SEGMENTATION USING OPTIMIZED CLUSTERING TECHNIQUES

The former chapter explained the MRI tissue segmentation based on K means and FCM clustering. From this chapter, it can be clearly understood that FCM technique renders reliable and efficient image segmentation of noisy images in comparison with K-means technique. The FCM has critical drawbacks. For instance,

- There is no better means for the determination of the centroid value and initial cluster centers; this would have larger effect on region segmentation, and
- It does not consider the spatial contextual information.

To get over these setbacks, there is an ever-increasing necessity to optimize the cluster centers in FCM segmentation. Specifically, to prevent the local maxima and for finding the initial cluster centers, metaheuristic optimization techniques such as Genetic Algorithm (GA) and Firefly Algorithm (FA) are incorporated with FCM in this chapter.

6.1. OPTIMIZED SEGMENTATION OF NOISY MRI BRAIN IMAGES

In this section, segmentation of brain MRI images which is based on GA based FCM and FA based FCM with noisy images, is proposed. These algorithms help in detecting and segmenting the brain tissues such as GM, WM and CSF. Optimal results are gained by the application of this segmentation technique. It gives results with accuracy although it has the slow converging property. The new algorithms based on noisy images segmentation are described in the later section.

6.1.1. Genetic Algorithm

In the domain of Artificial Intelligence (AI), a GA is a search heuristic that imitates the procedure of natural choices. This heuristic (also sometimes referred to as a metaheuristic) is by routine used for the generation of helpful solutions for optimization
and search issues. GA attribute their belonging to the greater class of Evolutionary Algorithms (EA), which develop solutions to optimization issues using techniques influenced by natural evolution, such as inheritance, mutation, selection, and crossover.

GA are applied in bioinformatics, phylogenetics, computational science, physics, pharmacometrics and other fields. In GA, a population of solution candidates to an optimization issue is developed towards better solutions. Each candidate solution has a set of characteristics (its chromosomes or genotype) which can be mutated and modified; conventionally, solutions are represented in binary in the form of strings of 0s and 1s, but other forms of encodings are also available.

GA is a search technique used in the computation for finding real or approximate solutions for optimization issues. It is marked as global search heuristics. This algorithm is a specified class of evolutionary algorithms which have their inspiration from evolutionary biology such as inheritance, mutation, selection and crossover.

GA was initially formulated by J. Holland (1975) in Charbonneau, 2002. It is in accordance with the “survival of the fittest” in Darwin’s theory of evolution. In comparison with other search algorithms such as random seek, gradient descent and simulated annealing, the main benefit of GA is its simplicity with strong robust behavior. Since the global parallel search has been conducted through GA process by Jamshidi and Pilevar, 2013, the search space is big and it can be adapted consistently towards the direction consisting of an optimization solution, so global optimum can be easily determined.

The evolution generally begins from a population of stochastically generated individuals, and is an iteration based process, with the population in each iteration known as a generation. In each generation, the fitness of each individual in the population is assessed; the fitness is typically the value of the objective function in the optimization problem that is being resolved. The fittest individuals are randomly selected from the current population, and each individual’s genome undergoes modification (recombination and possibly random mutation) to create a new generation. The new generation of candidate solutions is then utilized in the next iteration of the algorithm.
Generally, the algorithm stops when either a maximum number of generations has been developed or an acceptable fitness level has been attained for the population. In every generation, the fitness of each individual in the population is computed. Multiple individuals are chosen from the current population (according to their fitness) and altered (recombined and possibly mutated), forming a new population. Then, the new population is made use in the next iteration of the algorithm (Alata et al., 2008).

A typical GA needs:

1. A genetic representation of the solution domain, and
2. A fitness function for the evaluation of the solution domain.

The flowchart representation for general GA is illustrated in Figure 6.1.

![Flowchart representation of GA](image)

Figure 6.1: Flowchart representation of GA

An array of bits is a standard representation of each candidate solution. Arrays of other types and structures can be made use of in a similar way. The important property
that makes these genetic representations convenient is the easy alignment of their parts due to their fixed size, thus facilitating simple crossover operations. Variable length representations may also be utilized, but crossover implementation is more complicated in this case. Tree-like representations are investigated in Genetic Programming (GP), and graph-form representations are examined in evolutionary programming; a blend of both linear chromosomes and trees is inquired in gene expression programming.

As soon as the genetic representation and the fitness function are defined, a GA continues towards initializing a population of solutions and then improving it through repetitive application of the mutation, crossover, inversion and selection operators.

**Initialization**

The size of the population relies on the type of the problem, but usually comprises of several hundreds or thousands of possible resolutions. Frequently, the initial population is produced in a random manner, letting the whole range of possible solutions (the search space). Sometimes, the solutions may be "seeded" in locations where there are probabilities of optimized solutions to be found.

**Selection**

During every successive generation, a portion of the existent population is chosen for breeding a new generation. The selection of separate solutions are done through a fitness-based process, where the fitter solutions (as measured by a fitness function) generally have more potential to be chosen. Few selection techniques rank the fitness of each solution and select the best solutions by preference. Other methods conduct the rating of only a random sample of the population, as the earlier process may consume a huge amount of time.

The fitness function is defined over the genetic representation and is a measure of the quality of the solution represented. The fitness function is problem based at all times. For example, in the knapsack problem, one may need to increase the total value of objects that can be dumped in a knapsack of some fixed capacity. The solution might be represented as an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) denotes the presence of the object in the knapsack. It is not likely that every such representation is valid, as the size of objects may surpass the capacity of the knapsack.
The fitness of the solution is the summation of values of all objects in the knapsack, if the representation is valid or 0 otherwise.

In a few problems, it is difficult or even impossible to provide a definition for the fitness expression; in these cases, a simulation may be brought into use for the determination of the fitness function value of a phenotype, or interactive genetic algorithms are also used. The following step is the production of a second generation population of solutions from those which are selected through a combination of genetic operators: crossover and mutation.

**Crossover**

In sexual reproduction, as it seems in the real world, the genetic material of the two parents is combined when the gametes of the parents unite. Generally, chromosomes are split randomly and merged, resulting in some genes of a child emerging from one parent while others emerge from the other parents. This mechanism is known as crossover. It is a potential tool for the introduction of a new genetic material and preserving genetic diversity, but with the excellent characteristic that good parents also generate children with amazing performance or even better ones. Many investigations have reached the conclusion that crossover is the cause why sexually reproducing species have faster adaptation over asexually reproducing ones. Although reproduction techniques which are based on the usage of two parents are more "biology inspired", some research (Eiben et al., 1994). Ting, 2005 hints that more than two "parents" are successful in producing high quality chromosomes.

**Mutation**

The final component of simple GA is mutation—the random deformation of the genetic information of an individual with the help of radioactive radiation or other environmental factors. In actual reproduction, the probability for a certain gene to be mutated is nearly the same for all genes.

**Termination**

This propagation process is repeated till a condition for termination is reached. Commonly seen terminating conditions are

- A solution is obtained satisfying minimum criteria,
- Certain number of generations attained,
- assigned budget (computation time/money) reached,
- The highest ranking solution's fitness is going to be reached or has reached a plateau where the successive iterations produce better results no more,
- Manual inspection, and
- Combinations of the above.

The process of GA, which is applied for center selection in FCM clustering technique is discussed above.

6.1.2. Genetic Algorithm Based Fuzzy C Means Clustering

In the recent work, FCM clustering is presented for the segmentation of the brain tissues types such as GM, WM and CSF. This FCM method also has few important disadvantages which is described as above. For overcoming these setbacks, and to find the initial cluster center values, GA optimization is proposed with three significant modifications. Four major functions are performed by the GA such as initialization, selection, mutation and crossover.

The initiation of Fuzzy membership matrix is performed by applying uniform distribution. Roulette wheel selection is made use for the selection operation. In this technique, all the chromosomes (individuals) in the population (pixels) are positioned on the roulette wheel in accordance with their fitness value. Every individual is allotted a section of Roulette wheel. The size of each segment in the Roulette wheel is relative to the value of the fitness of the individual, that is, the size of the segment increases with the increase in the value of the fitness. Then, the virtual roulette wheel is spinned. The individual which corresponds to the segment along which roulette wheel makes its stop is then chosen. The process is repeated till the selection of required number of individuals is done. Individuals with higher fitness have more chances of selection. This may result in biased selection towards the individuals with high fitness. It is also possible that sometimes the best individuals of a population can be missed. There is no assurance that good individuals will propagate into next generation.

Roulette wheel selection makes use of exploitation technique in its approach. Considering that it attains the local minima, GA chooses the mutation method to get off it.
The inclusion of mutation improves the ability of the genetic algorithm in finding near optimal solutions. The pixel intensity is transformed into the bit strings. The mutation operator is the bit string flip search bit of the bit string with a low probability. The Roulette wheel selection technique is used for the selection of a small probability value.

The crossover step performs the recombination of the bits (genes) of the two selected strings or chromosomes. Among the two crossover methods, i.e., Single point and two points, single point crossover operator is selected for this work.

The next operation of mutation is conducted in a bit-by-bit basis. Since every bit has an equal probability of mutation, a random number in [0, 1] is generated and if the generated number is \( p_m < 0.1 \), the chromosomes is chosen for mutation. This way, for each chromosome, the feasibleness of the chromosome for mutation is tested. For identifying the bit position of mutation, a random number in [0, n-1] is generated, where n is the word- length of the chromosomes. If the random number generated is \( p \), the \( p \)th bit of the chosen chromosomes will undergo mutation. Mutation assures that the convergence of the algorithm happens to the global minima rather than getting stuck in local minima.

The GA based FCM segmentation algorithm is given below.

Step 1: The cluster centers \( k \), population size \( N \), crossover probability \( p_c \) and mutation probability are initialized,

Step 2: A population \( P \) of individuals are stochastically generated and each individual is a set of membership functions for all the \( m \) items. Compute fuzzy membership function by uniform distribution function,

Step 3: Each chromosome denotes a solution which is a sequence of cluster fuzzy membership values. For an \( N \)- dimensional space, each cluster center is mapped to \( N \) sequential genes in the chromosome which is computed from Step 2,

Step 4: Cluster centers \( k \) are got by the division of the chromosomes and the fitness value of each chromosomes are computed by making use of the equation given below:

\[
U_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{||x_i - c_k||}{||x_i - c_k||} \right)^{m-1}}
\]  

(6.1)
Step 5: The suitable individuals for the next generation is found by using the Roulette-wheel selection operation,

Step 6: The objective function of Eq. (6.2) is defined,

\[ J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \| x_i - c_j \|^2 , 1 \leq m < \infty \]  

(6.2)

Step 7: The crossover operation on the population is carried out,

Step 8: The mutation operation on the population is performed,

Step 9: The evolution terminates if the termination criterion is met. If not, Steps 2 to 7 are repeated,

Step 10: The best fitness value generated by genetic algorithm is taken for consideration, and

Step 11: The cluster center generated by genetic algorithm is regarded as the initial value for FCM algorithm. The final cluster results are achieved by FCM. The results of GA based FCM on noisy image is illustrated in Figure 6.2.

Figure 6.2: (a) Original Image (b) Skull Stripped Image (c) GA based FCM Clustering (d) GM (e) WM (f) CSF
When compared to the other clustering techniques, the GA based FCM clustering technique outperforms in the segmentation of MRI brain tissues. Nevertheless, GA was proposed to eliminate the drawbacks of the FCM; still, these methods are affected from over segmentation problem. The important demerit of these methods is the hardship involved in the search for the suitable number of classes.

Unlike other artificial intelligence techniques, the GA cannot ensure constant optimization response times. In addition, the difference between the shortest and the longest optimisation response time is much large in comparison with traditional gradient methods. Unfortunately, this genetic algorithm property restricts the genetic algorithms' utilization in real time applications. Hence, for that a FA for cluster centroid selection is used.

6.1.3. Firefly Algorithm

FA is a nature-influenced metaheuristic optimization algorithm, inspired by the flashing behavior of fireflies Yang (2013). The principal aim for a firefly's flash is to play the role of a signal system for attracting other fireflies. The algorithm comprises of a population-based iterative process with multiple agents (considered as fireflies) simultaneously solving an optimization problem which is considered. Agents communicate with each other, by means of bioluminescent glowing, which helps them to search cost function space more efficiently than in standard distributed random search. Intelligence optimization technique follows the assumption that the solution of an optimization problem can be considered as agent (firefly) which glows in proportion to its quality in a considered problem setting. Subsequently, each brighter firefly attracts its partners (regardless of their sex), that makes the search space to be explored with more efficiency. Yang, 2010 developed this Firefly Algorithm by assuming as mentioned in Jagadeesan and Sivanandam, 2013,

1. All fireflies are unisexual, such that one firefly will be attracted by all other fireflies,

2. Attractiveness is proportional to their brightness, and in the case of any two fireflies, the one with less brightness will be attracted by the one with higher brightness Borges et al (2013); Nevertheless, as their distance goes on increasing the brightness decreases; In the FA, the optimization procedure is dependent on the brightness of the
fireflies and the mobility of fireflies towards their brighter counter parts (Yang, 2013). Each and every firefly is attracted to the other, based on the brightness $\beta$, because, the fireflies are all unisexual in accordance with the first statement about artificial fireflies. As a firefly’s attractiveness is relative to the light intensity as seen by neighbouring fireflies, the variation of attractiveness $\beta$ with the distance $r$ is defined by,

$$
\beta = \beta_0 e^{-\gamma r^2}
$$

(6.3)

where $\beta_0$ is the attractiveness at $r = 0$, and

3. If no other firefly is brighter than a given firefly, it will move in random. The movement of a firefly $i$ which is attracted to another more attractive (brighter) firefly $j$ is determined by objective function:

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

(6.4)

where the second term is due to the attraction. The third term is randomization with $\alpha$ being the randomization parameter, and $\epsilon_t$ is a vector of random numbers drawn from a Gaussian Distribution or Uniform Distribution at time $t$. If $\beta_0 = 0$, it becomes a simple random walk. On the other hand, if $\gamma = 0$, it reduces to a variant of PSO (Yang, 2008).

As $\alpha$ basically controls the randomness (or, to some extent, the diversity of solutions), it can tune this parameter during iterations such that it can keep on varying with the iteration counter $t$. So a good way to express $\alpha$ is by using,

$$
\alpha_t = \alpha_0 \delta, 0 < \delta < 1
$$

(6.5)

where $\alpha_0$ is the initial randomness scaling factor, and $\delta$ is a cooling factor essentially. For major applications, $\delta = 0.95$ to 0.97 (Yang, 2008) can be used. As to the initial $\alpha_0$, simulations show that FA will be more effective if $\alpha_0$ is associated with the scaling of design variables. Let $L$ be the average scale of the problem of interest, $\alpha_0 = 0.01L$ initially. The factor 0.01 rises from the fact that random walks needs a number of steps for reaching the target while keeping a balance on the local exploitation without
jumping too far in a few steps (Yang, 2009) and (Yang, 2010). The parameter $\beta$ controls the attractiveness, and parametric studies advise that $\beta_0 = 1$ can be used for most of the applications. Still, $\gamma$ should also be related to the scaling $L$. Generally, $\gamma = 1/\sqrt{L}$ can be set with the population size $n = 15$ to $100$, even though the best range is $n = \frac{25}{4}$ to $40$. The typical flowchart representation of the FA is shown in Figure 6.3.

![Flowchart representation of FA](image)

**Figure 6.3: Flowchart representation of FA**

Nonetheless, FA has two significant merits over other algorithms: automatic subdivision and the ability to deal with multimodality.

Primarily, the basis of FA is attraction, and attractiveness reduces with distance. This results in the fact that the entire population can be automatically subdivided into subgroups, and each group can teem around each mode or local optimum. Amidst all these modes, the best global solution can be got.

Secondly, this subdivision lets the fireflies the ability for finding all the optima at the same time if the population size is adequately higher than the number of modes.
Mathematically, $1/\sqrt{\gamma}$ controls the average distance of a group of fireflies that can be observed by neighboring groups. Hence, a whole population can be subdivided into subgroups with an average distance provided. In the utmost case when $\gamma = 0$, the entire population will not subdivide. This automatic subdivision capability increases its suitability for highly nonlinear, multimodal optimization issues. Additionally, the parameters in FA can be tuned for controlling the randomness as iterations continue, so that convergence can also be rushed up by the tuning of these parameters. These above benefits make it flexible for dealing with continuous problems, clustering and classifications, and combinatorial optimization as well.

### 6.1.4. Firefly Algorithm Based Fuzzy C-Mean Clustering

In this technical work, the chief contribution is a dynamic clustering technique for brain tissue segmentation such as GM, WM and CSF from brain image. For overcoming the limitations of GA in GA-FCM clustering techniques, FA is incorporated with FCM for MRI tissues segmentation. For the purpose of segmentation of MRI brain images automatically and enhancing the capability of the FCM to automatically extract the proper number of tissues and position of the cluster centers from MRI images, FA with FCM is proposed. In this section, the capability and performance of the firefly algorithm in determining the values of the near optimal cluster centres in the initialization phase of the FCM will be described.

Thus, the proposed clustering technique comprises of two phases:

• For the determination of the optimal cluster centers, firefly does the inspection of the search space of the given dataset and then the values of the cluster centers will be retrieved employing FA.

• Starting the initialization of the FCM algorithm on the basis on the evaluated results in the first phase for refining them and then to reduce the disadvantages of FCM algorithm such as falling into the local optima and being vulnerable to initialization sensitivity (Alomoush et al., 2013):

$$A = (s_1\{a_1, a_2, \ldots, a_d\}, s_2\{a_1, a_2, \ldots, a_d\}, s_3\{a_1, a_2, \ldots, a_d\}) \quad (6.6)$$

The values of the near optimal cluster centres will be found out by making use of firefly algorithm searching process. A denotes the collection of the feasible array of each pixel and $a_i$ represents the numerical feature which describes the cluster centers and $a_i \in \ldots$
Also, \( s_i \) represents each cluster center and is defined by the numerical characteristic \( d \in \{a_1, a_2, \ldots, a_d\} \).

As a consequence, each solution has an accurate size equaling \((c \times d)\), ‘d’ defines the number of features that is a representation of the given dataset and \( c \) represents a pre-defined number of clusters. The parameter setting of the firefly algorithm (number of fireflies \((n = 110)\), max iteration = 1000, \( \beta = 1 \) and \( \gamma = 1 \)) was cautiously chosen based on preliminary experiments, then the assessment step of initialization phase will begin and the solutions in every cluster centres will be initialized in a random manner.

Here, the clustering technique proposed includes the following two phases:

1. All the fireflies make the examination of the search space of the given dataset in the initial stage depending on the objective function, in order to determine the global optimum cluster centers. The centers value is decided by the firefly algorithm, and

2. The result of the first phase is employed for the initialization of the FCM algorithm. The significant impact of this technique is that it is useful for solving the problem of slipping into the local optima and the vulnerability to initialization sensitivity clustering. Table 6.1 demonstrates the parameters used in this algorithm like Beta \((\beta)\), Alpha \((\alpha)\), Gamma \((\gamma)\), Number of Generations, Number of Fireflies, radius and epsilon \(\varepsilon\).

### Table 6.1: Parameters of Firefly Algorithm

<table>
<thead>
<tr>
<th>Parameters Setting</th>
<th>Notation in Algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brightness</td>
<td>Objective Function</td>
</tr>
<tr>
<td>Beta ((\beta)=0.20)</td>
<td>Attractiveness</td>
</tr>
<tr>
<td>Alpha ((\alpha)=0.25)</td>
<td>Randomization Parameter</td>
</tr>
<tr>
<td>Gamma ((\gamma)=1.0)</td>
<td>Absorption coefficient</td>
</tr>
<tr>
<td>Number of Generations=100</td>
<td>Iterations</td>
</tr>
<tr>
<td>Number of Fireflies=80</td>
<td>Population</td>
</tr>
<tr>
<td>R</td>
<td>Radius, Time interval</td>
</tr>
<tr>
<td>Epsilon ((\varepsilon)=0.001)</td>
<td>Epsilon</td>
</tr>
</tbody>
</table>
Algorithm for Firefly Algorithm based FCM Segmentation

Step 1: Fixing the parameters of clusters c, Attractiveness coefficient $\beta$, Randomization coefficient $\alpha$, Absorption coefficient $\gamma$, Number of generations $N$, Number of fireflies,

Step 2: Initialization of the population of fireflies $x_i (i = 1, 2 \ldots n)$,

Step 3: The light intensity for $x_i$ is computed by $f(x_i)$,

Step 4: Movement of the firefly $i$ and $j$ based on attractiveness. firefly $i$ is updated as the new membership matrix,

Step 5: The brightness should be correlated with the objective function:

$$X_i^{t+1} = X_i^t + \beta \exp[-\gamma r^2] (X_j^t - X_i^t) + \alpha_i \epsilon_t$$

(6.7)

Step 6: Attractiveness changes with distance $r$ via $\exp[-\gamma r]$,.

Step 7: The evaluation of new solution is done and updation of light intensity of the firefly is conducted,

Step 8: If not one of the firefly is brighter than $I_i$, $I_i$ moves randomly,

Step 9: Proportional to the brightness, the fireflies are rated and the current one is found as the best firefly until maximum iteration is attained, and

Step 10: The best firefly generated by firefly algorithm is determined as the initial value of FCM algorithm. And then the final cluster results are got by FCM.

The FA begins by initiating the population of fireflies $i=80$ and each and every firefly is different from the others. This diversity is proportional to the brightness ($\beta$)=0.20 of the fireflies, which decides the internal movement of the fireflies. Fitness value is computed by using $f(x_i)$. Each firefly is updated by using the light intensity co-efficient $\gamma$= 1.0, making the imitation of each generated firefly population. Then moves the fireflies, based on the brightness of fireflies. When the iterative process is on, (Sivaramakrishnan and Karnan, 2014), the best solution is simultaneously kept on updated and the process continues until maximum (100) iteration is accomplished. Once the iterative process comes to a finale, the evaluation of the best cluster center is done and the post process is kicked off for getting the best results, is illustrated in Figure 6.4.
Figure 6.4: (a) Original Image (b) Skull Stripped Image (c) FA based FCM Clustering (d) GM (e) WM (f) CSF

Thus, the FAFCM is successful in the determination of the tissues of the MRI brain images without any previous information. Also, FAFCM has the capability to reduce the disadvantages of Fuzzy clustering, such as low convergence rate, falling into the local minima and vulnerability to initialization sensitivity. Nevertheless, the tissue segmentation results do suffer from noise in MRI image. It can be eliminated by using noise removal filters which is explained in the next sections.

6.2. OPTIMIZED SEGMENTATION OF DENOISED MRI BRAIN IMAGES

In this stage, segmentation of brain MR images, based on FCM clustering with GA and FA, is proposed after the denoising process is accomplished. The detailed explanation of the denoising framework is studied in Chapter 4. Accurate and robust segmentation of brain tissue by MRI is a very critical issue in many applications such as surgery and radiotherapy. The aim is the segmentation of the GM, WM and CSF regions in an efficient manner, by making use of GA based FCM and FA based FCM with noise removed samples. The algorithms presented with denoising are described in the next
section. Generally, FCM stops when either the number of generations that has been produced reaches a maximum level, or an acceptable solution (global centroid value) may or may not have been attained. To get over these limitations, GA is incorporated along with FCM Method for the determination of the global optimal value of segmentation results for two purposes: a genetic representation of the solution domain and a fitness function for the evaluation of the solution domain.

6.2.1. Genetic Algorithm Based Fuzzy C Means Clustering

Genetic Algorithm is proposed for developing an optimized fuzzy segmentation technique which will help in optimizing the performance of pure FCM. Multiple works have employed GA to image processing and to segmentation in particular. GA is well suited for achieving the best center value in the FCM, and hence, enhanced segmentation results for MRI images.

The important benefit of utilizing GA is the determination of the global optimal value of the criterion, by simulation of the evolution of a population, till the survival of best fitted individuals. The survivors are individuals generated by crossing-over, mutation and selection of individuals from the earlier generation (Shen et al., 2005). The search capability of GAs can be utilized for the clustering a set of n unlabeled points in N dimension into K clusters (Dass and Swapna, 2012). In this system, the similar idea can be used on MRI brain images. The input image is transformed into a gray level image of size \( m \times n \).

The method proposed, GA along with fuzzy clustering algorithm for segmentation of MRI brain tissues are as follows: First all parameters like cluster \( (K) \), population size \( (p) \), crossover rate, mutation rate are set as specified in Table 6.2. Each chromosome denotes a solution with the cluster centers like WM, GM and CSF. In GA, the population size \( p \) is required. In FCM 100 chromosomes are generated; each chromosome is of size 3. Each chromosome of the population is a powerful solution got by FCM algorithm with three clusters. FCM algorithm makes the assignment of pixels to each tissue by making use of fuzzy membership function. This algorithm is an iteration based optimization technique that helps in minimizing the cost function and parameter \( q \) controls the fuzziness of the resulting partition.
The membership function denotes the probability that a pixel is in a specific cluster. Then, the fitness function is calculated for all chromosomes. Not all the chromosomes are propagated to the next generation; the Roulette wheel selection strategy is employed for the selection of the parents for the next iteration. A single point crossover followed by mutation operation is conducted to generate new chromosome. Again the fitness is computed for the chromosomes. Then, the processes of fitness computation, selection, crossover and mutation are executed for 200 times. Each time, the fittest chromosome is preserved till the last generation. If the termination criteria are met, the current population will be the best solution, if not it will revert to population initialization step.

After the iterative procedure comes to an end the best cluster center of WM (75.92), GM (103.88) and CSF (142.07) are fixed and the post process is initialized for obtaining the best results. The optimized cluster centers got by GA technique are given as the initial cluster input for FCM algorithm. At last, GA based FCM segmentation algorithm correctly isolates the (clusters) cerebral tissues of MRI brain images in a correct manner. Figure 6.5 denotes the real MRI denoised image, skull stripped image by making use of mathematical morphology operations, optimized clustered image by using GA and isolation of GM, WM and CSF. In this technique, the estimation metrics yields better performance in comparison with other clustering methods. The step by step algorithm of

<table>
<thead>
<tr>
<th>Parameter Initial</th>
<th>Values</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster Value</td>
<td>3</td>
<td>Number of cluster centers</td>
</tr>
<tr>
<td>Population size</td>
<td>100</td>
<td>Number of chromosomes</td>
</tr>
<tr>
<td>Crossover Probability</td>
<td>0.8</td>
<td>Probability of crossover rate</td>
</tr>
<tr>
<td>Mutation Probability</td>
<td>0.1</td>
<td>Probability of mutation rate</td>
</tr>
<tr>
<td>Number of generations</td>
<td>200</td>
<td>Maximum number of generations</td>
</tr>
</tbody>
</table>
GA based FCM is defined as above, but rather than using the input image, the considered input image samples are the denoised image using the optimized total variation filtering technique.

Figure 6.5: (a) OTVF Denoised Image, (b) Skull Stripped Image, (c) GA based FCM Clustering (d) GM (e) WM (f) CSF

6.2.2. Firefly Algorithm based Fuzzy C Means Clustering

FA is introduced for developing a optimized fuzzy segmentation technique which will help in optimizing the performance of pure FCM method. Various works have employed (Alsmadi, 2014) FA to data mining and image processing in specific. FA is well suited to accomplish this goal. The chief advantage of making use of FA for segmentation is their capability to decide the global optimal value of the criterion by modeling the evolution of a population till maximum iteration or minimal change of objective function. The search capability of FAs can be utilized for properly clustering a set of n unlabeled points in N dimension into three clusters such as WM, GM and CSF. In this technique, the
same kind of idea can be applied on MRI brain images. The conversion of input image is
done into a gray level image of size \( m \times n \).

**Global Optimum Value Identification:** The cluster centers of the provided
dataset are encoded by each and every Firefly Population Search (FPS) vector: The
solution vector can be defined in Eq. (6.8)

\[
a = \left( a_1 a_2 \ldots a_d, a_1 a_2 \ldots a_d, \ldots \right)
\]

Here, each single vector has an actual size of \((c \times d)\), where \(c\) denotes given
number of clusters and \(d\) represents the number of feature sample bordering the given
dataset, a numerical characteristic of cluster centers. In this technical work, the firefly
algorithm is made use for obtaining the global optimum cluster – centers value in the
initialization phase in FCM algorithm. The optimized cluster centers got by FA technique
in section 6.1 are given as the initial cluster input for FCM algorithm.

![Figure 6.6](image.png)

*Figure 6.6: (a) OTVF Denoised Image (b) Skull Stripped Image (c) FA based FCM
(d) Gray Matter (e) White Matter (f) Cerebrospinal Fluid*
At last, FA based FCM segmentation algorithm correctly provides the separation of the soft tissues of MRI brain images, the OTVF images are considered as input image as shown in Figure 6.6. In this technique, the evaluation metrics shows that the FA based FCM segmentation algorithm gives better performance in comparison with the other clustering methods.

6.3. SUMMARY

In this chapter, optimized FCM clustering that includes the parameter optimization for improving the segmentation results is implemented. In this research, skull stripping is employed for the removal of the non-cerebral tissues and also utilized for the extraction of the cerebral tissues of the brain. Here, the GA and FA based FCM clustering technique is realized for improving the segmentation of cerebral tissues such as GM, WM and CSF results for later use of identification of the abnormalities in MRI brain images. The performance of FA based FCM clustering technique is better in segmenting MRI brain tissues under various conditions of under segmentation, over segmentation and incorrect segmentation. The proposed FA based FCM clustering resolves the randomness issue by using Chaos and Levy Flights theory. For the multiple purposes of increasing the global search mobility, for tuning the attraction co-efficient behavior and randomization co-efficient behavior of fireflies, random based metaheuristic optimization techniques are incorporated with FCM in Chapter 7.