Current Trends in Technology and Science
ISSN : 2279-0535. Volume : 04, Issue : 02 (Feb.- Mar. 2015)

Brain Tumor Segmentation Using Fuzzy C Means With Ant Colony Optimization Algorithm

Ganesh S. Raghtate
Research Scholar, B. D. COE, Sevagram, Wardha, India. Email ID: gsraghtate2012@gmail.com
Suresh. S. Salankar
Professor, G. H. Raisoni COE, Nagpur, India. Email ID: suresh.salankar@gmail.com

Abstract — In computer vision, image segmentation is an important problem and plays vital role in medical imaging. Analysis and diagnosis of tumor in MRI brain image involves segmentation as very essential steep. It separates the region of interest objects from the background and the other objects. Several approaches are used for MRI brain tumor segmentation. Fuzzy C Means (FCM) is most widely used fuzzy clustering algorithm. The accuracy of this algorithm for segmentation is not efficient due to limitation in initialization. In this paper, ant colony algorithm with min max ant system is used to improve the segmentation accuracy by maximum 32 % and reduce the computational time by maximum 2.5 times respectively.

Keyword — Magnetic Resonance Image (MRI), Brain Tumor segmentation, Fuzzy Interference System (FIS), Fuzzy C Means (FCM), Ant Colony Algorithm (ACA), Min Max Ant System (MMAS).

1. Introduction

Image segmentation is a process in which the image is partitioned into regions which are homogeneous in nature with respect to one or more characteristics. In medical field it is used for brain tumor detection and other various applications like detection of coronary border, surgical planning, measuring tumor volume and its volumetric response to therapy, classification of blood cells, detection of micro calcification on mammograms, heart image extraction from cardiac cine angiograms etc.

The brain tumor segmentation is achieved by using the methods such as thresholding, region growing and clustering. Clustering is the most popular approach for segmentation of brain MR image and performs better than the other methods.

Clustering is about dividing or partitioning a given data set into clusters (groups) such that the data points in a cluster are more similar to each other than points in different clusters. In clustering process, there are no predefined classes and no examples that would show what kind of desirable relations should be valid among the data. Clustering produces initial categories in which values of a data set are classified during the classification process.

In this paper, clustering algorithm such as fuzzy C Means (FCM) is implemented to extract the suspicious region in MRI image. Ant colony algorithm with Min Max Ant System is used to improve the segmentation accuracy and reduce the computational time respectively.

2. Literature Review

Image segmentation is an important basic operation for meaningful analysis and interpretation of acquired image. There are various methods for image segmentation. These methods are classified into three major classes i.e. thresholding, region based segmentation methods and clustering algorithm.

Thresholding is a powerful manual approach for segmenting images having light objects on dark backgrounds [1]. A multilevel image is converted into a binary image. It selects a threshold T to divide the image pixels into several regions and separate objects from the background. Any pixel (x, y) is considered as part of object if its intensity is greater than or equal to threshold value i. e., $f(x, y) \geq T$, else pixel belongs to background [2, 3]. Depending on threshold value [4], this approach is classified into global and local thresholding.

Segmentation algorithm based on region is relatively simple and more immune to noise [4, 5]. Segmentation algorithms based on region mainly includes region growing and region splitting and merging. Region growing is a procedure [3] that groups pixels into sub regions or larger regions based on predefined criterion [6].

Clustering is an unsupervised learning task, where one needs to identify a finite set of categories known as clusters to classify pixels [4]. It is used when classes are known in advance. A similarity criteria is defined between pixels [7] and then similar pixels are grouped together to form clusters. In clustering technique, an attempt is made to extract a vector from local areas in the image. A standard procedure for clustering is to assign each pixel to the nearest cluster mean.

G. Karmakar ,L. Dooley et al. [8] proposed a new algorithm called fuzzy rules for image segmentation incorporating texture features (FRIST), which includes two additional membership functions to those already defined in GFRIS(generic fuzzy rule based image segmentation). FRIST incorporates the fractal dimension and contrast features of a texture by considering image domain specific information. FRIST exhibits considerable improvement in the results obtained compared with the GFRIS approach for many different image types.

Current Trends in Technology and Science
ISSN : 2279-0535. Volume : 04, Issue : 02 (Feb.- Mar. 2015)

Tie Qi Chen and Yi Lu [9] developed a fuzzy clustering algorithm that iteratively generates color clusters using a uniquely defined fuzzy membership function and an objective function for clustering optimization. The region segmentation algorithm merges clusters in the image domain based on color similarity and spatial adjacency. Martin Tabakov [10] described a way of medical image segmentation using an appropriately defined fuzzy clustering method based on a fuzzy relation. The considered relation is defined in terms of Euclidean distance.

Ahmed Mohamed N., Yamany Sameh M. et al. [11] presented an algorithm for fuzzy segmentation of MRI data and estimation of intensity inhomogenities using fuzzy logic. The algorithm is formulated by modifying the objective function of the standard fuzzy C means algorithm to compensate for such inhomogenities and allow the labeling of a pixel to be influenced by the labels in its immediate neighborhood.

3. Image Acquisition

The MRI data is obtained from open data source http://www.cancerimagearchive.net/display/public/collections. A sample of total 10 MRI brain images is taken for segmentation purpose. These images are with the default size of 512 x 512. The following fig.1 displays a MRI Brain Image.

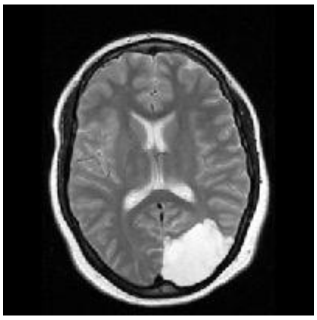


Fig.3: Acquired Brain MRI image

4. Skull Removal

Skull stripping is a major phase sometimes refers to a pre-process in MRI brain imaging applications which refers to the removal of brain non-cerebral tissues. The grayscale image is converted to binary image by thresholding. The output image BW replaces all pixels in the input image with luminance greater than threshold with the value 1 (white) and replaces all other pixels with the value 0 (black). Otsu's method [6] is used, which chooses the threshold to minimize the intra class variance of the black and white pixels.

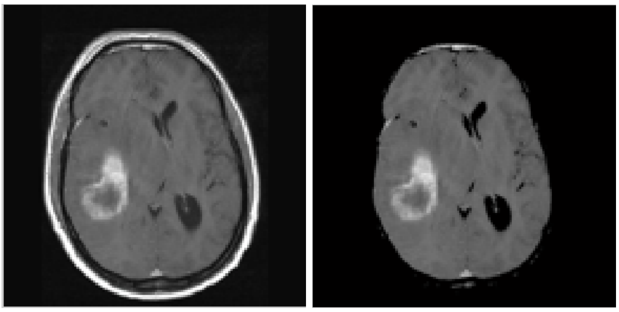


Fig. 4. (a) Original Image (b) Skull Removed Image

5. Image Enhancement

Image enhancement makes a graphic display more useful for display and analysis. Image enhancement consists of gray level and contrast manipulation, noise reduction, edge crispening and sharpening, filtering, interpolation and magnification.

Fuzzy inference system is selected for image pre processing, as it have higher PSNR value as compared to others.

5.1. Fuzzy Inference System

Fuzzy inference system is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping provides the basis from which decisions can be made. The process of fuzzy inference involves membership functions, fuzzy logic operators and if-then rules. Fuzzy inference system is associated with fuzzy-rule-based system and fuzzy-expert system.

The steps followed for image enhancement are:

Step 1: Morphological Processing
Step 2: Conversion of image into fuzzy domain data
Step 3: Membership Modifications
Step 4: Defuzzification
Step 5: Displaying the enhanced image.

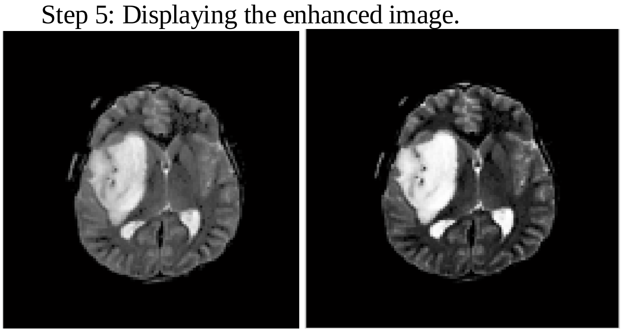


Fig 5.1 (a) Original Image (b) Enhanced Image

6. Image Segmentation

Clustering algorithms are classified as hard clustering (k-means clustering) fuzzy clustering, etc. Fuzzy c-means is a popular soft-clustering method. Fuzzy c-means is one of the most promising fuzzy clustering methods.

Current Trends in Technology and Science
ISSN : 2279-0535. Volume : 04, Issue : 02 (Feb.- Mar. 2015)

6.1. Introduction To Fuzzy C Means (FCM)

This algorithm works by assigning membership to each data point corresponding to each cluster centre, on the basis of distance between the cluster centre and the data point [13]. More the data is near to the cluster centre more is its membership towards the particular cluster centre. Clearly, summation of membership of each data point should be equal to one. After every iteration, the up-gradation of the membership and cluster centers is done.

Parameters:

n : is the number of data points.

vj: represents the cluster centre.

m: is the fuzziness index m Є [1, ∞].

c: represents the number of cluster centre.

μ_{ij}: represents the membership of data to cluster centre.

d_{ij}: represents the Euclidean distance between i^{th} and j^{th} data and cluster centre.

Main objective of FCM is to minimize:

$$J\,(u,v) = \sum_{i=1}^{n}\sum_{j=1}^{c}\left(\mu_{i,j}\right)^{m}\|x_i - v_j\|^2 \quad \text{…. (6.1.1)}$$

Where ||xi –vj||, is the Euclidean distance between i^{th} data and j^{th} cluster centre.

Algorithmic steps for FCM:

Let X ={x1, x2, x3 ..., xx} be the set of data points and V = {v1, v2, v3 ..., vv}be the set of centers.

Step 1: Randomly select c cluster centers.

Step 2: Calculate the fuzzy membership function µij using:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \quad \text{……. (6.1.2)}$$

Step 3: Compute the fuzzy centers vj using:

$$v_j = \frac{\left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^{m} x_i\right)}{\left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^{m}\right)} \quad \text{……. (6.1.3)}$$

Vj=1, 2, …, c.

Step 4: Repeat Step 2&3 until the minimum ’J’ value is achieved or ||Uk+1−Uk|| < β where,

k: is the iteration step.

β: is the termination criterion between [0, 1].

U = (µij) + c is the fuzzy membership matrix.

J: is the objective function.

The less accuracy of FCM is due to the fact that it is sensible to initialization. Thus to increase the segmentation accuracy Ant Colony Algorithm (ACA) is used. ACA initializes the cluster center to best proper value thereby increasing the segmentation accuracy.

6.2. Ant Colony Algorithm

The parameters taken here are total ants K and Tinit. Tinit is the starting initial value of pheromone matrix.

Construction of ant solution gets possible through the local search on the solution space i.e., the image matrix [14]. Ants decide to move from node i to another j through the probabilistic action rule which is as follows,

$$P_{ij}(n) = \frac{\left(\left(T_{i,j}\right)^{n-1}\right.}{\sum_{j\epsilon\Omega_i}\left(\left(T_{i,j}\right)^{\prime}\right.} \quad \text{……. (6.2.1)}$$

if, jεΩi

where (Ti,j)(n-1) is pheromone information in the previous loop while moving from node i to node j; Ωi is the neighborhood nodes for the recent ant given that it is in the node i; the constants α and β influences the pheromone information and heuristic information, respectively.

The local pheromone update is performed as followed by the equation:

$$T_{ij} = (1-\varphi)\, T_{ij} + \varphi\, T_o \quad \text{……. (6.2.2)}$$

Where φε (0, 1] is the pheromone decay coefficient and To is the pheromone initial values. The offline pheromone update is performed by the equation as follows:

$$T_{ij} = \begin{cases} (1-\rho)T_{ij}^{(n-1)} + \rho.\Delta_{ij}^{(k)} & \text{,if (i,j) belongs to best tour} \\ T_{ij}^{(n-1)} & \text{,else} \end{cases} \quad (6.2.3)$$

Exploitation is the process of attaining the maximum probability path. The exploitation of the learned experience is applied during solution construction with the help of pseudo-random proportion rule of ACS.

After applying ACA to image processing it is found that it increases the segmentation accuracy of FCM to a greater extent. But it increases the computational time as well. Thus to reduce the computational time max-min ant system is used. This reduces time nearly to 50% as that of ACA keeping segmentation accuracy nearly same as that of ACA.

6.3. Ant Colony Algorithm

The Max-Min Ant System (MMAS) is a direct improvement over AS [15]. The main modifications introduced by MMAS with respect to AS are the following.

First, to exploit the best solutions found, after each iteration only one ant (like in ACS) is allowed to add pheromone. Second, to avoid search stagnation, the allowed range of the pheromone trail strengths is limited to the interval [Tmin, Tmax], that is, Tmin<Tij<Tmax.

Last, the pheromone trails are initialized to the upper trail limit, which causes a higher exploration at the start of the algorithm. After all ants have constructed a solution, the pheromone trails are updated according to

$$Tij\ (t+1)= (1-\rho)*Tij(t)+\Delta Tijbest \quad \ldots\ldots (6.3.1)$$

where, $\Delta Tijbest = 1/Lbest$. The ant which is allowed to add pheromone may be the iteration-best solution Tib, or the global-best solution Tgb. Hence, if specific arcs are often used in the best solutions, they will receive a larger amount of pheromone. Experimental results have shown that the best performance is obtained by gradually increasing the frequency of choosing Tgb for the trail update.

Trail limit, In MMAS lower and upper limits on the possible pheromone strengths on any arc are imposed to avoid search stagnation. In particular, the imposed trail limits have the effect of indirectly limiting the probability Pij of selecting a city j when an ant is in city i to an interval [Pmin; Pmax], with $0 < Pmin \leq Pij \leq Pmax \leq 1$. Only if an ant has one single possible choice for the next city, then Pmin = Pmax = 1. Experimental results suggest that the lower trail limits used in MMAS are the more important ones, since the maximum possible trail strength on arcs is limited in the long run due to pheromone evaporation.

Trail initializations, the pheromone trails in MMAS are initialized to their upper pheromone trail limits. Doing so the exploration of tours at the start of the algorithms is increased, since the relative differences between the pheromone trail strengths are less pronounced.

7. Experiments And Results

The brain tumor segmentation is implemented by using Matlab 7.9. The experimental results are tested in Intel Core 2 Duo CPU 2GHz processor with 1GB RAM.

A) Skull Removal Results:

The removal of non-cerebral tissues from MRI brain image is achieved by using the skull removal method (Otsu's method). The results are as shown,

Original Image	Skull Removed	Original Image	Skull Removed

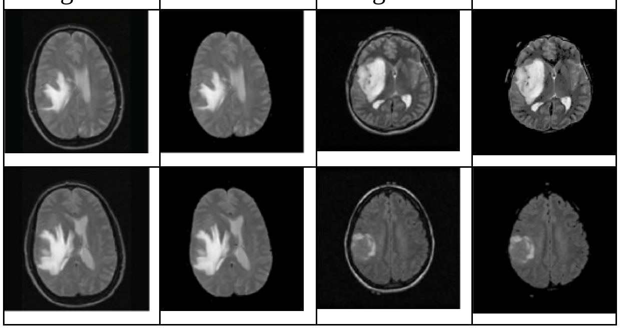


Fig 7.1: Skull Removal from MRI Images.

B) Enhancement Results:

Skull removed image is enhanced using Fuzzy Inference system. If the enhanced image can make observer perceive the region of interest better, then we can say that the original image has been improved.

Input Image	Enhanced Image	Input Image	Enhanced Image

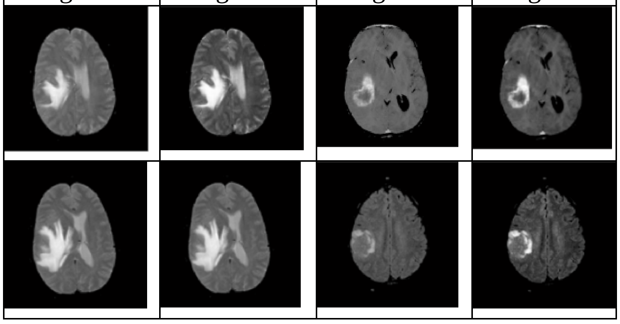
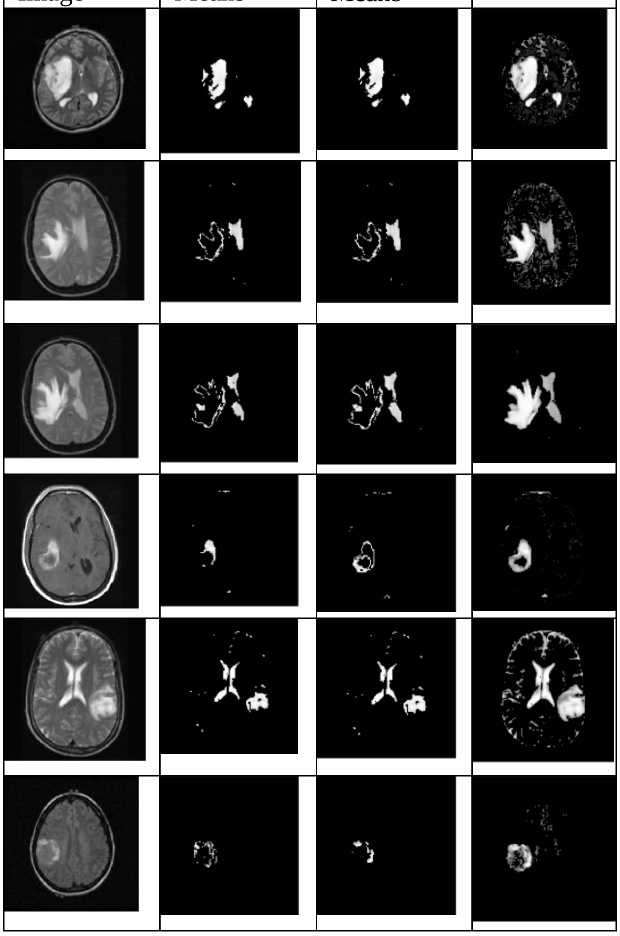


Fig7.2: Enhanced Image using Fuzzy Inference System

C) Segmentation Results:

MRI image segmentation using Fuzzy C Means, Fuzzy C Means with Ant Colony System and Fuzzy C Means with Optimized Ant Colony System with Min Max Ant System is shown.

Original Image	Fuzzy C Means	Fuzzy C Means	Optimized



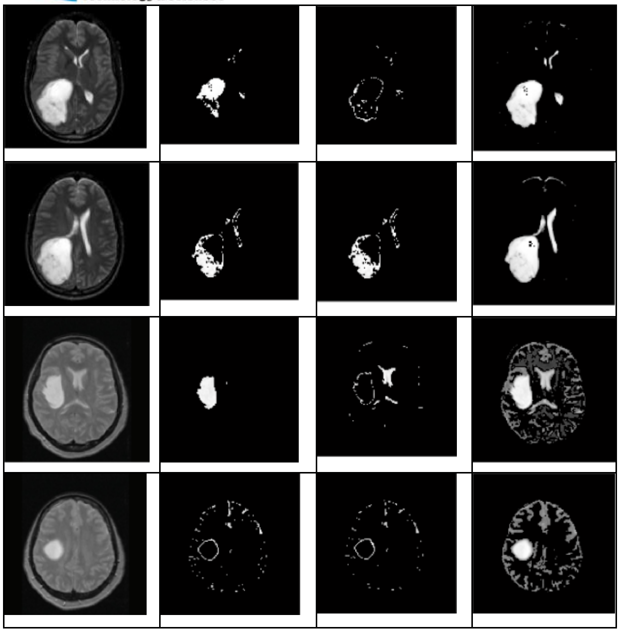


Fig7.3: Segmentation using Fuzzy C Means, Fuzzy C Means with ACO, Fuzzy C Means with Optimized ACO

TABLE 7.1: PERFORMANCE OF FUZZY C MEANS.

Sr. No.	Fuzzy C Means		
	PSNR (dB)	P. Time (Sec)	SA (%)
1	12.6439	7.2813	70.8313
2	12.0188	5.6406	65.9241
3	11.4978	6.5625	64.2944
4	13.8460	6.7969	63.7817
5	11.1795	8.5469	56.9519
6	16.1612	5.9531	73.1506
7	12.9953	5.6719	91.4063
8	12.2569	3.7813	90.6067
9	11.6965	7.5625	66.4673
10	12.7333	7.0313	70.2148

TABLE 7.2 PERFORMANCES OF FUZZY C MEANS WITH ACO.

Sr. No.	Fuzzy C Means with ACO		
	PSNR (dB)	P. Time (Sec)	SA (%)
1	21.0444	79.1094	97.6868
2	20.6212	71.9375	96.3013
3	20.3045	73.9219	96.5942
4	22.6321	126.3594	97.1313
5	19.3843	75.6875	96.1609
6	23.0877	73.9219	97.8271
7	22.6311	127.9219	98.8342
8	21.4403	74.7031	98.3582
9	22.0384	80.9688	96.9421
10	22.3728	140.2031	97.8394

TABLE 7.3: PERFORMANCE OF FUZZY C MEANS WITH OPTIMIZED ACO.

Sr. No.	Fuzzy C Means with Optimized ACO		
	PSNR (dB)	P. Time (Sec)	SA (%)
1	20.8815	30.7656	96.7041
2	20.7336	28.7500	96.1426
3	20.9499	26.1875	96.6370
4	23.4818	27.1094	97.0154
5	18.9609	30.2813	95.5017
6	24.2533	28.8906	97.2168
7	23.0660	30.6719	98.7793
8	21.7168	28.0156	98.3643
9	21.9469	28.8594	97.3938
10	22.4367	28.5625	97.5037

TABLE 7.4: PSNR (dB) OF SEGMENTATION METHODS.

Sr. No.	Fuzzy C Means	Fuzzy C Means ACO	Optimized ACO
1	12.6439	21.0444	20.8815
2	12.0188	20.6212	20.7336
3	11.4978	20.3045	20.9499
4	13.846	22.6321	23.4818
5	11.1795	19.3843	18.9609
6	16.1612	23.0877	24.2533
7	12.9953	22.6311	23.066
8	12.2569	21.4403	21.7168
9	11.6965	22.0384	21.9469
10	12.7333	22.3728	22.4367

TABLE 7.5: PROCESSING TIME (Sec) OF SEGMENTATION METHODS.

Sr. No.	Fuzzy C Means	Fuzzy C Means ACO	Optimized ACO
1	7.2813	79.1094	20.8815
2	5.6406	71.9375	20.7336
3	6.5625	73.9219	20.9499
4	6.7969	126.359	23.4818
5	8.5469	75.6875	18.9609
6	5.9531	73.9219	24.2533
7	5.6719	127.922	23.066
8	3.7813	74.7031	21.7168
9	7.5625	80.9688	21.9469
10	7.0313	140.203	22.4367

TABLE 7.6: SEGMENTATION ACCURACY (%) OF SEGMENTATION METHODS.

Sr. No.	Fuzzy C Means	Fuzzy C Means ACO	Optimized ACO
1	70.8313	97.6868	96.7041
2	65.9241	96.3013	96.1426
3	64.2944	96.5942	96.637
4	63.7817	97.1313	97.0154
5	56.9519	96.1609	95.5017
6	73.1506	97.8271	97.2168
7	91.4063	98.8342	98.7793
8	90.6067	98.3582	98.3643
9	66.4673	96.9421	97.3938
10	70.2148	97.8394	97.5037

Current Trends in Technology and Science
ISSN : 2279-0535. Volume : 04, Issue : 02 (Feb.- Mar. 2015)

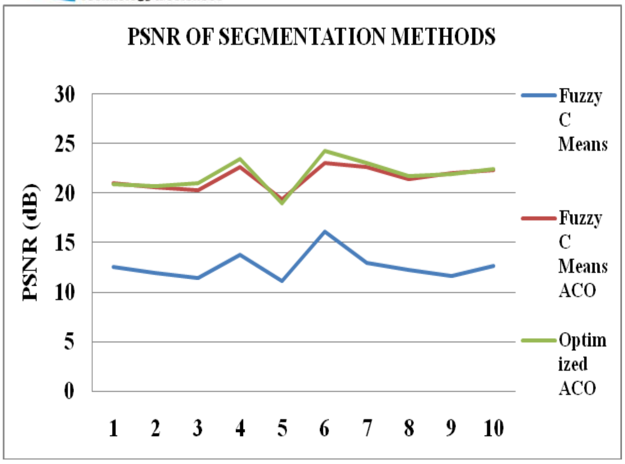


Fig.7.4: PSNR of segmentation methods

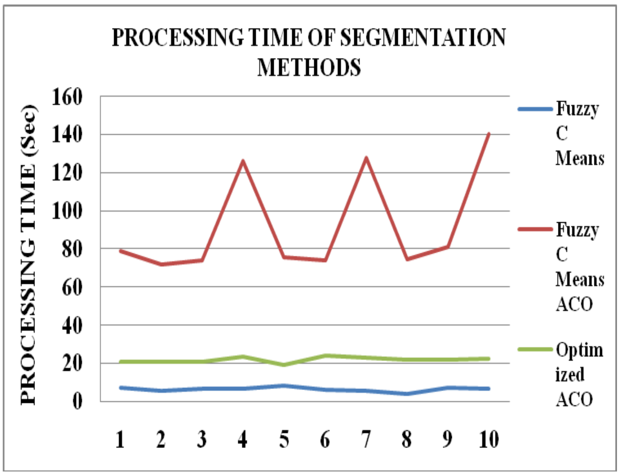


Fig.7.5: Processing Time of segmentation methods

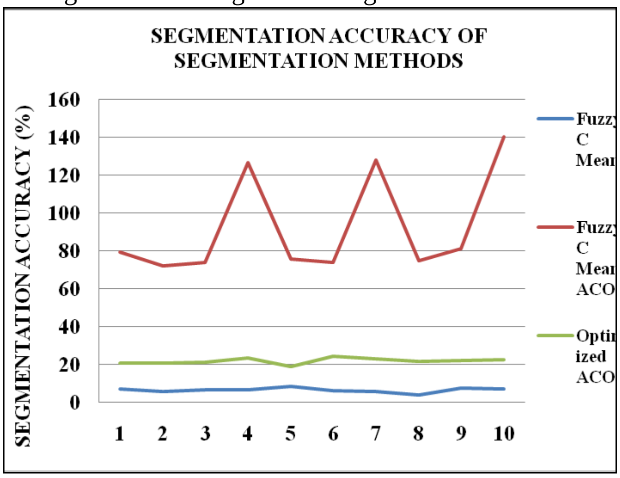


Fig.7.6: Segmentation Accuracy of segmentation methods

8. Quality Measures

There are various methods for calculating the performance of segmentation technique some of them are,

8.1. Peak Signal To Noise Ratio (PSNR)

In order to evaluate the performance of different Segmentation methods, image quality measurement is required and known as the peak signal-to-noise ratio (PSNR). The Mean absolute Error (MAE) and the Peak Signal to Noise Ratio (PSNR) are the two error metrics frequently used to compare the quality of image. PSNR in decibels (dB) is computed by using,

$$PSNR = 20 \log 10 \left(255^2 / MAE\right) \quad \ldots\ldots. (8.1)$$

Where,

$$MAE = \frac{\sum_{M,N} \left[I_1(m,n) - I_2(m,n)\right]^2}{M * N} \quad \ldots\ldots. (8.2)$$

8.2. Segmentation Accuracy (SA)

By finding the optimal correspondence between a dataset's annotated class labels and the clusters in a given partition, a performance measure may be derived that reflects the proportion of instances that were correctly assigned. "A high value for this measure generally indicates a high level of agreement between a clustering and the annotated natural classes". It may be noted that this measure is only applicable when the number of clusters 'C' is the same as the number of natural classes. Segmentation Accuracy is defined as:

Segmentation Accuracy =

$$\left[\frac{\text{Number of correctly classified pixels}}{\text{Total Number of pixels}}\right] * 100 \quad \ldots\ldots. (8.3)$$

8.3. Convergence Rate Or Execution Time

Convergence rate is defined as the time period required for the system to reach the stabilized condition. The lesser the execution time better is the clustering technique. Computation time (also called "running time") is the length of time required to perform a computational process. Representation a computation as a sequence of rule applications, the computation time is proportional to the number of rule applications.

9. Conclusions

The less accuracy of FCM is due to the fact that it is sensible to initialization. Thus to increase the segmentation accuracy of FCM, Ant Colony Algorithm (ACA) is used. ACA initializes the cluster center to best proper value thereby increasing the segmentation accuracy. But it increases the computational time as well. Thus to reduce the computational time max-min ant system is used. The modifications suggested were found to be giving better performance than other promising findings available in literature [1, 9, 10 and 10]. This reduces time nearly to 50% as that of ACA keeping segmentation accuracy nearly same as that of ACA.

REFERENCES

[1] Rastgarpour M. and Shanbehzadeh J. Application of AI Techniques in Medical Image Segmentation and Novel Categorization of Available Methods and Tools, Proceedings of international Multiconference of Engineers Computer Scientists 2011 Vol I, IMECS 2011, March 16 – 18, 2011, Hongkong.

[2] Wahba Marian, An Automated Modified Region Growing Technique for Prostate Segmentation in Trans – Rectal Ultrasound Images, Master's Thesis, Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario, Canada, 2008.

[3] L. Aurdal, " Image Segmentation beyond Thresholding", Norsk Regnescentral, 2006

[4] V. K. Dehariya, S.K. Shrivastava, R. C. Jain, "Clustering of Image Data Set Using K Means and Fuzzy K Means Algorithms", International Conference on CICN, pp. 386 – 391, 2010

[5] H. Zhang, J. E. Fritts, S. A. Goldman, "Image Segmentation Evaluation: A Survey of Unsupervised methods", computer vision and image understanding, pp. 260 – 280, 2008.

[6] Y. Chang, X. Li, "Adaptive Image Growing", IEEE Trans. On Image Processing, Vol. 3, No. 6, 1994.

[7] Zhang, Y.J, An Overview of Image and Video Segmentation in the last 40 years, Proceedings of the 6 th International Syposium on Signal Processing and Its Applications, pp. 144 – 151, 2001.

[8] Karmakar, G., Dooley, L., Murshed, M. Fuzzy rule for image segmentation incorporating texture features, Proceedings of international conference on image processing, Vol.1, 2002, pp. 797-800.

[9] Chen Tie Qi and Lu Yi. Color image segmentation- an innovative approach. Pattern recognition, vol. 35, 2002, pp. 395-405.

[10] Tabakov Martin. A fuzzy clustering technique for medical image segmentation. Proceedings of international symposium on evolving fuzzy systems, September 2006, pp. 118-122.

[11] Ahmed M. N., Yamany S.M et al. A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data, IEEE transactions on medical imaging, Volume 21, Issue 3, March 2002, pp. 193 – 199.

[12] Otsu, N., "A Threshold Selection Method from Gray-Level Histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 9, No. 1, 1979, pp. 62-66.

[13] Gordillo, N., Montseny, E., Sobrevilla, P. ,||A New Fuzzy Approach to Brain Tumor Segmentation||, Fuzzy Systems (FUZZ), 2010 IEEE International Conference on , 18-23 July 2010, pp.1-8, , doi: 10.1109/FUZZY.2010.5584178.

[14] M. Karnan, T. Logheshwari, "Improved implementation of brain MRI image segmentation using ant colony system", IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), pp. 1-4, 2010.

[15] A. Sheikh, R.K. Krishna, "Segmentation of brain MRI for tumor detection using ant colony optimization", Proc. of Int. Colloquiums on Computer Electronics Electrical Mechanical and Civil, 2011.

AUTHOR'S PROFILE

Ganesh S. Raghtate, received B.E. Degree in Electronics Engineering from Bapurao Deshmukh College of Engineering, Sevagram in 2001 and M. E. Degree in Electronics and Telecommunication Engineering from Shri Shankaracharya College of Engineering and Technology, Bhilai in 2008. He is doing research in Rastrasant Tukadoji Maharaj Nagpur University, Nagpur. His current research focuses on Image Processing, Texture Analysis and Neural Network.

Suresh S. Salankar, received B. E. Degree in Power Electronics from Bapurao Deshmukh College of Engineering, Sevagram in 1987, M.Tech in System and Control Engineering from Indian Institute of Technology, Bombay in 1994 , Ph.D in Electronics and Telecommunication Engineering from Swami Ramanand Teerth Marathwada University, Nanded, India in 2008. He is currently working as Professor in G. H. Raisoni College of Engineering, Nagpur, India. He has 27 years of teaching experience. He is member of Indian Society for Technical Education, Institution of Engineers (India) and Computer Society of India. His research interests are in the design and evaluation of learning algorithms for Pattern Recognition Applications. It includes, in particular, neural network classifiers, Support Vector Machine Classifiers and Classifier combining stategies.He has published several papers in this areas.