SEGMENTATION USING RANDOM BASED OPTIMIZED CLUSTERING TECHNIQUES

The last chapter focused on optimized clustering based MRI tissue segmentation which is again based on modified FCM with GA and FA. The important feature of these techniques is the utilization of GA and FA Algorithm for the initialization of the cluster centers, and clustering is performed from thence, making use of the initial values. This way, it helps in avoiding the noisy pixel to be incorrectly placed under any class during the iterative process of FCM clustering algorithm. Thus, a better segmentation of MRI brain images, which were scanned for abnormality detection, was accomplished. However, the segmentation accuracy of the objective function of FA is very high in comparison to the GA. When comparing these two algorithms, the FA is termed as the best optimization algorithm for clustering process. The chief drawback of the GAFCM, is the difficulty faced during the search for the proper number of classes, in case of FCM, which misses the number of clusters. For this purpose, the user should input these algorithms with the number of clusters manually, which is always undefined for original images. Apart from this, these methods are affected by over segmentation too.

FCM algorithm still has many drawbacks, such as low convergence rate, falling into the local minima and vulnerability to initialization sensitivity. It is observed that the initial usage of the term ‘Swarm Intelligence (SI)’ was likely by Beni and Wang, 1993 in the terminology relating to cellular robotic system. In the recent times, this term also widens its scope to the field of optimization, where techniques based on swarm intelligence have found their application in quite a successful manner. Examples of notable swarm intelligence optimization techniques are ACO, PSO and ABC. Now, the most anticipated SI optimization techniques comprise the FA (Gandomi et al., 2013), the CS algorithm and Bat Algorithm (BA). FA is a novel population based optimization technique that has been used for solving many complicated issues successfully.
Random optimization searches for optimal solutions by involving stochasticity in some useful way (Hoos and Stützle, 2005). On the contrary, if optimization techniques yield the same results when doing the same things repeatedly, these methods turn out to be called deterministic. If the deterministic system behaves in an unpredictable manner, it reaches at a phenomenon of chaos (Feldman, 2012). Consequently, stochasticity in SI algorithms has a vital role as this phenomenon affects the exploration and exploitation in search procedure (Crepinšek et al., 2011). These partners of random global search denote the two foundations of problem solving, i.e., exploration represents the movement involved for the discovery of entirely new regions of a search space, whereas exploitation denotes the moves which focus on the search conducted along the neighborhood of hopeful, known solutions likely to be found during the search process. Both constituents are also known as intensification and diversification in another terminology. Still, these pertain to medium to long term strategies set according to the usage of memory (Tabu Search), whilst exploration and exploitation relate to short term strategies bonded to stochasticity.

7.1 RANDOMNESS IN SWARM INTELLIGENCE (SI) ALGORITHMS

Basically, stochasticity is utilized in SI algorithms for exploring new points by movement of the particles towards the search space. In lieu of this, many random distributions may be useful. For instance, each point of the search space is generated by uniform distribution applying the same probability. Then again, Gaussian Distribution (GD) is preferential towards the solution observed such that the smaller modifications happen frequently than larger ones. Also, the suitable distribution relies on the problem that is to be solved, more accurately, on a fitness landscape that creates the mapping of each position in the search space into fitness value. When the fitness landscape is flat, uniform distribution is more desirable for the random search process, while in rougher fitness landscapes Gaussian distribution should be more suitable.

With this inspiration, in this chapter, random based optimization technique is made use of for improving or tuning the behavior of firefly. The Chebyshev Chaotic map and Levy distribution is made use of for the optimization of the attraction and randomization co-efficient behavior of firefly algorithm. While the observed randomization techniques are popular and largely used (e.g. Levy flights and chaotic maps), the random
sampling in turbulent fractal cloud is obtained from astronomy, and, it is the first time it finds its usage for the optimization purposes.

7.1.1 Chaos Theory

Generation of random sequences, with a long period and good consistency, is very significant for the easy simulation of complex phenomena, sampling, numerical analysis, decision making and particularly in heuristic optimization. Its quality decides the reduction of storage and computation time for achieving the required accuracy. Chaos is a deterministic and stochastic-like process which is found in nonlinear and dynamic system, which is non-period, non-converging and bounded. Also, it owes its dependency to its initial condition and parameters. Applications of chaos in various disciplines include operations research, physics, engineering, economics, biology, philosophy and computer science. In the recent times, chaos widened to numerous optimization areas since it can escape from local minima easily and enhance global convergence when compared with other random optimization algorithms (Devaney, 2003). Using chaotic sequences in FA can be helpful in enhancing the robustness of the global optimality, and also improve the quality of the results.

In the random based optimization algorithms, the techniques using chaotic variables instead of random variables are called Chaotic Optimization Algorithm (COA) (Devaney, 2003). In these algorithms, due to the non-repetitive nature and stochasticity of chaos, it can conduct searches entirely at higher speeds rather than random searches depending on probabilities. For resolving this issue, one dimensional and non-invertible map is employed here for the generation of chaotic sets.

7.1.2. Levy Flights Theory

A Levy flight is a random walk where the step lengths have a heavy tailed probability distribution. Research works have proven that, the flight behavior of many animals and insects, manifested the general characteristics of LF. Fruit flies or Drosophila melanogaster discover their landscape, by making use of a series of straight flight paths, emphasized by a sudden 90 degree turn, resulting in a LF style intermittent scale free search pattern as shown in a study performed by Reynolds and Frye, 2007. Many researches reveal that Levy flights interspersed with Brownian motion can explain the
animals’ hunting patterns. Even light can have relevance to LF. Lately, such behavior has been employed to optimization and optimal search, and its promising capability is established by the preliminary results. Actually, the distribution of resources is non-uniform in nature. This signifies that the behavior of a normal forager who needs to explore these resources as soon as possible does not conform to Gaussian distribution. For the purpose of simulation of foragers search strategies, LF near their behavior (Jamil et al., 2013). It belongs to a particular class of α-stable distributions that is defined by a Fourier transform (Galassi et al., 2011):

\[
p(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-itx-\|ct\|^{\alpha}} \, dt
\]  

(7.1)

The α-stable means that it demonstrates similar probability density distributions for each variable that is randomly generated. This density function has two parameters: scale \( c \in \mathbb{R} \) and exponent \( \alpha \in [0, 2] \). The important characteristic of this distribution is that its variance is infinite. Astonishingly, for \( \alpha = 1 \) the density function cuts down to the Cauchy distribution, whilst for \( \alpha = 2 \) it is a Gaussian distribution with \( \sigma = \sqrt{2c} \).

For \( \alpha < 1 \) the tails of the distribution extremely widen. The most suitable setting of this parameter for optimization is hence \( \alpha \in (1.0, 2.0) \), where the distribution is non-Gaussian with no variance (with regard to LF) or with no mean, variance or higher moments defined (with respect to Cauchy distribution). Typically, the distinction between non-Gaussian and Gaussian distributions is that the tail of the distribution by the former is wider when compared to that by the latter. This, in turn, infers that the probability of producing very large modifications is much high by Levy flights rather than by GD.

The LF basically furnishes a random walk whose random step length is obtained from a Levy distribution. This has an infinite variance and also an infinite mean. Here, the steps form a random walk process with a power-law step-length distribution possessing a heavy tail. Few of the new solutions should be evolved by walk around the best solution obtained till now, which will help in speeding up the local search. For
ensuring that the system will not be stuck in a local optimum, a considerable fraction of the new solutions should be produced by far field randomization whose positions should be sufficiently far from the current best solution.

7.2. RANDOM BASED OPTIMIZED SEGMENTATION OF MRI BRAIN IMAGES

Provided the fact that FCM method possesses simplicity and accuracy and also because of the fuzzy nature of the image segmentation, several works on segmentation have made use of this method. Many works have attempted to reduce few of the weaknesses related with FCM. A significant issue in image segmentation is about guessing the number of parts of an image. A few of the techniques in the literature have neglected this factor and have conducted image segmentation with a predetermined number of segments. Nonetheless, in some particular cases such as MR images, the number of segments of an image can be predicted. But even in medical images, at certain times when quality of image is less or varying or there exists tumors in the image, there is not much possibility for the estimation of the number of segments. To have an accurate estimate of the number of segments in an image is as significant as the parameters which assure accuracy as boundary overlaps are highly dependent on that.

In this work, the proposed random based optimized segmentation technique increases the accuracy automatically and without expert help. In Tao et al., 2003, objective function is in accordance with the distance of each point from defined centers, and the degree of membership of each point to these centers is useful for the determination of the centers in the subsequent steps. By taking the predefined parameters and number of segments obtained by making use of the principle of maximum entropy into consideration, the segmentation results are enhanced. In this technique, the value of the membership of each pixel is clearly visible. Distinctions in the number of segments of an image have an effect directly on the membership of each pixel. The method that is presented in this paper uses the GA and the FCM objective function, and provides an automatic estimate of the number of segments for each given image. GAs are not the best choice at all times, because, in particular scenarios, the convergence time taken by the GA seems to be higher.
- Few optimization issues cannot be resolved by genetic algorithms. This happens due to poorly known fitness functions, which produce bad chromosome blocks, despite the fact that only good chromosome prevents cross-over, and
- Also, there is no complete guarantee that a genetic algorithm will produce a global optimum. It takes place frequent number of times when the populations own a lot of subjects.

For the purpose of overcoming these problems, particularly, the present study deals with the addition of an FA based FCM with Chebyshev Chaotic map and Levy distribution for solving the brain MRI image segmentation issue, since this is a very complex domain due to the obvious difficulties present in MRI segmentation. The next sections clearly analyses the working of the FA with Chebyshev Chaotic map and Levy distribution algorithm in fine tuning the FCM parameter for accomplishing efficient segmentation results.

7.2.1. Chaotic Maps based Firefly Algorithm

Chaos in natural sciences represents a deterministic system that behaves unpredictably (Feldman, 2012). In terms of mathematics, chaos indicates the system with no complete absence of order, but an absolute ordered system which contains some tinge of stochasticity. This term was first used by Li and Yorke, 1975. Generally, this phenomenon is regarded as a part of dynamical systems that transform over time. Chaotic behavior is mainly detected in mathematics by the use of iterative functions, returning the random values in each iteration. The generated sequential order of values by chaotic functions (also an orbit) varies, when the same is started from a different initial value. Surprisingly, each orbit restricts itself to the same threshold value, when the number of iterations reaches infinity. Factually, such behavior is a feature of the stochastic systems. The orbit is usually denoted as so called chaotic maps, where the set of input values is mapped respectively to a set of output values. Normally, attributes of chaotic maps are decided by the following suppositions (Feldman, 2012):

- The dynamic rule for the generation of the sequence of numbers is deterministic,
- The orbits are periodic (they are not repetitive),
- The orbits are bounded within limits (time series remain within upper and lower limits, generally, within the interval =[0,1], and
- The sequence has Sensitive Dependence on the Initial Condition (SDIC).

Stochastic optimization algorithms look for optimal solutions by utilizing randomness in some useful means. If optimization techniques yield the same results when doing the same things repeatedly, these methods turn out to be called deterministic. If the deterministic system behaves in an unpredictable manner, it reaches the phenomenon of chaos. Subsequently, stochasticity in SI-based algorithms plays the foremost role in the SI-based search process by trying to find new solutions. Hence, several efforts were inducted in the research of new randomized techniques. During the recent times, a theory of chaos provides a lot of deterministic time series of various characteristics.

The chaos based techniques can substitute the available random generators with success in many applications, due to the ever increasing exploration power of the random search process. Then again, these techniques have varied characteristics, and hence can easily be suited to the fitness landscapes of the diverse kinds of problems to be resolved.

The actual FA can be improved with chaos by two means. One way is that the chaotic map makes the replacement of some random distributed FA parameter for improving the performance (Fister et al., 2014). The other means is that, the firefly intricate structure is employed for tuning the algorithm parameters making use of chaotic map (Yang, 2014). Three parameters control a characteristic of the original FAs, i.e., step size of randomized move $\alpha$, attractiveness $\beta$ and absorption coefficient $\gamma$. The first parameter impacts the randomized term $\alpha \varepsilon_i$ in eq. (7.2), where the randomized parameter $\varepsilon_i$ is defined using chaos time series, as follows,

$$\varepsilon_i = C_i^{(k)}$$  \hspace{1cm} (7.2)

Following chaotic-enhanced form,

$$\beta_i = \beta_0 C_i^{(k)}$$  \hspace{1cm} (7.3)
Amazingly, the firefly social component of move can be stated by some simplifications based on (Yang, 2014) as follows,

\[ y_i^{(t+1)} = y_i^{(t)} - \beta \exp^{-\gamma y_i^{(t)^2}} \cdot y_i^{(t)} \] (7.4)

When it is assumed \( u_i^{(t)} = \sqrt{r} \cdot y_i^{(t)} \) the simplification of the above equation can be further given as,

\[ u_i^{(t+1)} = \lambda u_i^{(t)} (1 - u_i^{(t)}) \] (7.5)

Consequently, the obtained equation suggests a logistic chaotic map. This shows that the logistic map is yet an intrinsic characteristic of the social component in the FA. Lately, quite a lot of chaotic maps were explored chiefly by mathematicians and physicians and they find their application in various domains of manual process. In lieu of this, many of these were employed to different algorithms for the resolution of the various real-world scenarios. In this work, a Chebyshev map function is proposed which is described in the next section. Chebyshev map is specified by the following iteration function.

\[ X_{n+1} = \cos(n \cos^{-1}(X_n)) \] (7.6)

where \( n \) is an iteration number. Employing this map, the chaotic time series \( X_n \in (0,1) \) are got.

### 7.2.2. Levy Flights based Firefly Algorithm

In the implementation of LFFA, the real form of attractiveness function \( \beta(r) \) can be any monotonously decreasing functions such as the following generalized equation,

\[ \beta(r) = \beta_0 e^{-\gamma r^m}, m \geq 1 \] (7.7)

For a fixed \( \gamma \), the characteristic length turns \( \Gamma = \gamma^{-1} \to 1 \) as \( m \to \infty \). On the reverse, for a given length scale \( \Gamma \) in an optimization problem, the parameter \( \gamma \) can be utilized as a typical initial value, that is \( \frac{1}{\Gamma^m} \). The distance between any two fireflies \( i \) and \( j \) at \( x_i \) and \( x_j \) respectively, is referred to as the Cartesian distance.

\[ r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \] (7.8)
where \( x_{i,k} \) is the \( k^{th} \) component of the spatial coordinate \( x_i \) of \( i^{th} \) firefly. For other applications like scheduling, the distance can be time delay or any appropriate form. The motion of a firefly \( i \) which is attracted to another more attractive (brighter) firefly \( j \) is drawn from,

\[
x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \text{asign} \left| Rand - \frac{1}{2} \right| \oplus \text{Levy}
\]

where the second term is because of the attraction, whereas the third term is randomization via levy flights with \( \alpha \) being the randomization parameter. The product \( \oplus \) signifies entrywise multiplications. The \( \text{asign} \left| Rand - \frac{1}{2} \right| \) where \( Rand \in [0, 1] \) typically renders a random sign or direction while the random step length is obtained from a Levy distribution,

\[
\text{Levy} \sim u = t^{-\lambda}, (1 < \lambda \leq 3)
\]

which has an infinite variance along with an infinite mean. Here the steps of firefly movement are generally a random walk process with a power law step length heavy tail distribution.

The Levy distribution based firefly algorithm integration, along with FCM clustering for MRI brain tissue segmentation, is realized for raising the global search mobility rather than the Chaotic map based firefly algorithm. The Chaotic and Levy Flights based Firefly Algorithm along with FCM clustering for MRI brain tissue segmentation on noisy and denoised images are described clearly in this chapter.

7.3. RESEARCH CONTRIBUTION

The non-linearity of several optimization problems frequently leads to multiple local optima. To deal with this issue, global algorithms are generally used (Yang, 2008). Metaheuristic techniques are popular global optimization methods. These methods try to reproduce the social behavior or natural phenomena. Intensification and diversification are significant characteristics of the metaheuristic techniques. Intensification explores around for the current best solutions and chooses the best candidate points. The diversification
procedure lets the optimizer to look through the search space with more efficiency, mainly by randomization. Many new metaheuristic algorithms are introduced for global search. Such algorithms can help in increasing the computational efficiency, tackle larger problems and provide implementation of robust optimization codes.

During the recent times, Yang, 2010 proposed a potential metaheuristic algorithm, known as FA at the University of Cambridge. The FA is in accordance with the idealized behavior of the flashing properties of fireflies. The studies, conducted preliminarily, advise that the performance of the FA is superior in comparison with GA and PSO, and it is relevant for mixed variable and engineering optimization (Gandomi et al., 2011). Then again, recent advancements in theories and applications of nonlinear dynamics, particularly of chaos, have gained more attention in several fields. One among these fields is the application of chaos in optimization algorithms.

Sometime before, Chaotic sequences have been applied together along with some heuristic optimization algorithms such as GA (Gharooni-fard et al., 2010), Harmony Search (HS) (Alatas, 2010), Simulated Annealing (SA) (Mingjun and Huanwen, 2004), PSO (Alatas et al., 2009), Imperialist Competitive Algorithm (ICA) (Talatahari et al., 2012), ACO and BCO (Alatas, 2010) and Big Bang-Chaotic Big Crunch Optimization (BBCBCO) (Alatas, 2011).

This thesis proposes Chaotic FA based FCM technique and Levy Flights FA based FCM technique for image segmentation. The behavior of attraction co-efficient and randomization co-efficient in firefly can be fine tuned for finding the global search mobility for which stochastic based metaheuristic optimization techniques are introduced.

7.4. PROPOSED RANDOM BASED OPTIMIZED SEGMENTATION OF MRI BRAIN IMAGES

Randomness based optimized clustering methods like Chaotic and Levy Flights are realised into FA to find the global cluster centers as the initial cluster value of FCM. Lastly, FCM is useful for the segmentation of the MRI brain cerebral tissues like GM, WM and CSF regions. The Chebyshev Chaotic map and Levy distribution is useful for the
optimization of the attraction and stochasticity behavior of firefly algorithm. The work proposed for MRI brain tissues segmentation comprises of the following steps:

- Random based Optimized Segmentation of MRI noisy images, and
- Random based Optimized Segmentation of MRI denoised images.

In this stage, segmentation of brain MR images based on CFA based FCM clustering and LFFA based FCM clustering is proposed in two phases with the differentiation based on noisy image and denoised image. The aim is the segmentation of the GM, WM and CSF regions in an efficient manner with FCM parameter optimization. The algorithms proposed with noisy image and with denoised image process are similar, but the methods of taking the input image samples are different. In the random based optimized techniques of MRI cerebral tissues image segmentation on noisy image, the input image is taken without the removal of noise from skull stripped image samples.

### 7.4.1. Proposed Chaotic Firefly Algorithm based Fuzzy C Means Clustering

In FCM clustering for the selection of optimized centroid values, Chaotic Firefly Algorithm is incorporated with FCM clustering techniques for the segmentation of MRI cerebral tissues. In order to optimize the centroid values in FCM methods, random-based optimization algorithms, making use of chaotic variables, is infused with FCM for segmentation of the GM, WM and CSF regions which is referred to as Chaotic Optimization Algorithms (COA). Chaos is a phenomenon that is observed in Science and Mathematics, where a deterministic (rule-based) system behaves in an unpredictable manner. Assuming a Logistic equation to be defined as a map:

\[
x_{n+1} = r x_n (1 - x_n)
\]

where \(x_n \in (0,1)\) belongs to the input centroid value from the FCM clustering techniques and \(r\) is a parameter to determine how many number of map is needed for the completion of the centroid selection in FCM clustering segmentation methods. A sequence of numbers generated by iteration of a Logistic map (also orbit) with \(r = 4\) are chaotic.
7.4.2. Integration of Chaotic Firefly Algorithm with FCM Clustering

The random based optimization algorithms, in which the methods use chaotic variables in place of random variables, are referred to as COA. In these algorithms, because of the non-repetitive nature and stochasticity of chaos, it can conduct all the searches at speeds that are higher than stochastic searches which rely on probabilities. For resolving this problem, one-dimensional and non-invertible map is used here for the generation of chaotic sets. The Chebyshev chaotic map is expressed as the following equation:

\[ Y_{n+1} = \cos \left( k \cos^{-1}(Y_n) \right) \quad y \in (-1,1) \]  

(7.12)

In this work proposed, the attractiveness co-efficients \( \beta \) and \( \gamma \) are substituted with Chebyshev chaotic map for improving the performance of FA. To realize the map, the normalization of the values is done between 0 and 2. Lastly, chaotic map with FA is incorporated with FCM for the segmentation of the MRI brain tissues and improvement of the segmentation rate of optimization algorithm. 14 multimodal benchmark test functions are employed for the support of the efficiency of random based optimization algorithms. The steps of the proposed technique for resolving the optimization problems are as follows:

**Algorithm 7.1: Chaotic Firefly Algorithm based FCM Segmentation**

Step 1: The parameters of clusters \( c \), Attractiveness coefficient \( \beta \), Randomization coefficient \( \alpha \), Absorption coefficient \( \gamma \), Number of generations \( N \), Number of fireflies and population of fireflies, \( \{x_1, x_2, \ldots, x_n\} \) are generated,

Step 2: The light intensity for each firefly member, \( \{l_1, l_2, \ldots, l_n\} \) is computed,

Step 3: Computing the parameters \( (\beta, \gamma) \) using the following chebyshev map:

\[ Y_{n+1} = \cos \left( k \cos^{-1}(Y_n) \right) \quad y \in (-1,1) \]

where \( n \) is the iteration number,

Step 4: Moving each firefly \( x_i \) towards other brighter fireflies. The position of each firefly is updated by:

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

(7.13)
where $\alpha$ is computed by the following randomness equation as shown below:

$$\alpha^i = \alpha_{max} - (\alpha_{max} - \alpha_{min}) \left( \frac{l_{max}^i - l_{mean}^i}{l_{max}^i - l_{min}^i} \right)$$  \hspace{1cm} (7.14)

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

Step 5: The solution set is updated till the maximum iteration is attained,

Step 6: The best firefly generated by firefly algorithm with chaotic map is obtained and the cluster centers are got, and

Step 7: The best cluster center generated by firefly algorithm with chaotic map is fixed as the initial value of FCM algorithm. And then the final cluster results by FCM are obtained.

Finally, CFA based FCM segmentation algorithm rightly isolates the soft tissues of MRI brain images as shown in Figure 7.1 on denoised image and noisy image results is shown in Figure 7.2.

**Figure 7.1:** (a) Original Noisy Image (b) Skull Stripped Image (c) CFA FCM Clustering (d) GM (e) WM (f) CSF
Though it renders efficient tissue segmentation results, the chief drawback is that the approaches are more complicated, and hence pose much difficulty towards implementation. It consumes huge amount of Implementation time, more expertise is required and the code becomes less comprehensible.

![Figure .7.2: (a) OTVF Denoised Image (b) Skull Stripped Image (c) LFFA FCM Clustering (d) GM (e) WM (f) CSF](image)

### 7.4.3. Proposed Levy Flights Firefly Algorithm based Fuzzy C Means Clustering

In FCM clustering for the selection of optimized centroid values, Levy Flights Firefly Algorithm is combined with FCM clustering methods for segmenting the MRI tissues. To conduct the optimization of the centroid values of the FCM techniques, an FA is proposed which comprises of three idealized rules with the features as discussed in earlier chapter for centroid selection in FCM methods. But generally, FA has some problems which can be resolved by making use of the randomness of Levy flights. It can construct a new LFFA which can be expressed as follows for centroid selection in FCM used for segmentation of GM, WM and CSF regions in MRI images.
7.4.4. Integration of Levy Flights Firefly Algorithm based FCM Clustering

Levy flight is defined by the distribution of step sizes where the random walk happens on a discrete grid instead on a continuous space. For stimulating the search strategies, LF are nearer to their behaviour of fireflies. The random step length is obtained from a levy distribution. For the implementation of the Levy distribution, the randomness coefficient $\alpha$ values are substituted and normalized. At last, LF with FA is merged with FCM for the segmentation of the MRI brain tissues and enhancing the segmentation rate of optimization algorithm. 14 multimodal benchmark test functions are utilized for the validation of the efficiency of random based optimization algorithms.

Algorithm 7.2: Levy Flights Firefly Algorithm based FCM integration algorithm:

Step 1: The parameters of clusters $c$, Attractiveness coefficient $\beta$, Randomization coefficient $\alpha$, Absorption coefficient $\gamma$, Number of generations $N$, Number of fireflies and population of fireflies are initialized,

Step 2: Computing the light intensity $\{I_1, I_2, \ldots, I_n\}$ by employing the objective function,

Step 3: Moving the fireflies $i$ and $j$ based on the attractiveness via Levy flights and updating the firefly $i$ as the new membership matrix,

Step 4: The brightness should be related with the objective function in equation (7.10),

Step 5: Attractiveness varies with distance $r$ via Euclidean distance function,

Step 6: Evaluation of new solutions and updation of the light intensity of the firefly,

Step 7: If the current firefly $I_i$ is brighter than other fireflies, then move the firefly randomly,

Step 8: Ranking the fireflies based on their brightness and the current one is found to be the best firefly until maximum iteration is accomplished,

Step 9: The best firefly generated by firefly algorithm with levy distribution is found and the cluster centers are got, and

Step 10: This cluster center is determined as the initial value of FCM algorithm. And then the final cluster results are obtained by FCM.

Based on this procedure, the centroid values are correctly chosen by LFFA for FCM methods with noisy and denoised image framework. Lastly, LFFAFPCM segmentation algorithm performs the correct isolation of the soft tissues of MRI brain images as shown in Figure 7.3 and Figure 7.4.
Figure 7.3: (a) Original Noisy Image (b) Skull Stripped Image (c) LFFA based FCM Clustering (d) GM (e) WM (f) CSF

Figure 7.4: (a) OTVF Denoised Image (b) Skull Stripped Image (c) LFFA based FCM Clustering (d) GM (e) WM (f) CSF
7.5. SUMMARY

This chapter analyzed the random based optimized FCM clustering technique for resolving the centroid selection and randomness issue in FA for the production of tissue segmentation results accurately. As the previous work on image segmentation is done by introducing FA, stochasticity in SI algorithms plays a vital role, since this phenomenon impacts the exploration and exploitation in search process. The solution for this issue is given by Chebyshev chaotic map and levy distribution. In this research, skull stripping is employed for the removal of the non-cerebral tissues and the extraction of the cerebral tissues of the human brain. Then, the GM, WM and CSF are segmented with success, by applying FCM and optimized FCM clustering technique. At last, random based optimized clustering technique is proposed for tuning the attraction and randomization behavior, and hence the movement of fireflies for enhancing the tissue segmentation results clearly. The experimental results show that the proposed algorithm provides better segmentation results than the other methods in the literature for further applications which are analyzed in Chapter 8.