEGMENTATION TECHNIQUES

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The following figures 2 show the resulting output segmented images when processed with Fuzzy C-mean, PSO, DPSO and Proposed FO-DPSO respectively. Comparing the resulted segmented images with FCM-segmentation, FCM based PSO, DPSO method, and from Fig. 2, it can see that the proposed FCM based FO-DPSO method detects different regions and boundaries more accurately.

Table1: PERFORMANCE METRICS OF OPTIMIZATION TECHNIQUES

Parameters	Particle Swarm Optimiza tion	Darwinian Particle Swarm Optimizati on	Functional Order-Darwinian Particle Swarm Optimizati on
Iterations	12	12	12
Best Cost	.98	.85	.84
Computatio nal Time (sec)	1.96	1.67	0.98

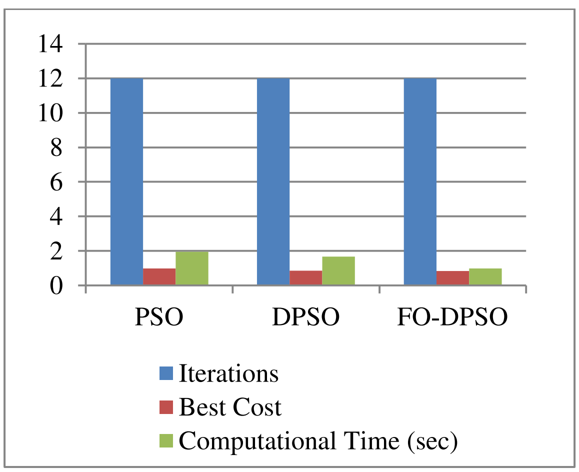

Fig. 3: TIME COMPARISON OF OPTIMIZATION-BASED SEGMENTATION TECHNIQUES=

Further comparison of these results is done by various ground truth-based parameters which are evaluated using the image segmented manually by the subject experts. The quantitative evaluation of the results in terms of similarity indices like DC (Dice Coefficient), SSIM (Structural Similarity Index) and JSI (Jaccard Similarity Index) are evaluated as depicted in table (1). From Tables 2, it can be seen that the values of all indices are highest for FCM_DPSO, which shows that the results are closest enough to manual segmentation by experts.

Table 2: PERFORMANCE METRICS OF OPTIMIZATION TECHNIQUES

Image	Method	DC	SSIM	JSI
Image A	**PSO**	0.9233	0.9249	0.9698
	DPSO	0.9652	0.9458	0.9703
	FO-DPSO	0.9698	0.9647	0.9781

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Image B	**PSO**	0.9249	0.9282	0.9218
	DPSO	0.9658	0.9641	0.9685
	FO-DPSO	0.9703	0.9735	0.9769
Image C	**PSO**	0.9264	0.9212	0.9275
	DPSO	0.9607	0.9446	0.9561
	FO-DPSO	0.9729	0.9715	0.9701

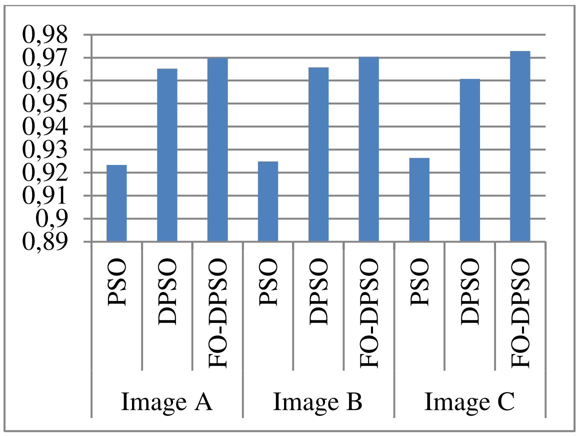

Fig. 4: DICE COEFFICIENT COMPARISON

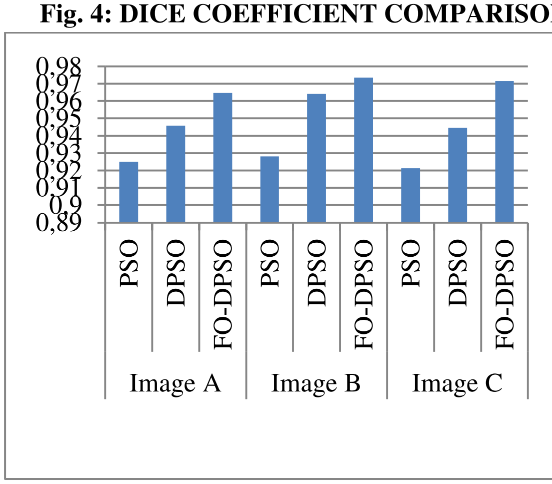

Fig. 5: SIMILARITY INDEX COMPARISON

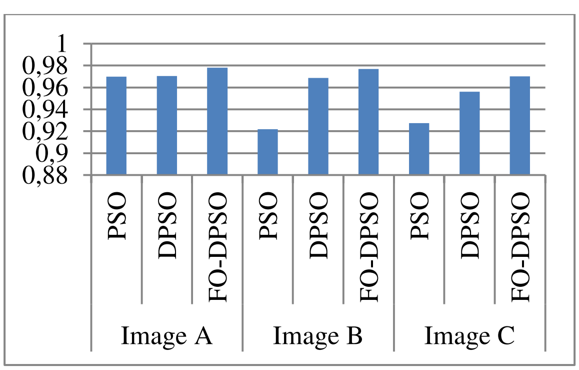

Fig. 6: JACCARD SIMILARITY INDEX COMPARISON

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V. CONCLUSION

The Functional Order DPSO (FODPSO) optimization approach was used in this paper for implementing a novel brain tumor segmentation method using FCM clustering algorithm. This novel segmentation method is best suited method for segmenting the brain tumor images depending on various optimization algorithms. FO-DPSO algorithm shows high performance than the other two algorithms in terms of processing time, DC, SSIM and JSI. By using FO-DPSO Optimization algorithm the processing time is reduced by 52.5% over PSO and 44% over DPSO. For the three images from the data set the similarity metrics are improved much better for proposed method than the other two algorithms. By employing additional optimization techniques, it is possible to improve the optimization for brain tumours. Using optimization methods, a lot of progress can be made in the segmentation of brain tumours.

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