CHAPTER 5

FUZZY BEE SEGMENTATION - METAHEURISTIC APPROACH FOR THE MEDICAL IMAGE SEGMENTATION PROBLEM

5.1 INTRODUCTION

There are certain disadvantages of Fuzzy C Mean (FCM) algorithm while classifying brain MRI. They are:

1. FCM is efficient with regards to health brain, whereas, it is efficiency decreases with abnormalities such as edema, tumor and so on.

2. Pixels are handled by FCM while it disregards neighborhood features.

3. The chances of iterative process getting stuck in local optima is more, when the cluster centre choosing process FCM forces it. By optimization methods, more probable solutions are got through. Solutions that have objective function values are called optimal solutions.

The natural behavior of the honeybees for best food sources is the inspiration for Artificial Bee Colony (ABC). In insects which follow a swarm behavior, only simple tasks can be performed by individual insects, while cooperative work can be determined through their intelligent behavior. There
are three groups of bees in a colony of artificial bees with regards to ABC algorithm. Information about their food sources is carried out by employed bees, its distance and direction from the nest and nectar amount of the source; new food sources are located by the scout bees and onlooker bees wait in the hive and food sources are found through the information that is shared by employed bees. Two prime behaviors are defined in ABC – recruitment of nectar source and abandonment of a source (Shokouhifar & Abkenar 2011).

A scheme of stochastic selection on the basis of fitness values is chosen in ABC algorithm, which is carried forward by onlooker bees which is similar to that of the “roulette wheel selection” in GA. Also, the neighbor source’s production mechanism which is used in ABC algorithm is similar to mutation process in GA. In ABC algorithm, there is no precise crossover unlike GA. The sharing of information between bees takes place through ABC by mutation process. A possible solution to optimization problem is represented through a food source in ABC and therefore, at the initialization step, there is random consideration of a set of food source position. The quantity of nectar present in the food source corresponds to the quality of solution which is represented by that source that is searched by the bee. Determination of the nectar amount of the food source existing at the initial positions are determined; while on the other hand, the quality value of initial solutions are calculated.

The major benefit of ABC over other optimization techniques include – simplicity, robustness and flexibility; utilizing fewer features compared to other techniques; easy hybridization compared to other optimization algorithms; handling objective cost with stochastic nature; easy implementation with basic mathematical and logical operations (Bolaji et al. 2013).
With regards to dimensional synthesis mechanism, a hybridized optimization technique for approach for design of linkages method is applied which combines both the merits of stochastic and deterministic optimization. Real-valued Evolutionary Algorithm (EA) is the basis for stochastic optimization approach which is used for exploring the design variable space extensively while searching for best linkage (Sedano et al. 2012).

A local optimization technique is used by deterministic approach to enhance the efficiency by decreasing the increased CPU time that are required by EA techniques in these types of applications. Moreover, implementation of deterministic technique takes in the EA in two stages. Fitness evaluation is the first stage where an effective new error estimator is used by deterministic approach. The solution that is acquired by evolutionary part of the algorithm is refined in the second stage of deterministic approach. The evaluation of various individuals in each generation avoids the removal of well-adapted linkages that various other methods would not detect. ABC-FCM technique is studied in this work.

5.2 OPTIMIZATION METHODS

Optimization procedure is to search a vector in a function which produces an optimal function. All values that are feasible are termed as available solutions and optimal solution is the extreme value. Generally, these optimization issues are solved through the optimization algorithms. Based on the nature of the algorithm, optimization techniques can be classified into two: deterministic and stochastic algorithms. Deterministic algorithms uses gradients such as hill climbing which involves rigorous move and the same set of solutions are generated if the iterations start with the same initial starting point. (Wang & Guo 2013).
While as opposed to this, different solutions are generated without the use of gradients in stochastic algorithms, even with same initial value. However, in general, even slightly different final values will converge to the same optimal solution in case of a given accuracy. Stochastic algorithms can be classified into two: heuristic and metaheuristic. Of late, the performance of metaheuristic algorithms which acquire their inspiration from nature is more powerful and is efficient in solving modern nonlinear numerical global optimization issues. Up to a certain extent, almost all metaheuristic algorithms try hard in striking a balance between randomization i.e. global and local search.

It is quite a challenging task in solving real-world optimization problems NP hard problems should be dealt with many applications. To find a solution to such issues, optimization tools are in vogue, although it cannot be guaranteed that an optimal solution will be obtained. Moreover, the issue is that there is no efficient algorithm for NP problems. Ultimately, many issues could be solved only through trial and error, with the help of various optimization techniques. Additionally, new algorithms have been developed to locate if these challenging optimization problems can be coped up with. Among these new algorithms, many algorithms such as Particle Swarm Optimization (PSO), Cuckoo Search (CS) And Firefly Algorithm (FA), have gained popularity due to their high efficiency (Fister Jr et al. 2013).

PSO – this is a stochastic optimization technique based on population, which is based on swarming of birds, fish schooling and flocking of bees. A global optimum is reached by initializing the solutions for this algorithm arbitrarily. The basis for this technique is the processes of movement and intelligence in an evolutionary system. With regards to PSO, every potential solution is represented as a particle. With every particle, two properties (position x and velocity y) are associated. In every iteration,
evaluation of a fitness function takes place for all particles in the swarm. Updating the velocity of, every particle is done by tracking two best positions, where ‘pBest’ represents particles traveled so far and ‘nBest’ is the neighborhood best. When the entire population is taken as its neighborhood, the best in the neighborhood becomes global best and is called ‘gBest’ (Zhang et al. 2010).

**GA** – the process of evolution in nature is the basis for this technique and this is an adaptive technique of global-optimization searching; to be precise, this gets its inspiration from the Darwinian principle of “survival of the fittest” according to which, this algorithm states that by natural selection an initial population of individuals are evolved in a particular manner, that there is a higher chance of survival for the fittest individual. A population of feature transformation matrices is maintained by GA. In a given population, each matrix is evaluated by the input patterns that are multiplied by the matrix which produce a set of transformed patterns which are passed on to a classifier. The patterns are then divided into a training set by the classifier and classification accuracy is evaluated by the testing set. As a measure of quality of the transformation matrix, the accuracy obtained returns to the GA to obtain set of transformed patterns (Kharrat et al. 2010).

This information is used by GA to search a transformation which reduces the dimensionality of the designs that are transformed and the precision while classifying is maximized. A vector called chromosomes encodes each feature and gene represents an element of the vector. Feature represents each bit in the binary vector. The ith feature participates in classification if its ith bit of the vector is equal to one. The fitness value is measured through the fitness of a chromosome and is decided whether the chromosome is good or not in a population. Arbitrary creation of the genetic process takes place in a population. Three operators are used by GA to
produce the next generation from current generation, reproduction, crossover and mutation. The chromosomes with low fitness re eliminated by GA and ones with high fitness are retained, leading to the migration of chromosomes of high fitness to the next generation. Until a good chromosome is found this process goes on (Wu et al. 2012).

**Ant Colony Optimization (ACO) algorithm** – Dorigo et al. proposed this algorithm, which is a multi-agent solution to optimization problems in a traveling salesperson. The inspiration for this algorithm is through investigation and researches in an ant colony. Through investigations, it is evident that ants are social insects that live in colonies and survive as a colony than as individuals. The astonishing fact about the ant colony is the manner in which they locate the shortest root to the source of food from nest. This can be grouped as mass intelligence which has interested the scientists recently (Yousefi et al. 2012).

A special chemical substance called pheromone is deposited by ants while moving on their way on search of food. The length of the path and quality of food are depended by the amount of pheromone. The pheromone is smelt by the other ants on the path and follow the same path and they also drop some pheromone on their way. Thus, the shorter paths get more pheromone and again the path with more pheromone is treaded upon more. The pheromone evaporates in a short time and shows the trace of the ants’ movement only for a limited time. Simple instinctive behavior of the ants is the basis for ants’ movements. To choose the path more pheromone is more probable but not deterministic. Thus, probability and stochasticity play a major role in ant colony algorithm. Another point which needs attention is the evaporation of the pheromone that is left in the path. As time passes, more pheromone evaporates and the chance of choosing a particular path is decreased (Soleimani & Vincheh 2013).
**CS algorithm** – this is a metaheuristic optimization technique suited to solve optimization techniques. CS optimization algorithm is proposed by researchers in the year 2009. The inspiration for it is through the obligate brood parasitism of a variety of cuckoo species which lay their eggs in a host birds’ nest. Direct conflict takes place between some host birds with intruding cuckoos. The obligate brood parasitic behavior of certain cuckoo species with Levy flight behavior of fruit-flies and certain birds is the inspiration for this algorithm (Bhandari et al. 2014).

With regards to Levy flight distribution, search for food by animals and bird take place in a random or quasi random manner, and a random walk is followed as the following step is based on the current place and probability of transition to the next state. Yang and Deb applied such behavior in CS optimization and its dominance over other distribution based random walk problems has been studied. A solution is represented by each egg in CS algorithm, while cuckoo egg represents a new solution. Overall, the objective to put forth the new and potentially better solution store place weak solutions in the nest; to be precise, each nest has one egg.

The echolocation behavior of micro-bats is the basis for **Bat Algorithm (BAT)** where the bat locates it prey in complete darkness. Xin-She Yang in the year 2010 proposed this algorithm. On the basis of echolocation, the bats also identify an obstacle and avoid it which is a very essential feature while flying in dark. The assumptions based on this algorithm are as follows:

- Distance is sensed by all bats with the help of echolocation and can all differentiate between food/prey and the barriers on their way;
They fly arbitrarily with a frequency that is fixed with a different wavelength and loudness to search for prey. Their wavelength can be adjusted automatically of their emitted pulses and the rate of pulse emission is adjusted depending upon the closeness of their target.

Though there can be variation in their loudness in a multiple ways, the assumption is that the loudness vary from a large/positive to a minimum constant value (Das 2013).

**Fire Fly (FF) optimization algorithm** – This technique can help in improving the global search and local optimization capacity. This is a non-gradient based algorithm, whose objective function is simple on the basis of evolutionary technique that can produce an effective outcome at the time of dealing with highly non-linear optimization issues with a few limitations. Bad numerical behavior can be avoided by these due to gradient evaluations. Similar to many other properly tested metaheuristic algorithms for optimization, an optimal solution is also found by FF algorithm to an issue through repetitively trying hard to improve the candidate solution through consideration of specific measure of solution quality (Dey et al. 2014).

**Shuffled Frog Leaping Algorithm (SFLA)** – This is an entirely novel algorithm which takes its inspiration from nature and is characterized by global search and easy implementation. SFLA is a combination of GA which is a gene-based memetic algorithm and PSO that is based on social behavior. The principle of SFLA is taken from a virtual population of frogs where individual frogs can be correlated to chromosomes in GA and a set of solutions are represented by them. Memeplexes denote the entire population of frogs which are divided into many subsets and every frog is distributed to a varying memeplex (Ladgham et al. 2015).
In every memeplex, frogs are described as a memetic vector with similar structure but varying adaptabilities. The environment is explored by their own strategies and they interact and relay information in order to improve their strategies. After specific number of memetic evolution, in a shuffling stage, information is exchanged between memeplexes. In this phase, there should be no prejudice during evolution towards a specific interval. Until reaching the criteria of convergence, memetic evolution and shuffling take place alternately or otherwise until reaching a stopping criterion. In several optimization problems, SFLA has shown effectiveness which is expensive computationally in solving by using other methods such as water distribution and ground water model calibration issues.

DE – optimization issues are solved through this technique which was proposed by Storn and Price, which is an adaptive global optimization technique, similar to that of GA. This belongs to the group of EA which has been identified thus far as the most efficient optimization algorithm with a simple structure, robustness and fast convergence. Differences in different particle mutations are used by DE and hybridization process is used in selecting better population particle which reaches the goal of global optimum work. This work DE/ rand /1/ bin mutation operator used. DE has the following advantages when compared to other EAs – it solves non-convex, multimodal, non-linear function optimization problem; there is a strong soundness; convergence algorithm is robust under similar accuracy requirements; multivariate function optimization issues are solved; operation is simple and programming is easy (Liu & Qiao 2015).

Simulated Annealing (SA) – this stochastic optimization technique was introduced by Kirkpatrick. An initial solution is selected in this and a new state is generated later on which generates a new random solution in the neighborhood of current solution which is called a neighbor solution.
Comparison and evaluation of this new state is done with previous solution. It is accepted if the solution from the new state is better, if it is not, then the acceptance and rejection is based on certain probability. Accepting poor solutions early in evolving deformable contour is a strong tool in exploring complex areas of image and get better final solutions. Then a method of local evolution is provided by SA of each of the points of a contour which allows the objects in a target to be represented more precisely (Auilera et al. 2012).

5.3 HYBRID OPTIMIZATION METHODS

The most popular global optimization schemes is metaheuristic algorithm which attempts in reproducing social behavior or natural phenomena. To solve various optimization problems, a number of metaheuristic algorithms have been proposed that are being used in numerous applications. Computational efficiency can be improved through such algorithms in solving larger issues and robust optimization codes can be implemented. More recently, a metaheuristic approach was proposed by authors in solving structural optimization problems with the help of CS algorithm along with Levy flights. Additionally, a new coupled eagle strategy was put forth in solving unconstrained and constrained global optimization, along with efficient Differential Evolution (DE). Moreover, in order to increase global search mobility for robust global optimization a new technique by the name of FA along with chaos was developed. The objective of modern metaheuristic algorithms is the expansion of global search ability with regards to three major reasons: finding a solution to a problem faster, to solve large problems and to obtain robust algorithms (Bhandari et al. 2014).

The inspiration for the working nature of CS algorithm is the life of cuckoo bird along with Lévy flight behavior of some birds and fruits flies. While on the other hand, ABC algorithm is in particular a good swarm-based approach for optimization, where the inspiration of search algorithm takes
place by the foraging behavior of bee colonies. The study shows that CS algorithm is quite promising and would outperform other techniques such as Wind Driven Optimization (WDO). CS algorithm is used in this work in finding optimal solution with the help of Kapur’s entropy. The objective of this work is in examining the search abilities of CS, Egg Lying Radius (ELR)-CS and WDO algorithms for segmentation utilizing multi-level thresholding. Additionally, better comprehensive comparative investigations are reached through studying the fitness function of both processes. Evolutionary technique based multilevel thresholding is examined as a constrained optimization problem.

Of late, image segmentation is carried out through feature-based segmentation technique such as Ant Colony Algorithm. Because of their intelligent searching ability, further optimization of segmentation take place but because of their computational complexity, they have low efficiency. Other than obtaining good segmentation result, the enhanced Ant System (AS) can also will provide a resolve to come through he FCM’s sensitiveness in initializing the condition of cluster centroid and centroid number. But very compact clustering result is sought by AS technique in the feature space. In order to enhance the performance of AS, Ant colony – Fuzzy c means Hybrid Algorithm (AFHA) is introduced. The compactness of cluster in feature space is enhanced by the FCM introduced into the AS by AFHA. But because of its computational complexity, its efficiency is low (Tan & Isa 2011).

Improved AFHA is introduced in order to increase the efficiency of AFHA. A sub-sampling is added by IAFHA in order to modify the AFHA in reducing computational complexity and improving its efficiency. Although there is an increase in the IAFHA’s efficiency, there are still issues with high computational complexity. Histogram Thresholding – Fuzzy C-means Hybrid
algorithm (HTFCM) is a new segmentation approach. It is made up of two modules that is histogram thresholding and FCM module. FCM’s initialization condition of cluster centroids and centroid number are obtained through the histogram thresholding module. To implement this, high computational module is not required compared to the other techniques in the ant system. This shows the simplicity of the proposed technique.

To evaluate the optimized values of neighborhood attraction features in Improved FCM (IFCM) clustering algorithm a combination of two algorithms namely GAs and PSO is done. A near optimal solution can be reached by GA but an exact solution cannot be reached, while search for optimal solution is improved through the group interactions of PSO. So, for the sake of further improvements a combined GAs/PSO, the Breeding Swarm (BS), algorithm was employed. Though BS algorithm can be perceived to be more complicated to GAs and PSO, an optimal solution can be found through it robustly than either GA or PSO. This is because of the combination of strengths of PSO with GAs at the same time. A global search is facilitated by GA in order to search a near optimal solution and search for optimal local solution is enhanced by PSOs group interactions (Forouzanfar et al. 2010). The proposed techniques are tested on three types of images square image, simulated brain Magnetic Resonance (MR) images, and real brain MR images. Both GAs and PSO are demonstrated at various noise levels through quantitatively and qualitatively and superior to previously proposed ANN technique in optimization of attraction parameters. However, there was significant improvement in results through BS algorithm. The BS-IFCM technique is a good technique for segmentation of noisy brain MR Images as results are nominated.

Histogram-based image segmentation is done through a new multilevel thresholding algorithm which is an improved variant of
Gravitational Search Algorithm (GSA), which is stochastic optimization technique introduced recently. When stuck at local optima, its capacity is strengthened to accomplish generation jumping by the use of the new technique of GA-GSA for image segmentation. Here, multi-level thresholding is achieved through the technique that employs both GA and GSA and the maximum entropy criterion which is the objective function. The ability of the proposed algorithm is demonstrated through the new method which employs two strategic images and the obtained performances can produce better results with the help of two other stochastic optimization techniques that is, PSO and GSA. The results of the study show significant improvement in performance compared to other popular contemporary techniques (Sun & Zhang 2013).

Gaussian Mixture Model (GMM) in brain MR image segmentation is estimated by the use of Expectation Maximization (EM) algorithm. But, this technique is deterministic and is prone to over-fitting the training data inherently and gets trapped in local optima. A hybridized Genetic and Variational EM (GA-VEM) technique for brain MR image segmentation is proposed in this work. In this work, estimation of GMM takes place through the Variational EM (VEM) algorithm in order to initialize the hyperparameters of conjugate prior distributions of GMM parameters which take place in VEM algorithm (Tian et al. 2011). As there is a capacity for the GA to obtain global optimization and there can be steady avoidance of over-fitting by VEM, the challenges in the conventional GA-EM based algorithms are overcome through hybrid GA-VEM algorithm. The technique was compared to the EM-based, VEM-based, and GA-EM based segmentation algorithms and the segmentation routines used in the statistical parametric mapping package and FMRIB Software Library in 20 low-resolution and 17 high-resolution brain MR investigation. The results of the study revealed that
Hybrid Parallel Ant Colony Optimization (HPACO) with FCM Algorithm is a very innovating technique with its basis on MRI brain image segmentation has been used in finding optimum label which minimizes Maximizing a Posterior (MAP) in segmenting the image. There are M and M1 colonies that are treated as slaves, while one colony for master. All pixels are visited in each colony without revisit. At first, the pheromone values for all colonies are initialized. Through Markov random field computation of posterior energy values or fitness value takes place. If it is less than global minimum, then local minimum is assigned to global minimum. Updating of the pheromone of the ant which generates global minimum is done. During final iteration, to optimum threshold value, global minimum returns to select initial clustering the FCM implementation in brain MRI segmentation (Karnan & Gopal 2010).

By overcoming the challenges, an enhanced variant of FCM technique is applied to image segmentation. The first enhancement takes place in the initialization step of the algorithm, utilizing PSO metaheuristic in order to overcome trapping of solution in local minima. Classification criterion is the second concern which was enhanced by the introduction of local information and Mahalanobis distance so that segmentation will be better when concerned with noise and the geometric shape of the clusters are taken into account. Ultimately, the results were refined in the post segmentation stage through the detection and re-clustering potentially misclassified pixels through the use of new local criteria which is optimized by greedy algorithm. In particular, a metaheuristic optimization algorithm is made use of in the post-segmentation stage instead of greedy algorithm, so that it is not trapped in a local optimum and a multi-objective optimization
approach is applied so as to integrate and combine the advantages of two or more criteria.

As K-means clustering is simple and fast, it is used generally for image segmentation. But then, K-means depend mostly on the number of clusters present initially and it falls easily into local optima. Because of this, it is difficult to achieve satisfactory results most of the time. PSO can achieve good global optimization capability because it is an evolutionary computation technique. Along with PSO, there can be an improvement in the global optimization capability of K-means clustering. But there is an obvious disadvantage in K-means clustering as it easily falls into local optima. A new image segmentation technique called Dynamic PSO and K-means clustering algorithm (DPSOK) is proposed in this work which has its basis on Dynamic PSO (DPSO) and K-means clustering. (Li et al. 2015). The methods of calculating its inertia weight and learning factors are enhanced, so as to ensure DPSOK technique keeps an equilibrium optimization capability. Results of the study show that DPSOK technique can improve effectively the global search capability of K-means clustering. Image segmentation quality and efficiency is improved in DPSOK algorithm in comparison to PSOK-means clustering algorithm.

In the intensity space, the issue of partitioning MRI brain images is considered as an automatic clustering issue. A new technique called Dynamic Fuzzy Clustering using the Harmony Search algorithm (DCHS) is proposed. The search capabilities of metaheuristic Harmony Search (HS) is taken advantage of by the search capabilities of this approach in automatically determining the number of clusters without any previous idea, and the proper location of cluster centers. Through the incorporation of concept of variable length encoding in every harmony memory vector, variable numbers of
candidate cluster centers are represented by DCHS at every iteration. Moreover, a new operator called “empty operator” is introduced in supporting the selection of empty decision variables in the harmony memory centers (Moh’d Alia et al. 2011).

To improve the clustering quality of DCHS, in the algorithm’s final step hybridization with FCM is introduced. Introduction of this step to DCHS calls the FCM algorithm just once to fine-tune the best solution which has been optimized by DCHS. From harmony memory, selection of solution vector with highest fitness value take place and initial values for FCM cluster centers are considered. In such case, cluster centers are modified by FCM until the variance of the clusters are minimum yielding more compact clusters. As a consequence, there is a decrease in the results achieved through DCHS within each cluster’s members and simultaneously there is an increase in the variation between clusters (inter-cluster variation).

5.4 METHODOLOGY

For better accuracy through bagging and boosting, the segmentation of fuzzy bee is used. In this section, ABC and hybrid ABC-FCM methods are described.

5.4.1 Artificial Bee Colony (ABC) Algorithm

Karaboga in the year 2016 introduced ABC which are comparatively a recent global optimization model. Foraging activity of honey bees is the inspiration for ABC. Starting at the time of inception, successful employment of ABC is done in various optimization issues (Karaboga & Ozturk 2010).
Solution to most of the problems is denoted through ABC, while the amount of nectar in food sources is denoted through the fitness value. There are three kinds of bees present within the hives - employed onlooker and scout bees. The number of employed or onlooker bees are almost similar to the quantity of solutions present in a population seeking solution. A set of cycles are comprised in ABC. Three major components are present with every cycle: 1) making employed bees move toward food sources and assessing quantity of nectar, 2) choosing food sources by onlooker bees and 3) defining scout bees as well as the exploration of fresh potential food sources.

First, an arbitrary original population of Np solutions is created by ABC. All solutions are D dimensional vectors, wherein D is the quantity of optimization variables (Salima et al. 2012).

To create first solution for the $i^{th}$ employed bee, Equation (5.1) is utilized

$$x_{ij} = x_{min}^j + \text{rand}(0,1) \times (x_{max}^j - x_{min}^j)$$

$$i = 1, \ldots, N_p \text{ and } j = 1, \ldots, D$$

(5.1)

wherein the $x_{min}^j$ and $x_{max}^j$ are the lower bound and upper bound of the $j^{th}$ component of the solution $z_{i,j}$.

Once the initialization stage is done, all employed bees search neighbourhood for food sources in their memory and alter it through Equation (5.2)

$$u_{ij} = x_{ij} + \phi_{ij} \times (v_{ij} - x_{ij})$$

$$i, k = 1, \ldots, N_p, i \neq k \text{ and } j = 1, \ldots, D$$

(5.2)
Employed bees update their memory with the novel solutions if their quality is improved else, the old solutions are retained and trails are incremented by 1, implying that the solutions have not been enhanced.

Once all employed bees terminate the search procedure, the experience is shared with the onlooker bees. All onlooker bees are sent to the food sources with probability $p_i$ through the equation given below (5.3):

$$p_i = \frac{fit_i}{\sum_{k=1}^{N_p} fit_k} \quad (i = 1, ..., N_p) \quad (5.3)$$

As soon as the sources are chosen, potential food source locations are produced by the onlookers from earlier memory using the Equation (5.2). The new solutions are evaluated by onlookers similar to the employed bees and their fitness is contrasted to those in their memory. If the new solutions possess same or better quality the ones acquired previously, then the old solutions are substituted by the new ones. Otherwise, the previous solutions are maintained and there is improving the respective trains by 1.

Once there are updated solutions for the onlookers, the one with the maximum value is noted. If the solution’s trail reaches above a particular limit, then the solution is considered as discarded and then the employed bee becomes a scout bee. Fresh solutions are provided by the scout bee randomly through Equation (5.1) and the fitness of novel solution are contrasted and the old ones. If the fresh solutions prove to be better than the old ones, they get replaced and the trail value is 0. Then the scouts will become employed bees.
The procedure is repeated until it reaches maximum number of cycles Maximum Cycle Number (MCN) is reached. Bees with greater fitness values are denoted through optimal solution. The ABC algorithm (Pandey & Kumar 2013) is given in Figure 5.1:

1. Initialize the population of solutions $X_{i,j}$, $i = 1,...,SN$, $j = 1,...,D$.
2. Evaluate the population.
4. Repeat.
5. Produce new solutions $V_{i,j}$ for the employed bees by using (5.2) and evaluate them.
6. Apply the greedy selection process.
7. Calculate the probability values $P_{i,j}$ for the solutions $X_{i,j}$ by (5.3).
8. Produce the new solutions $V_{i,j}$ for the onlooker bees from the solutions $X_{i,j}$ selected depending on $P_{i,j}$ and evaluate them.
9. Apply the greedy selection process.
10. Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution $X_{i,j}$ by (5.1).
11. Memorize the best solution achieved so far.
13. Until $Cycle = Maximum Cycle Number (MCN)$.

**Figure 5.1 ABC Algorithm**

The flowchart for ABC algorithm as shown in Figure 5.2:
5.4.2 Proposed Hybrid ABC-FCM Algorithm

To start with, the capacity of global searches is utilized by ABC-FCM algorithm in order to search for optimal solutions as initial clustering centres for FCM. Secondly, algorithm which is suggested uses up FCM for optimization of initial clustering centres and global optima are captured (Liu et al. 2013).

A randomly distributed initial population is created through ABC-FCM of SN solutions, where the size of employed or onlooker bees represented through SN. Thus, cluster centres are represented through the bees. All solutions $x_i$ ($i = 1, 2, ..., SN$) are D-dimensional vectors. Here, D is
the quantity of optimisation variables. Potential solutions are denoted by the issue to be optimized, while the quantity of nectar represents food source and are correlated to the fitness of respective solutions. This is computed through Equation (5.4):

$$fit_i = \frac{1}{1 + f_i} = \frac{1}{1 + J_m(U,V)}$$  

(5.4)

wherein $J_m(U,V)$ is the objective function of FCM. Smaller the value of $J_m(U,V)$ greater the individual fitness and better the clustering outcome.

In ABC-FCM, when a location is not capable of being enhanced even more by a set quantity of cycles, the food source is considered abandoned. If the abandoned source is $x_i$, then, the scout finds a novel food source to be substituted with $x_i$. The operation may be given by (5.5):

$$x_i^j = x_{\text{min}}^j + \text{rand}[0,1](x_{\text{max}}^j - x_{\text{min}}^j)$$  

(5.5)

A robust search procedure where exploration and exploitation are performed at the same time is ABC-FCM. Random searching by scouts is the basis for global searches of algorithm and neighbor production techniques take place through employed and onlooker bees (Alsmadi 2015). So, ABC-FCM can be deemed as an effective technology as it combines exploitation (local search) with exploration (global search).

The algorithm given below clearly delineates the steps followed by the suggested ABC-FCM technique is shown in Figure 5.3 the values are set as SN represents the initial population and going by standards we have set to 15. The maximum iterations (MCN) was set at 500. C defines the number of clusters and we set it to 2. M is a real number set to 4 and epsilon is the error criterion set at 0.01
1. Set variables of ABC as well as FCM such as population size SN, maximum cycle number MCN, cluster number C, m, $\varepsilon$;
2. Set membership matrix U through equation (4.2);
3. Create initial population (cluster centre) $c_{ij}$ through equation (4.3) as well as valuate fitness of population through equation (5.4);
4. With:
a. Cycle=1,
b. s=1,
c. Provide fresh solutions $u_{ij}$ for employed bees through equation (5.2) and valuate them,
d. Employ greedy selection procedure for employed bees,
e. Compute probability values $P_i$ for solutions $u_{ij}$ through equation (5.3),
f. Provide fresh solutions $u_{ij}$ for onlookers from solution $c_{ij}$ chosen on the basis of $P_i$ and valuate them,
g. Employ greedy selection procedure for onlooker s,
h. When searching time around employed bees is greater than specified limit and improved solutions are not discovered, position vectors may be reset arbitrarily as per equation (5.5). Go to Step b.
i. When iteration values are greater than maximum quantity of iterations (i.e. cycle>MCN), output most optimal cluster centre. Else, go to Step a.
5. Update membership matrix $\mu_{ik}$ through equation (4.2). Update cluster centres $v^j_k$ through equation (4.3);
6. If $\max_{r,k} |\mu_{ik}^{t} - \mu_{ik}^{t-1}| \leq \varepsilon$, then stop. Else, go back to Step 5 and stop when criterion is fulfilled.

Figure 5.3 ABC-FCM Algorithm
The segmentation process for ABC-FCM algorithm as shown in Figure 5.4:

![Segmentation Process for Hybrid ABC-FCM Algorithm](image)

**Figure 5.4 Segmentation Process for Hybrid ABC-FCM Algorithm**

5.5 **RESULTS AND DISCUSSION**

The FCM segmentation-bagging, FCM segmentation-boosting, fuzzy bee segmentation-bagging and fuzzy bee segmentation-boosting classifiers are used. The classification accuracy, average precision and average recall as shown in Tables 5.1 to 5.3 and Figures 5.5 to 5.7.

**Table 5.1 Classification Accuracy for Fuzzy Bee Segmentation**

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM Segmentation- Boosting</td>
<td>91.84</td>
</tr>
<tr>
<td>FCM Segmentation - Bagging</td>
<td>93.06</td>
</tr>
<tr>
<td>Fuzzy Bee Segmentation - Boosting</td>
<td>94.29</td>
</tr>
<tr>
<td>Fuzzy Bee Segmentation Bagging</td>
<td>95.92</td>
</tr>
</tbody>
</table>
Figure 5.5 Classification Accuracy for Fuzzy Bee Segmentation

From the Figure 5.5, it can be observed that the fuzzy bee segmentation bagging method increased classification accuracy by 4.34% for FCM segmentation-boosting, 3.02% for FCM segmentation-bagging & 1.71% fuzzy bee segmentation - boosting.

Table 5.2 Average Precision for Fuzzy Bee Segmentation

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM Segmentation- Boosting</td>
<td>0.91855</td>
</tr>
<tr>
<td>FCM Segmentation - Bagging</td>
<td>0.93055</td>
</tr>
<tr>
<td>Fuzzy Bee Segmentation - Boosting</td>
<td>0.94315</td>
</tr>
<tr>
<td>Fuzzy Bee Segmentation Bagging</td>
<td>0.95955</td>
</tr>
</tbody>
</table>
From the Figure 5.6, it can be observed that the fuzzy bee segmentation bagging method improved average precision by 4.36% for FCM segmentation-boosting, 3.06% for FCM segmentation - bagging & 1.72% for fuzzy bee segmentation - boosting.

Table 5.3 Average Recall for Fuzzy Bee Segmentation

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Average Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM Segmentation- Boosting</td>
<td>0.91755</td>
</tr>
<tr>
<td>FCM Segmentation - Bagging</td>
<td>0.9301</td>
</tr>
<tr>
<td>Fuzzy Bee Segmentation - Boosting</td>
<td>0.9421</td>
</tr>
<tr>
<td>Fuzzy Bee Segmentation Bagging</td>
<td>0.9585</td>
</tr>
</tbody>
</table>
From the Figure 5.7, it can be observed that the fuzzy bee segmentation bagging method increased average recall by 4.36% for FCM segmentation-boosting, 3% for FCM segmentation-bagging & 1.72% for fuzzy bee segmentation-boosting.

5.6 CONCLUSION

The objective of image segmentation is in separating the structure of interest objects from the background and other objects. Segmentation of brain MR images are developed through many approaches, among which are FCM algorithm that is used widely in MR image segmentation. The challenges in FCM is discussed in this work; in spite of the performance of FCM being simple and robust, it does not vouch safe for high accuracy and also provides noisy or abnormal images; as such there is an in-built noise in MRI images because of the operator, equipment, and environment which might hinder the accuracy of the images. ABC was introduced in this work before performing FCM clustering algorithm, so as to avoid sensitivity to noise. The algorithm studied in this work is found to be efficient with respect
to speed, performance and getting trapped in local minima points. From the results obtained, ABC was found to provide better results compared to GA and ACO techniques. Also, optimal solutions can be reached through ABC algorithm. Results show that the fuzzy bee segmentation bagging method increased classification accuracy by 4.34% for FCM segmentation-boosting, 3.02% for FCM segmentation-bagging & 1.71% fuzzy bee segmentation -boosting.