AN ARTIFICIAL FISH SWARM OPTIMIZED FUZZY MRI IMAGE SEGMENTATION APPROACH FOR IMPROVING IDENTIFICATION OF BRAIN TUMOUR

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***Abstract*—In image processing, it is difficult to detect the abnormalities in brain especially in MRI brain images. Also the tumor segmentation from MRI image data is an important; however it is time consuming while carried out by medical specialists. A lot of methods have been proposed to solve MR images problems, quite difficult to develop an automated recognition system which could process on a large information of patient and provide a correct estimation. Hence enhanced k-means and fuzzy c-means with firefly algorithm for a segmentation of brain magnetic resonance images were developed. This algorithm is based on maximum measure of the distance function which is found for cluster center detection process using the Mahalanobis concept. Particularly the firefly algorithm is implemented to optimize the Fuzzy C-means membership function for better accuracy segmentation process. At the same time the convergence criteria is fixed for the efficient clustering method. The Firefly algorithm parameters are set fixed and they do not adjust by the time. As well Firefly algorithm does not memorize any history of better situation for each firefly and this reasons they travel in any case of it, and they miss their situations. So there is a need of better algorithm that could provide even better solution than the firefly algorithm. To attain this requirement as a proposed work the Artificial Fish Swarm Algorithm to optimize the fuzzy membership function. During surveying of the previous literature, it has been found out that no work has been done in segmentation of brain tumor using AFSA based clustering. In AFSA, artificial fishes for next movement act completely independent from past and next movement is just related to current position of artificial fish and its other companions which lead to select best initial centers for the MRI brain tumor segmentation. Experimental results show that presented method has an acceptable performance than the previous method.**

Keywords-Brain Tumor, MRI Brain Images, K-Means And Fuzzy C-Means Firefly Algorithm, Mahalanobis Concept, Fuzzy C-Means Membership Function, Convergence Criteria, Artificial Fish Swarm Algorithm, MRI Brain Tumor Segmentation.

I. Introduction

Brain tumors are the tumors that cultivate in the brain which is one of the diseases rooted in the brain. As all know tumor is an abnormal growth originated by cells reproducing themselves in an uncontrolled way. A benevolent brain tumor consists of benevolent or harmless cells and has individual boundaries; it may cure through surgery only. The composition and role of the brain can be studied noninvasively by doctors and researchers by means of Magnetic Resonance Imaging (MRI). The MRI image in Figure 1 is really a thin horizontal slice of the brain where the white area at lower left is the tumor. Segmentation is an essential method in most medical image investigation. The clustering to magnetic resonance (MR) brain tumors sustains efficiency where it is appropriate for biomedical image segmentation as the number of clusters is typically known for images of particular regions of the human investigation. The preceding methods for brain tumor segmentation are thresholding, region growing [2] & clustering where the thresholding is the simplest scheme of image segmentation. Thresholding can be exploited to generate binary images from a greyscale image.

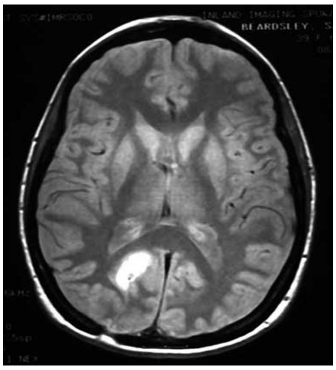

Figure 1: MRI Brain Tumor Image

Through the thresholding procedure, individual pixels in an image are manifest as "object" pixels if their value is larger than some threshold value that is presumptuous an object to be brighter than the background and as "background" pixels otherwise that convention is known as threshold. The threshold based approach having the drawback of lack of sensitivity and specificity so that accuracy of classification decreased. The primary stage in region growing [2] is to choose set of seed points and the choice is based on some user standard for instance, pixels in a certain gray-level range, pixels uniformly spaced on a framework, etc. The initial region starts as the opt location of these seeds. The regions are then grown from these seed points to neighbouring points depending on a region membership condition. The condition could be, for illustration, pixel intensity, gray level texture or colour. Given that the regions are grown on the foundation of the condition, the image information itself is significant.

Currently, there are lot of methodology for classifying MR images such as fuzzy methods, neural networks, atlas methods, knowledge based techniques, shape methods, variation segmentation. Image segmentation is the crucial step in image analysis, which is applied to divide the input image into meaningful regions. There exists two classifications to recognize a pattern, and they are supervised classification and unsupervised classification. A frequently exploited unsupervised classification method is a Fuzzy C Means algorithm [3]. As we know clustering is a method of partitioning or grouping a specified sector unlabeled pattern into a number of clusters such that related patterns are allocated to a collection that to be a cluster. There are two major advances to clustering which is crisp clustering and fuzzy clustering methods. One of the features of crisp clustering process is that the boundary between clusters is completely definite but in several real cases the boundary between clusters cannot be obviously definite. Several patterns may be a member of more than one cluster.

In that case of, the fuzzy clustering process presents a better and more constructive system to classify these patterns which is used for medical image data analysis and modelling, image segmentation etc. For pattern recognition clustering is exercised in image processing, and typically entails a high volume of calculation that desires important amount of memory which could reason repeated disk entrance, construction the process incompetent. The cluster centre initialized by random numbers in FCM, and it needs further number of iteration for converging to an ultimate actual cluster centre [3]. Segmentation is the separation of a digital image into the same regions to make straightforward the image depiction into impressive that is more significant and easier to examine. It is an essential method in the majority medical image study and classification for computer aided diagnosis. Mainly image segmentation techniques can be classified into three categories: region-based methods, edge-based methods and pixel based methods. Pixels in the area are similar to each other with regard to some feature property like color, intensity or texture.

K-means clustering is a main technique in pixel based methods. Since pixel-based methods are straightforward and computational complexity is comparatively low evaluated with other region-based or edge-based methods, the application is more feasible. In addition K-means clustering is appropriate for biomedical image segmentation since the number of clusters is typically known for images of particular regions of the human composition. In this proposed work, initially analyses color based k-means with FCM clustering segmentation method. The K-means and fuzzy c-means (FCM) clustering algorithm is soft segmentation method, and it has aroused comprehensive attention. There have been many different families of fuzzy clustering algorithms proposed. The convergence criteria are checked at last and the best clustering will be obtained. The fuzzy Membership function can be used to obtain segmentation via fuzzy pixel clustering. The FCM algorithm that incorporates spatial information into the membership function is used for clustering, while a conventional FCM algorithm does not completely utilize the spatial information in the image. To get an optimized cluster results the Artificial Fish Swarm Algorithm is used where the optimal membership function value is obtained to get a better initial cluster centers. This method is one of the best approaches of the Swarm Intelligence technique with significant benefits like high convergence rate, flexibility, fault tolerance and high truthfulness.

The rest of the document is organized as follows. Section 2 explains the literature review, Section 3 describes the medical imaging techniques with firefly technique, Section 4 gives the clustering algorithms step by step and their implementation with AFSA, Section 5 gives the experimental results and finally Section 6 discusses the conclusion and future scope.

II. Previous Work

The FCM algorithm allocates pixels to every category by using fuzzy memberships. Let $X = (x_1, x_2, .., x_n)$ indicates an image with n pixels to be separated into c clusters, where x_i represents multispectral (features) data. The algorithm is an iterative optimization that reduces the cost function using the Kullback-Leibler (KL) criterion defined as follows:

$$J = \sum_{j=1}^{n}\sum_{i=1}^{c} u_{ij}^{m} \left\| (x_j - v_i)\log_2 \frac{x_j}{v_i} \right\|^2$$

Where u_{ij} symbolizes the membership function of pixel $x_j$in the ith cluster, $v_i$is the ith cluster center, and m is an invariable. The parameter m manages the fuzziness of the resulting partition, and m is fixed in this revise. The cost function is reduced when pixel close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far from the centroid. The membership function symbolizes the probability that a pixel goes to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain. The membership functions and cluster centers are reorganized by the following:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{2/(m-1)}}$$

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}}$$

Where $u_{ij} \in [0, 1]$.

Preliminary with an initial guess for each cluster center, the FCM converges to a solution for v_i representing the local minimum or a load point of the cost function. Convergence can be observed by comparing the changes in the membership function or the cluster center at two successive iteration steps. One of the significant characteristics of an image is that neighboring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm. To develop the spatial information, a spatial function is defined as.

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik}$$

Where $NB(x_j)$represents a square window centered on pixel x_j in the spatial domain. Just like the membership function, the spatial function h_{ij} symbolizes the probability that pixel x_j belongs to ith cluster. The spatial function of a pixel for a cluster is large if the majority of its neighborhood belongs to the same cluster. The spatial function in incorporated into membership function as follows:

$$u_{ij}^{'} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} h_{kj}^{q}}$$

Where p and q are parameters to control the relative importance of both functions. In a homogenous region, the spatial functions strengthen the original membership, and the clustering result remains unchanged. However, for a noisy pixel, this formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions or spurious splashes can easily be approved. The spatial FCM with parameter p and q is denoted $FCMS_{p,q}$.

The clustering is a two-pass process at each of iteration. The first pass is the same as that in standard FCM to calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain, and the spatial function is calculated from that. The FCM iteration proceeds with the new membership that is included with the spatial function. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations is less than a threshold.

A. Firefly Based Optimized Cluster Method

Firefly Algorithm (FA) is a nature-inspired algorithm based on the flashing behaviors of the firefly swarm [18]. The main principle for the sparkle of fireflies is to signal to attract other fireflies. The assumption of FA consists of three rules. (1) all fireflies are unisex thus that one firefly will be fascinated to other fireflies regardless of their sex; (2) an essential and motivating behavior of fireflies is to radiance brighter mainly to attract victim and to share food with others; (3) attractiveness is comparative to their brightness, so each agent firstly travels toward a neighbour that glows brighter. In the FA, the fireflies are randomly dispersed in the search space. The fireflies hold a luminescence excellence, called luciferin, which emanates light proportional to the quality [16]. Every firefly is attracted by the brighter glow of other estimated fireflies. The attractiveness reduces as their distance increases [17]. If there is no brighter one surrounded by the scope of a firefly, it will travel randomly in the search space. In our applications, the decision variables are the three spatial transform parameters as t_x,t_y and θ. The brightness is associated as the objective function is formulated as Equation in below section. The actions of applying FA to inflexible image registration can be typed into two phases.

B. Distinction of light intensity

The brightness is correlated to the objective values, hence for a maximization/minimization problem; a firefly with advanced intensity will attract another firefly with higher probability, and vice versa. Suppose that there survives a swarm of *n* fireflies and x_i stands for a solution for a firefly i, whereas $f\ (x_i)$ signifies its corresponding fitness value. Here the brightness *I* of a firefly is correspondent to the fitness value

$$I_i = f(x_i)\ 1 \leq i \leq n$$

C. Movement in the direction of attractive flies

The attractiveness β of the firefly is proportional to the light intensity obtained by the adjacent fireflies [19]. Assume β_0 is the attractiveness with distance $d = 0$, hence for two fireflies i and j at locations x_i and x_j, their attractiveness is calculated as

$$\beta_d(i,j) = \beta_0 \exp\{-\gamma d(i,j)^2\}$$

$$d(i,j) = \|x_i - x_j\|$$

Where *d (i, j)* denotes the distance between fireflies *i* and j, γ denotes the light amalgamation coefficient. Understand firefly *j* is brighter than firefly *i*, then firefly i will move to a new position as

$$x_i(t+1) = x_i(t) + \beta_0 exp\{-\gamma d^2\}(x_j - x_i)$$

III. Related Work

Since the substance cost is one of the most important reasons in the manufacture of a structure, it is preferable to diminish it by minimizing the weight of the structural structure. All of the techniques utilized for minimizing the weight has it in mind to attain an optimum intend having a set of design variables under certain design criteria. Gholizadeh et.al [4] optimum design of constructions is typically attained by choosing the design variables such that an objective function is reduced even as all of the design restrictions are fulfilled. Kazemzadeh et.al [5] as truss structures are extensively utilized for structural purposes, optimum design of this type of structures has an immense significance. Usually, in design optimization of truss constructions, the objective is to discover the best feasible construction with a minimum weight. The great development of structural optimization took place in the early 1960s and from then on, various general approaches have been expanded and assumed to structural optimization. The most important thought behind using the metaheuristic algorithms is to deal with complex optimization problems where other optimization methods have unsuccessful to be successful. These techniques are now identified as one of the most practical advances for solving many real world difficulties.

The convenient advantage of metaheuristic is positioned in both their efficiency and general applicability. Actually, metaheuristic are the most all-purpose types of stochastic optimization algorithms, and are applied to an extremely wide collection of difficulties. Recently, metaheuristic algorithms are appeared as the global search approaches which are accountable to deal with the complex optimization difficulties. With taking a focus on literature surveys it can be examined that the most popular metaheuristic are genetic algorithm (GA) [6], ant colony optimization (ACO) [7], particle arm optimization (PSO) [8], harmony search (HS) [9] and firefly algorithm (FA) [10]. Lamberti and Pappalettere et.al [11] attained a complete review of the metaheuristic and their applications. The FA is an optimization technique, enlarged recently by Yang [10] at Cambridge University. It is stimulated by social behavior of fireflies and the occurrence of bioluminescent communication. The advantage of FA to PSO and GA was verified using various test purposes [10, 12]. Gandomi *et al*. [13] developed the FA to resolve standard mixed-variable and non-convex optimization difficulties. In [5] FA was utilized to attain shape optimization of structures.

In recent times, an intelligent universal method, referred to as AFSA was projected to take care of function approximation, pattern recognition, process judgment and calculation, optimization design and other applications. Jianget.al [14] utilized a new estimation technique, called the Spread Spectrum Code Estimation. The estimation technique by AFSA is insensitive to initial values, has a strong robustness, and has a faster convergence speed and better estimation precision compared to the estimation method by GA and PSO. The result illustrates that the technique can attain the optimal or sub-optimal solution. Consequently, Chen et.al [15] suggested a hybrid of AFSA and PSO for feed forward neural network training. The hybridization of AFSA and

PSO has not only the Artificial Fish behaviours of swarm and pursue, other than also takes benefit of the information of the particle. L.X.Li et.al [16] developed a new evolutionary computation technique; Artificial Fish Swarm Optimization (AFSO) was first. AFSO possess similar attractive characteristics of genetic algorithm (GA) for instance independence from gradient information of the objective purpose, the ability to resolve complex nonlinear high dimensional troubles.

A. Enhanced Hits Algorithm

In this work, first the input image is read from the source where the colour model is applied. The L*a*b* color space that is also known as CIELAB or CIE L*a*b* allows us to enumerate these visual dissimilarities. The L*a*b* color

space is obtained from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' on behalf of where color falls along the red-green axis, and chromaticity-layer 'b*' representing where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. We can calculate the difference between two colors using the Mahalanobis distance metric. Convert the image to L*a*b* color space [17]. After this classify the Colors in 'a*b*' Space Using K-Means clustering to separate groups of objects. K-means clustering takes care of each object as having a position in space. It discovers partitions such that objects within each cluster are as close on each other as possible, and as far from objects in other clusters as possible. K-means clustering wants that you to indicate the number of clusters to be partitioned and a distance metric to enumerate how close two objects are to each other. Because the color information exists in the 'a*b*' space, your objects are pixels with 'a*' and 'b*' values. Use K-means to cluster the objects into three clusters using the Mahalanobis distance metric. For each object in our input, K-means returns an index in proportion to a cluster. Label each pixel in the image with its cluster index. With pixel labels, we have to divide objects in image by color, which will result of segmentation.

B. K-Means Algorithm

The k-means algorithm dispenses feature vectors to clusters by the minimum distance, which allocates a new feature vector $\mathbf{x}(q)$ to the cluster $\mathbf{c}(k)$ such that the distance from $\boldsymbol{x}$ to the center of $\mathbf{c}(k)$ is the minimum over all K clusters.

The basic k-means algorithm is as follows:

STEP 1: Place the first K feature vectors as initial centers

STEP 2: Allocate each sample vector to the cluster with minimum distance value.

STEP 3: Calculate new mean as new center for each cluster.

STEP 4: If any center has changed, then go to step 2, else terminate.

C. Fuzzy C-Means (FCM)

The fuzzy c-means clustering algorithm is a deviation of the popular k-means clustering algorithm, wherein a degree of membership of clusters is integrated for each data point. The centroids of the clusters are calculated based on the degree of memberships in addition to data points. The arbitrary initialization of memberships of occurrences utilized in both traditional fuzzy c-means and k-means algorithms make possible the incapability to construct consistent clustering outcomes and regularly outcome in objectionable clustering results. These algorithm efforts by allocating membership to every data point equivalent to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. The fuzzy membership function was explained in section 3. The algorithm is explained as follows:

Input: Unlabeled data set $\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2 \ldots . \mathrm{x}_\mathrm{n}\}$

// n- number of data points,$\mathrm{x}_\mathrm{k} \in \Re^\mathrm{p}$, p- number of feature in each vector

Main Output: C-partition of X

Common Additional Output: Set of vectors $\mathrm{V} = \{\mathrm{v}_1, \mathrm{v}_2 \ldots . \mathrm{v}_\mathrm{c}\} \subset \Re^\mathrm{p}$

v_i - Cluster centre

Initial Choices

Number of clusters $1 < c < n$

Maximum number of iterations T

Weighting exponent (Fuzziness degree) m

m=1: crisp

m=2: Typical

Termination measure $\mathrm{E}_\mathrm{t} = \|\mathrm{V}_\mathrm{t} - \mathrm{V}_{\mathrm{t}-1}\| \leftarrow$ 1-norm

Termination threshold $0 < \varepsilon$

Initialize cluster centers $V_0 = \{v_{1,0}, \dots . v_{c,0}\} \subset \Re^p$

Altering optimization

$t \leftarrow 0$

repeat

$t \leftarrow t + 1$

$U_t = F_\partial(V_{t-1})$

$V_t = G_\partial(U_{t-1})$

until ($t = T$ or $\|V_t - V_{t-1}\| \leq \varepsilon$

$(U, V) \leftarrow (U_t, V_t)$

Sample Illustration

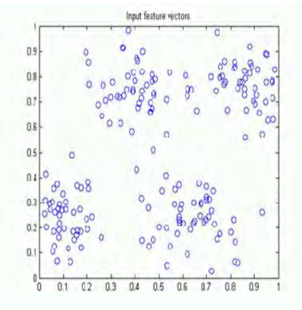

Figure 1: X, n=188, p=2

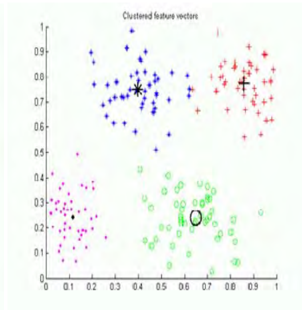

Figure 2: Visual Vision concept of the Artificial Fish

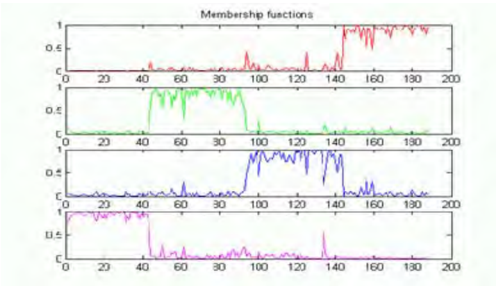

Figure 3: Rows of U (Membership Functions)

D. Artificial Fish Swarm Algorithm based Clustering

As we know in water world, fishes can discover areas that have more foods, which is done with individual or swarm search by fishes. In relation to this characteristic, artificial fish (AF) model is represented by prey, free-move, swarm and follow behaviors. AFs search the problem space by those behaviors. The location, in which AF lives, considerably is solution space and other AF's sphere. Objective function is Food consistence degree in water area is AFSA. Lastly, AFs attain to a point which its food consistence degree is maxima also referred as global optimum. Current position of AF is exposed by vector $X = \{x_1, x_2 \dots . x_n\}$. The *visual* is equivalent to sight field of AF and X_v is a position in *visual* where the AF desires to go. Then if X has better food consistence than current position of AF, it departs one step toward X_v which origins change in AF position from X to X_{next}, other than if the current position of AF is better than X_v, it keeps on searching in its *visual* area. Food consistence in position X is fitness value of this position and is shown with f(X). The *step* is the same to maximum length of the progress. The distance between two AFs which are in X_i and X_j positions is shown by using Mahalanobis. AF model consists of two divisions of variables and functions. Variables include *X* (current AF position), *step* (maximum length step), *visual* (sight field), *try-number* (the maximum test interactions and tries) and *crowd factor* d (0<d<1). As well functions are made of prey behavior, free move behavior, swarm behavior and follow behavior. In each step of optimization process, AF looks for locations with better fitness values in problem search space by performing these four behaviors based on algorithm process.

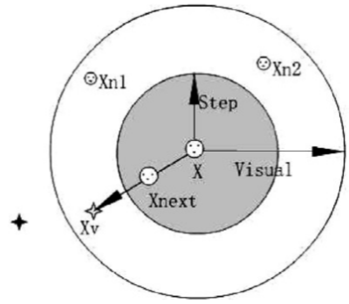

Figure 4 Artificial Fish Swarm Algorithm based Clustering

As a result of analyzing advantages and disadvantages of Fuzzy C-Means Clustering Algorithm, a method of image segmentation based on Fuzzy C-Means Clustering Algorithm and Artificial Fish Swarm Algorithm is suggested. In terms of the values of the membership of pixels the image is segmented, Artificial Fish Swarm Algorithm is introduced into Fuzzy C-Means Clustering Algorithm, and through the behavior of prey, follow, swarm of artificial fish, the optimized clustering center could be chosen adaptively, then the values of the membership of pixels available with Fuzzy C-Means Clustering Algorithm, and the image segmentation is completed. The evaluation results show the effectiveness and feasibility. For *circumventing* the dependence of the validity of clustering on the space distribution of high dimensional samples of Fuzzy C Means, a dynamic fuzzy clustering method based on artificial fish swarm algorithm was proposed. Through introducing a fuzzy equivalence matrix to the similar degree among samples, the high dimensional samples were mapped to two dimensional planes. Then the Mahalanobis distance of the samples was approximated to the fuzzy equivalence matrix gradually by using artificial fish warm algorithm to optimize the coordinate values. In conclusion, the fuzzy clustering was acquired. Intended for clusters of individual fish behavior in the initial state for the X_i, any exploration of a state X_j, calculate d_{ij}, if j's position is not too crowded place i move to j, or else implementation of the foraging behavior and foraging behavior of the state is a random choice, consequently difficult in the short time between the individual fish to find categories. If the initial heuristic is known when the quantity of information can further enhance the convergence speed. In this the clustering is done to void the iteration process which we can see in the above steps. To achieve this goal we are setting criterion function called Kullback-Leibler's criterion. This is done based on the objective function $K - L_{\varepsilon}$ which is mainly focused on the probability density function be P and Q. The Kullback-Leibler (KL) criterion measures the difference between two density functions p and q supported by (Entropy) E. At the same time ε as is an arbitrary positive parameter, we can guess the following special and useful formulas according to the different ε value: in fact the criterion function will be positive when this $\varepsilon \in [0,1]$. The Kullback-Leibler (KL) criterion will be

$$K - L_{\varepsilon} = \frac{1}{\varepsilon - 1} \log_2 \left(\sum_{i=1}^{n} p_i^{\varepsilon} q_i^{1-\varepsilon} \right), \varepsilon \in [0,1]$$

The proposed method, not only avoided the dependence of the validity of clustering on the space distribution of high dimensional samples, however also elevated the clustering efficiency. Experiment results show that it is an efficient clustering algorithm. The algorithm for AFSA is given below:

Algorithm 1 Fish swarm intelligent algorithm

Input: $m. l, u, nfe_{max}, \varepsilon, \delta, \mu_{\delta}, \theta, \eta$

Iteration ← 1; r← 1;

$(x^1, \ldots\ldots\ldots\ldots, x^m) \leftarrow intialize\ ()$

While termination criteria are not satisfied do

For i=1,…m do

Compute the "visual"

if visual scope is empty then

$y^i \leftarrow Random(\ x^i)$

else

if visual scope is crowded then

$y^i \leftarrow Search(\ x^i)$

else

if center point is better than x^i then

$y_1^i \leftarrow Swarm(\ x^i)$

else
$y_1^i \leftarrow Search(\ x^i)$
end if
if best function value is better than f(x^i) then
$y_2^i \leftarrow chase\ (\ x^i)$
else
$y_2^i \leftarrow search\ (\ x^i)$
end if
$y^i = \arg min \{f(y_1^i) f(y_2^i)$
end if
end if
end for
for i=1,,,,,,,m do
$x^i \leftarrow select(x^i, y^i)$
end for
if iteration >rm then
if "stagnation" occurs then
Randomly choose a point x^l
$y^l \leftarrow leap\ (x^l)$
end if
$r \leftarrow r + 1$
$\delta = \mu_\delta \delta$
end if
$iteration\ \leftarrow iteration + 1$
end while

IV. Results And Discussion

Brain tumor images were segmented by using different clustering algorithms and optimization algorithm. Here it is clearly seen that the object is segmented from the background. The tumor part of the brain is seen separately from the other part of the brain. The clustering algorithm used here is K-Means with Fuzzy-C means algorithm.The results obtained for the clustering algorithms are given in this section. In this the recall rate and the execution time is calculated and compared with the different clustering methods with the support of number of input dataset. The recall would indicate the proportion of correctly clustered states to the total number of actual positive states. Thus, a high precision and high recall are desirable for browsing behavior detecting system.

Figure 5 represents the recall rate comparison among the two different algorithms. This graph shows the recall rate of two different clustering methods based on two parameters of recall and number of Input images. From the graph we can see that, when the number of Input images is improved the recall rate also improved in proposed system which is represented as blue line but when the number of number of Input images is improved the recall rate is reduced in existing system than the proposed which are represented. From this graph we can say that the recall rate of AFSA based k-Means with FCM is increased which will be the best for the image segmentation**.**

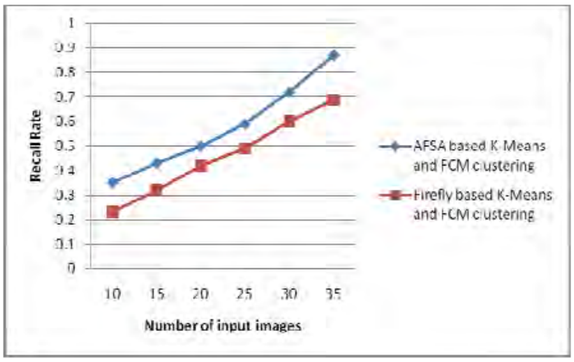

Figure 5: Recall rate comparison

Figure 6 represents the Execution time comparison among the two different algorithms. This graph shows the Execution time of two different clustering methods based on two parameters of Execution time and number of Input images. From the graph we can see that, when the number of number of Input images is improved the Execution time is reduced in proposed system which is represented as blue line but when the number of number of Input images is improved the Execution time is increased in existing systems which are represented. From this graph we can say that the Execution time of AFSA based k-Means with FCM is reduced which will be the best for the image segmentation.

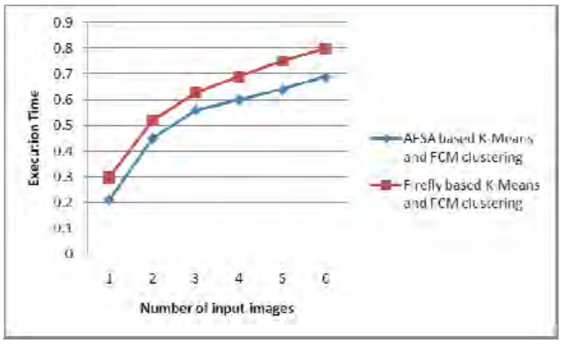

Figure 6: Execution time comparison

V. Conclusion And Future work

The AFSA algorithm is one of the mainly right methods for swarm intelligence optimization. Here we are using the AFSA based image segmentation method. The image is segmented in terms of the values of the membership of pixels; Artificial Fish Swarm Algorithm is established into Fuzzy C-Means Clustering Algorithm and K-Means algorithm. Through the values of the membership of pixels available with Fuzzy C-Means Clustering Algorithm, and high ability of AFSO in global searching in addition to high ability of K-means in local searching has been used cooperatively for the image segmentation is accomplished. The experiment indicates that the proposed method is to a certain extent efficient and highly effective.

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