# A Novel Fuzzy Clustering based Modified Firefly Algorithm with Chaotic Map for MRI Brain Tissue Segmentation

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**Abstract:** In this modern world, computational intelligence and metaheuristic algorithms have become more and more popular in artificial intelligence, machine learning, engineering design, data mining and image processing applications. A newly developed nature-inspired metaheuristic optimization algorithm, Firefly Algorithm is inspired by the flashing and attraction behavior of fireflies. In order to improve/tune the behavior of firefly, random based optimization technique is used. In random based optimization algorithms, the methods using chaotic variables instead of random variables are called Chaotic Optimization Algorithm. Then, the integration of Chaotic Firefly Algorithm along with Fuzzy C Means clustering for MRI brain tissue segmentation is implemented for increasing the global search mobility. Experimental results show that proposed algorithm gives better performance compared with Firefly Algorithm based Fuzzy C Means and Fuzzy C Means methods by using evaluation metrics such as Under Segmentation, Over Segmentation and Incorrect Segmentation.

**Keywords:** Skull Stripping, Fuzzy C-Means, Firefly Algorithm, Chaotic Map and MRI Brain Images.

## 1. Introduction

Magnetic Resonance Imaging (MRI) has been leading cross-sectional brain imaging method in medical practice. MRI, which provides better contrast between the different tissues in the body than Computed Tomography (CT), is an inexpensive diagnostic tool for abdominal, cardiac, pelvic, thoracic and vascular imaging [1]. The advantages of MRI over other diagnostic imaging modalities are its high spatial resolution and excellent discrimination of soft tissues. Brain Imaging has been used in many medical applications that are helpful in the detection of brain abnormalities such as brain tumor, stroke and paralysis. Over the decades, skull stripping has been one of the major preprocessing phases in brain imaging applications [2] and for further analysis of MRI brain images. Previous studies involving MRI brain images and skull stripping used in clinical applications are brain mapping, brain tumor volume analysis, tissue classification, brain tumor segmentation and epilepsy analysis.

Segmentation is an image processing operation which aims to partition an image into identical regions composed of pixels with the same characteristics according to predefined criteria [3]. Image Segmentation plays an important role and challenging problem in image analysis as well as in high-level image interpretation and understanding such as robot vision, object recognition and medical imaging [4]. Different segmentation techniques can be done in literature by using thresholding, region growing, clustering, compression, histogram, partial differential equation and model based methods.

Clustering is an unsupervised learning algorithm, which is mainly used for medical imaging, and a common technique used for statistical data analysis used in many areas including machine learning, pattern recognition, data mining, image analysis, and bioinformatics [5]. Clustering algorithms and the classifier methods are likely in function but clustering does not use training data instead they iterate between segmenting the image and characterizing the properties of each class. Therefore they are otherwise named unsupervised methods. In a sense, clustering methods [6] train themselves using the available data. The commonly used clustering algorithm is Fuzzy C Means (FCM)

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algorithm. FCM is a method of clustering which allows one piece of data to belong to two or more clusters.

## 2. Skull Stripping

Skull stripping is an essential part in neuro-imaging applications and it refers to the removal of non-cerebral tissues such as skull, scalp, vein or meninges [7]. Numerous techniques have been applied in skull stripping studies including watershed algorithm, region growing techniques and mathematical morphology. The watershed techniques can cause over segmentation, sensitivity to noise, poor detection of significant areas with low contrast boundaries and poor detection of tin structures. The region growing techniques is that the user has to select the seed regions and threshold values. Therefore by addressing this problem Park et al. [8] introducing a 2D region growing algorithm that automatically selects seed regions that correspond to the brain and non-brain regions.

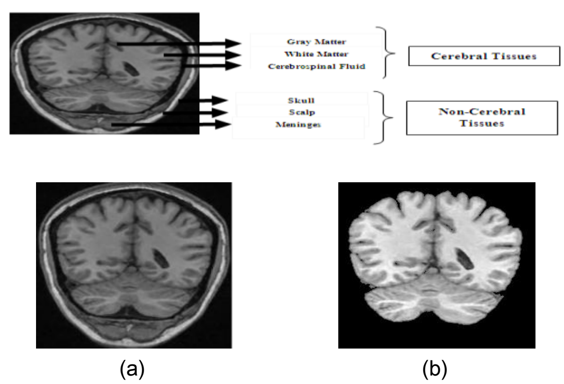


**Fig.1.** (a) Original MRI Slice, (b) Skull Stripped MRI Slice

In this paper, the mathematical morphology is used for extracting image components useful in the representation and description of region shape such as boundaries, skeletons and convex hull. The mathematical opening operation is used to separate the brain tissues from surrounding tissues as well as morphological dilation and closing are required for the segmentation of the brain tissues without holes. As morphological operation provides a simple and efficient way for integrating distance and neighborhood information in segmentation [9] as well as offers a unified and powerful approach to numerous image processing problems. The Figure1 shows the original MRI brain image and preprocessed image without skull regions.

## 3. Fuzzy C Means Segmentation

FCM algorithm is one of the most popular fuzzy clustering methods widely used in various tasks of pattern recognition, data mining, image processing etc. The advantages of fuzzy clustering algorithm includes straight forward execution, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data [10]. FCM algorithm can be obtained by a little modification in the k-means algorithm. In this paper, FCM is used for segmentation of MRI brain cerebral tissues into three clusters namely White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF). The experimental results for FCM segmentation algorithm correctly separates the cerebral tissues of MRI brain images as shown in figure2. FCM is a local search optimization algorithm, it will meet to the local minimum point and this clustering effect would have a greater impact if the global centroid values are not properly clustered and it will not take into the spatial contextual information. To overcome this drawback, an optimization technique is required.

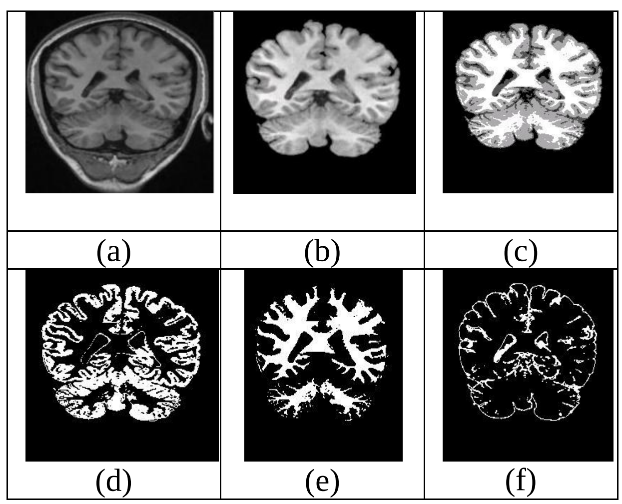


**Fig.2.** (a) Original Image, (b) Skull Stripped Image, (c) Fuzzy C-Means Clustering, (d) Gray Matter, (e) White Matter, (f) Cerebrospinal Fluid

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## 3. Firefly Algorithm

Firefly Algorithm (FA) is a nature-inspired metaheuristic optimization algorithm, inspired by the flashing behavior of fireflies [11]. The main purpose for a firefly's flash is to act as a signal system to attract other fireflies. Xin-She Yang (2010) invented this firefly algorithm by assuming [12]:

- All fireflies are unisexual, so that one firefly will be attracted to all other fireflies;
- Attractiveness is proportional to their brightness, and for any two fireflies, the less bright one will be attracted by (and thus move to) the brighter one [13]; however, the brightness can decrease as their distance increases;
- If there are no fireflies brighter than a given firefly, it will move randomly.

The brightness should be associated with the objective function:

$$X_i^{t+1} = X_i^t + \beta exp\left[-\gamma r_{ij}^2\right]\left(X_j^t - X_i^t\right) + \propto_t \epsilon_t \quad (1)$$

In the FA, the optimization process depends on the brightness of the fireflies and the movement of fireflies towards their brighter counterparts [11]. Every firefly is attracted to the other depending on brightness because the fireflies are all unisexual according to the first assumption about artificial fireflies. In this work, the firefly algorithm is used for obtaining the global optimum cluster centers values in the initialization phase in FCM algorithm. Here, the proposed clustering method consists of two phases:

1. Depends on the objective function in the beginning, all the fireflies examines the search space of the given dataset, to determine the global optimum cluster centers. The centers value determined by the firefly algorithm.
2. The outcome of the first phase is used to initialize the FCM algorithm.

The main impact of this method is used to solve the problem of falling into the local optima and vulnerable to initialization sensitivity clustering.

### 3.1 Integration of FA based FCM Segmentation

FA is introduced to develop an optimized fuzzy segmentation technique which will optimize the performance of pure FCM. Various works have applied [14] FA to data mining and image processing particularly. FA is well adapted to achieve this goal. The main advantages of using FA [15] for segmentation lie in their ability to determine the global optimal value of the criterion by simulating the evolution of a population until maximum iteration or minimum change of objective function.

The searching capability of FAs can be used for the purpose of appropriately clustering a set of n unlabeled points in N dimension into three clusters such as WM, GM and CSF. In this method, the similar idea can be applied on MRI brain images. The input image is converted into a gray level image of size m×n. Table1 refers the parameters used in this algorithm like Beta (β), Alpha (α), Gamma (γ), Number of Generations and Number of Fireflies.

**Table1:** Parameters of Firefly Algorithm

| Parameters Setting | Notation in Algorithms |
|---|---|
| Brightness | Objective Function |
| Beta($\beta$)=0.20 | Attractiveness |
| Alpha($\propto$) =0.25 | Randomization Parameter |
| Gamma($\gamma$) =1.0 | Absorption coefficient |
| Number of Generations=100 | Iterations |
| Number of Fireflies=80 | Population |

The firefly algorithm starts by initializing the population of fireflies i=80 and each firefly is different from the other in the swarm. The differentiation is based on the brightness ($\beta$)=0.20 of the fireflies, what determines the internal movement of the fireflies. Fitness value is calculated by using $f(x_i)$. Update each firefly by using the light intensity coefficient $\gamma = 1.0$, making the copy of each generated firefly population then move the fireflies according to attractiveness between the fireflies. During the iterative process, the best solution is

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continuously updated and the process goes on until maximum (100) iteration is reached. After the iterative process comes to an end the best cluster center of the evaluation is determined and the post process is initiated to obtain the best results. The optimized cluster centers obtained by FA technique are provided as the initial cluster input for FCM algorithm. At last, FA based FCM segmentation algorithm correctly separates the soft tissues of MRI brain images as shown in figure3. In this method, the evaluation metrics produces better performance compared with the other clustering methods.

### 3.2 Algorithm for Integration of Firefly Algorithm based FCM Segmentation

Step1: Set the parameters. Set the number of clusters c, Attractiveness coefficient β, Randomization coefficient α, Absorption coefficient γ, Number of generations N, Number of fireflies$x_i$.

Step2: Initialize the population of fireflies $x_i (i = 1,2, \dots, n)$.

Step3: Calculate the light intensity for $x_i$ by calculating$f(x_i)$.

Step4: Move fireflies i and j according to attractiveness. Update firefly i as the new membership matrix

Step5: The brightness should be associated with the objective function:

$$X_i^{t+1} = X_i^t + \beta exp[-\gamma r_{ij}^2](X_j^t - X_i^t) + \propto_t \in_t$$

Step6: Attractiveness varies with distance r via $exp[-\gamma r]$

Step7: Evaluate new solutions and update light intensity.

Step8: If no one of the firefly brighter than $I_i$, Ii move randomly.

Step9: Rank the fireflies and find the current one is the best firefly until maximum iteration is reached.

Step10: The best firefly generated by firefly algorithm is found and got the cluster centers.

Step11: Set the cluster center generated by firefly algorithm as the initial value of FCM algorithm. And then get the final cluster results by FCM.

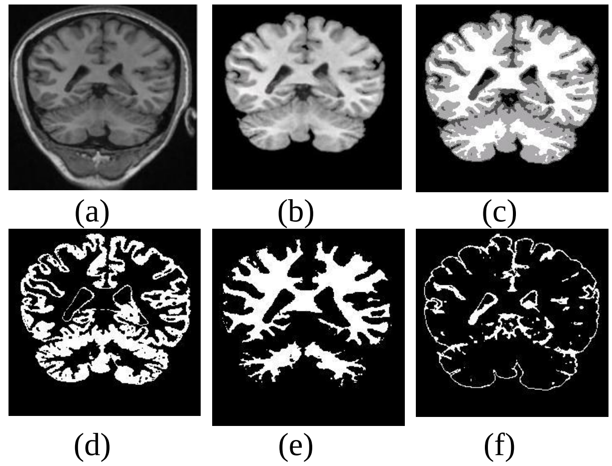

**Fig.3.** (a) Original Image, (b) Skull Stripped Image, (c) FA based FCM Clustering, (d) Gray Matter, (e) White Matter, (f) Cerebrospinal Fluid

### 4. Proposed Firefly Algorithm with Chaotic Map based FCM Segmentation

Chaos has drawn more attention in many fields, especially of optimization algorithms. Mathematically, Chaos is randomness of a simple deterministic dynamical system and chaotic system may be considered as sources of randomness. Chaotic sequences have been proven easy and fast to generate and store long sequences. Recently, chaotic sequences have been adopted instead of random sequences and very interesting and good results have been shown in many applications such as secure transmission, nonlinear circuits, DNA computing, image processing, etc. This Chaos has been introduced into FA so as to increase its global search mobility for robust global optimization. In literature, Gandomi et al, [16] used 12 different chaotic maps to tune the movement of fireflies. Coelho et al [17] applied hybrid firefly and chaotic algorithm for reliability-redundancy design of an over speed protection system for a gas turbine.

### 4.1 Integration of Chaotic FA with FCM technique

At random based optimization algorithms, the methods using chaotic variables instead of random variables are called Chaotic Optimization Algorithms (COA). In these algorithms, due to the non-repetition and

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ergodicity of chaos, it can carry out overall searches at higher speeds than stochastic searches that depend on probabilities [18]. To resolve this problem, herein one-dimensional and non-invertible map is utilized to generate chaotic sets. The chebyshev chaotic map is written as the following equation:

$$Y_{n+1} = cos\left(kcos^{-1}(Y_n)\right)\ Y \in (-1,1) \quad (2)$$

In this proposed work, the attractiveness coefficient β and γ is replaced with chebyshev chaotic map to improve the performance of FA. To implement the map, the values are normalized between 0 and 2. Finally, the FA with Chaotic map is integrated to FCM for segmenting the MRI brain tissues and improving the performance successfully as shown in figure4. And the parameters of proposed method are shown in table2. The steps of the proposed technique for solving the optimization problems are as follows:

### 4.2 Algorithm for Integration of Chaotic Firefly Algorithm based FCM Segmentation

Step1: Generate the initial population of fireflies, $\{x_1, x_2, x_3, \dots, x_n\}$.

Step2: Compute intensity for each firefly member, $\{I_1, I_2, I_3, \dots, I_n\}$.

Step3: Calculate the parameters (β, γ) using the following chebyshev map:

$$Y_{n+1} = cos\left(kcos^{-1}(Y_n)\right)\ Y \in (-1,1)$$

where n is the iteration number.

Step4: Move each firefly $x_i$ towards other brighter fireflies. The position of each firefly is updated by:

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r^2}\left(x_j(t) - x_i(t)\right) + \alpha\varepsilon_i$$

where α computed by the following randomness equation as shown below:

$$\propto^i = \propto_{max} - (\propto_{max} - \propto_{min})\left(\frac{I^i_{max} - I^i_{mean}}{I^i_{max} - I^i_{min}}\right)$$

In this equation $\propto^i$ represents randomness parameters at cycle i. $\propto_{max}$ and $\propto_{min}$ represent maximum and minimum randomness parameters defined in the algorithm respectively. $I^i_{max}$ and $I^i_{min}$ represent maximum light intensity, minimum light intensity and mean value of light intensity of all fireflies at cycle i respectively.

Step5: Update the solution set until the maximum iteration is reached.

Step6: The best firefly generated by firefly algorithm with chaotic map is found and got the cluster centers.

Step7: Set the cluster center generated by firefly algorithm with chaotic map as the initial value of FCM algorithm. And then get the final cluster results by FCM.

**Table2.** Parameters of Chaotic Firefly Algorithm

| Parameters Setting | Notation in Algorithms |
|---|---|
| Brightness | Objective Function |
| Beta($\beta$)=0.20 | Attractiveness |
| Alpha($\propto$) =0.25 | Randomization Parameter |
| Gamma($\gamma$) =1.0 | Absorption coefficient |
| Number of Generations=100 | Iterations |
| Number of Fireflies=80 | Population |
| Epsilon ($\in$)=0.001 | |
| Chebyshev Map | One of the Chaotic Map |

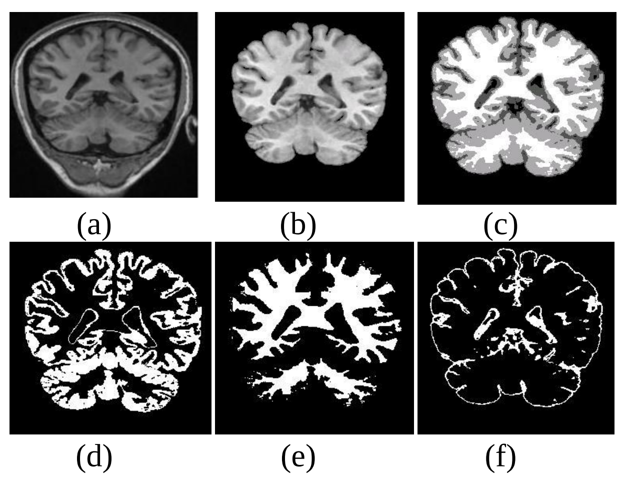

**Fig.4.** (a) Original Image, (b) Skull Stripped Image, (c) Chaotic FA based FCM Clustering, (d) Gray Matter, (e) White Matter, (f) Cerebrospinal Fluid

### 5. Performance Evaluation Metrics

The results are generated by using the MATLAB simulation. The methodology is

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examined with MRI Brain Images. The MRI brain images are first converted to gray scale images and then clustered the soft tissues by FCM, FA based FCM and proposed Chaotic FA based FCM techniques.

**Table.3.** Performance Metrics for MRI Brain tissue segmentation.

| Brain Tissues | Performance Metrics (%) | FCM | FA based FCM | Chaotic FA based FCM |
|---|---|---|---|---|
| WM | UnS | 0.59 | 0.35 | 0.33 |
| | OvS | 0.43 | 0.33 | 0.26 |
| | InCS | 0.33 | 0.26 | 0.10 |
| GM | UnS | 0.94 | 0.80 | 0.80 |
| | OvS | 0.87 | 0.30 | 0.30 |
| | InCS | 0.50 | 0.10 | 0.07 |
| CSF | UnS | 0.89 | 0.50 | 0.39 |
| | OvS | 0.72 | 0.39 | 0.39 |
| | InCS | 0.63 | 0.39 | 0.11 |

In order to evaluate the segmentation performance quantitatively [19], some definitions are required.

- $N_{fp}$ is the number of pixels that do not belong to a cluster and are segmented into the cluster.
- $N_{fn}$ is the number of pixels that belong to a cluster and are not segmented into the cluster.
- $N_p$ is the total number of pixels that belong to a cluster.
- $N_n$ is the total number of pixels that do not belong to a cluster.

The evaluation metrics are defined [19] as follows:

- Under Segmentation (UnS): $UnS = N_{fp}/N_n$, represents the percentage of negative false segmentation.
- Over Segmentation (OvS): $OvS = N_{fn}/N_p$, represents the percentage of positive false segmentation.
- Incorrect Segmentation (InCS): $InCS = (N_{fp} + N_{fn})/N$ , represents the total percentage of false segmentation.

## 6. Conclusion

In this research, skull stripping is used to remove the non-cerebral tissues and to extract the cerebral tissues of the human brain. Then, the GM, WM and CSF are successfully segmented by using FCM and optimized FCM clustering method. Finally, random based optimized clustering technique is proposed to tune the attraction movement of fireflies for improving the tissue segmentation results clearly. Table3 clearly shows the Chaotic FA based FCM algorithm significantly reduces the incorrect segmentation rate to 0.10%, 0.07% and 0.11% respectively. The experimental result shows, the proposed algorithm is providing better segmentation result than the existing methods for further usage.

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