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MRI Brain Image Segmentation by Clustering Using an Optimal Multi-Objective Adaptive Fuzzy C Means (MAFCM) Algorithm

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Abstract: Images in the field of medicine are of vital interest to medical practitioners because they help to diagnose the right disease. They are used to find the abnormalities in the working and status of the human system, based on which the correct treatment can be planned for the patients. But, the images may not be accurate and may contain noise which may have occurred due to various reasons. Therefore, it is necessary to improve the quality of the image. Segmentation helps to identify the occurrence of any abnormality in the human body from the MRI image. In the proposed system, the MRI brain image is preprocessed using Gaussian filtering to enhance the quality of the image by removing the noise. Segmentation is performed on the preprocessed image by clustering using the optimal Multi-Objective Adaptive Fuzzy C Means (MAFCM) algorithm which combines both FCM and Cuckoo search algorithms for identifying the important parts of the brain that help to identify the disease, example brain tumor. The multi-objective feature of the proposed algorithm leads to optimal results which is better than the existing techniques in terms of computation complexity and time complexity. The performance of the proposed system is compared with the existing Adaptive Fuzzy K Means (AFKM) and Optimally Enhanced Fuzzy K-C-Means (OEFKCM) segmentation methods in terms of the parameters such as structural similarity index measure, structural content, mean square error and peak signal to noise ratio and is found to exhibit better results in terms of efficient identification of the disease.

Key words: Segmentation, Gaussian filter, brain MRI image, clustering, Multi-objective Adaptive Fuzzy C Means (MAFCM), FCM, cuckoo search

INTRODUCTION

Image segmentation is a major research area and it has endless applications. Segmentation is required in various applications like image analysis for identifying objects or dividing the image into regions for enhancement. The regions resulting from dividing an image are said to be homogeneous because division is performed based on certain criteria like color, texture and motion.

The abnormalities in the human body can be sensed by various medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computerized Tomography (CT) and Ultrasound (US) techniques. These techniques help the radiographer to make effective decisions based on the image under consideration. In MRI signals are produced by powerful magnets that polarize and excite hydrogen nuclei in the human tissue. These signals are detected and spatially encoded to produce images of the body (Shrivastava *et al*., 2014).

The brain is the most important part of the central nervous system. Brain tumor is an intracranial solid neoplasm. Uncontrolled cell division which leads to abnormality in the brain is the cause for tumors to be created (Shrivastava *et al*., 2014).

Axial view of the brain image, that is, two dimensional view is obtained by the MRI scan and it is less harmful than CT scan. Different methods of diagnosis are present to determine the cause of the symptoms mentioned by the patient, like biopsy, MRI or CT scan. The extent of the tumor (Kawadiwale and Rane, 2014) and the exact location of the tumor can be effectively identified by an MRI scan and it is a better technique than biopsy and CT scan. Manual segmentation is a difficult process because of the minute variations that cannot be identified between the original and the affected part of the image. The huge volumes of MRI makes segmentation a labor intensive and costly process and results in the necessity for an effective segmentation method.

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Medical images obtained by specialized equipments are prone to noise and are inaccurate (El Houby, 2015). The presence of artifacts and heterogeneous distinction lead to less clarity of the region of interest. No image is noise free. Therefore, there is a need for performing refinement and removal of noise on the image (Verma and Sharma, 2010; Kumar *et al*., 2013). Preprocessing of the image is necessary before performing image segmentation. Preprocessing changes a neighborhood of pixels of the input image into a new one in the output image. This is called as filtering. There are many filtering methods like mean filter, median filter, low pass filter, high pass filter, etc. Gaussian filter (Deb and Roy, 2014) is more preferred because, it provides better results than the mean filter in terms of a noise free image.

Clustering is one of the methods of performing data mining (Laxman and Sastry, 2006). Clustering (Beevi and Sathik, 2012; Aneja and Rawat, 2013; Khashandarag *et al*., 2013; Sheikh *et al*., 2015) is a method of unsupervised learning and a common technique for image analysis. Clustering is the process of assigning a set of observations or data points into subsets or clusters in such a way that data points in the same cluster are similar in some specific sense (Deb and Roy, 2014). Commonly used clustering algorithms in image segmentation are the K means algorithm and the fuzzy C means algorithm (Suganya and Shanthi, 2012). In the K means algorithm data are clustered by iteratively calculating the mean intensity for each of the classes and classifies each pixel in the class with the closest mean. This is the process of segmenting the image using K means method. Fuzzy C-means finds its application in image processing for clustering of objects in an image. Although, a lot of methods are available for MR image segmentation, fuzzy segmentation methods are preferred because, it is a soft segmentation method and retains much information of the original image than hard segmentation methods, example k means clustering. Fuzzy C Means (FCM) clustering assigns pixels to fuzzy clusters without labels and has the characteristic of allowing pixels to be a part of multiple clusters with different degrees of membership. Because of this feature, FCM is often used for segmentation of MR images. Computational complexity and performance degradation with noise are the disadvantages of FCM. Noise can be removed by preprocessing through filtering and computations can be made less complex by optimizing the segmentation process.

Clustering performed by using any of the fuzzy clustering algorithms (Wu and Yang, 2005; Wang and Zhang, 2007; Saad and Alimi, 2012) should be optimized in order to obtain high quality clusters. Clusters obtained by the application of fuzzy C-means algorithm are not optimized because of the problems inherent in the algorithm. One major limitation is that the number of clusters must be pre-assumed. One optimization algorithm is the ant colony optimization (Mary and Kasimir, 2010) algorithm which can be used. But, because of its low speed and its dependence on more number of parameters it may not lead to optimized clusters. But, it may be used for refining the clusters produced by fuzzy C-means method (Mary and Kasimir, 2010). Optimal placing of the pixels of an image into clusters may be considered which increases the quality of the clusters which in turn helps in accurate diagnosis of the disease.

In our proposed optimal multi-objective adaptive fuzzy C means method, initially the input MRI brain image is preprocessed to remove the noise. Preprocessing is performed by filtering using Gaussian filters. Segmentation is performed on the preprocessed MRI image using the Optimal MAFCM method which leads to image segments of high quality (Daniel and Vignesh, 2014). The special property that must be exhibited by each optimal cluster is that, it should be compact and separated from other clusters (Wu and Yang, 2005; Wang and Zhang, 2007; Saad and Alimi, 2012).

Literature survey

Optimal enhancement of the fuzzy K-C-means clustering algorithm: Medical images obtained using specialized equipments contained error due to noise, non uniform brightness of the image and inhomogeneous contrast. Hence, there was a need to refine the image, remove the noise and enhance the regions of interest. Amsaleka and Latha (2014) have proposed a method to identify the number of clusters and to increase the number of clusters by using an optimized hybrid method which combines both the particle swarm optimization and cuckoo search techniques. Cuckoo Search (CS) and Particle Swarm Optimization (PSO) were both meta-heuristic algorithms inspired by birds. Communication took place through, cuckoo birds that informed each other the suitable place for laying the egg. Swarm intelligence used in PSO was added to Cuckoo search to achieve this. Once the number of clusters was determined, it was provided as input to the Fuzzy K-C Means (FKCM) algorithm for clustering. The main objective of FKCM was to make the number of iterations equal to that of FCM and still obtain the optimized result. As a result of which even in the case of lower number of iterations, the result obtained was perfect. Using the existing FKCM mechanism, the number of clusters obtained was lesser and hence, the selection of the number of iterations was not optimized and convergence took place at a wrong minima. The proposed Optimally Enhanced Fuzzy K-C-Means (OEFKCM) clustering algorithm lead to better results when compared to FKCM clustering by avoiding the looping problem and reducing the time. It also has faster convergence in a fewer iterations independent of the number of clusters considered initially.

Adaptive fuzzy k means clustering algorithm: Medical images corrupted due to noise had to be enhanced to improve the image quality. Physicians used these medical images to identify abnormalities in the human body and to plan the treatment for the affected patients. Sulaiman have proposed a clustering method called Adaptive Fuzzy K Means (AFKM) for segmentation of the MRI image of the human brain to identify the abnormalities. This method performed image segmentation using AFKM clustering to identify three main regions namely White Matter (WM), Grey Matter (GM) and Cerebrospinal Fluid spaces (CSF). These regions were very important for analysis and diagnoses of the disease. The AFKM method was a combination of the conventional K means method, the Moving K Means (MKM) method and the standard FCM algorithm. The main objective of MKM method was to assign each data to the nearest center or cluster. FCM allowed each data to belong to two or more clusters or centers. The aim was to reduce the objective function of AFKM. The degree of a particular data element belonging to a particular cluster was related to the inverse of the distance to the cluster. The new position for each centroid was computed for all iterations that took place. Clustering was improved by AFKM method using the belongingness concept which measured the degree of relationship between the respective centers and its members. The process was repeated in an iterative manner until the center did not undergo a change and all the data have been considered. The segmented image produced by the proposed method was analyzed both quantitatively and qualitatively. The mean square error, a benchmark measure was used for quantitative analysis. The proposed AFKM clustering method was found to produce clearer and sharper segmentation of the MRI brain image than the standard FCM algorithm.

Modified K means clustering algorithm: Image segmentation divided the image into many homogeneous regions or clusters. It was mainly used to identify the regions of interest in medical images. Multiplicative noise was present in MRI images and reducing, it was a difficult task. The modified K means algorithm proposed by Shrivastava *et al.* (2014) was found to perform accurate segmentation which was very crucial for correct diagnosis of the disease. The modified K means algorithm when applied for segmenting the brain MRI image was found to produce better results than the standard fuzzy C means clustering and K means clustering algorithms in terms of the performance measuring parameters such as structural similarity index measure, structural content, mean square error and peak signal to noise ratio.

Fuzzy K-C-means clustering algorithm: Funmilola *et al.* (2012) have proposed the fuzzy K-C-means clustering algorithm for segmentation of the MRI image of the human brain. The proposed algorithm was a combination of the standard K means algorithm and fuzzy C means algorithm. It resulted in better time utilization during segmentation. Fuzzy K-C-means clustering lead to an optimum result by making the number of iterations equal to that present in the fuzzy C means approach. Accurate result was obtained even in the case of lower number of iterations. The proposed method was more oriented towards the properties of fuzzy C means, for example, it worked on grey scale images and had the same number of iterations as in the case of fuzzy C means. Fuzzy K-C-means was found to be faster than the existing methods and, it lead to more accuracy because, it was a method possessing the highest iteration value and segments in the shortest period of time.

Clustering algorithms in brain tumor detection: Brain tumor occurred due to abnormal growth by the uncontrolled reproduction of the cells themselves (Selvy *et al*., 2011) have given a view of the performance analysis of various clustering algorithms on segmentation for detecting the brain tumor from the MR image of the axial view of the human brain. The clustering algorithms considered are K-means, SOM, hierarchical clustering and fuzzy C-means. The gray-level MR image was converted to a color space image before applying the clustering algorithms. The performance of these algorithms was evaluated based on execution time and accuracy. The K means clustering and SOM had lesser execution time than the other clustering algorithms. The K means clustering and hierarchical clustering produced better results in terms of number of tumor pixels and also achieved 95% result. SOM and FCM achieved 80% result.

Automated tool for brain tumor detection using MRI brain image: Manikandan *et al.* (2013) have proposed a cluster based segmentation method for automatic detection of brain tumor. Film artifacts and skull stripping was performed on the input MRI brain image. Noise was automatically identified and removed using a suitable filter. Segmentation was performed using K means clustering algorithm and brain tumor tissues were extracted and located from the MRI brain image.

Segmentation by k means clustering and morphological filtering: Rohini have proposed a segmentation method for the MRI brain image using K means clustering algorithm and morphological filtering. Morphological filtering was performed after segmentation to avoid regions that have not been accurately clustered as a result of segmentation for locating the brain tumor.

Preprocessing and segmentation by k means clustering: Malathi and AR (2015) have proposed a method for preprocessing and segmentation of the MRI brain image. Preprocessing of the image converted the RGB input MR image to grayscale. Grayscale MRI input images were displayed as two dimensional matrices with pixels as its elements. Median filter was used to remove the presence of noise. Sharpening of the image was performed using Gaussian filtering mask. Segmentation was performed on the preprocessed image using K means clustering algorithm which helped in efficient detection of brain tumor.

In our proposed research, prior to segmentation, noise removal is performed on the MRI brain image as a preprocessing step using Gaussian filters. Then, we perform segmentation by clustering using the optimal multi-objective AFCM method. This method involves an objective function based on a multi-objective model and combines the features of FCM and cuckoo search (Babukartik and Dhavachelvan, 2012; Vaijayanthi *et al*., 2014) to perform segmentation of the image in an optimized manner. The image segments produced by applying the proposed method are compared with that of the image segments produced by the existing AFKM method and the OEFKCM method. The comparison shows that the image segments of the proposed optimal MAFCM method are of better quality (Varnan *et al*., 2011) as shown in the experimental results section and help in accurate diagnosis of the disease. The proposed technique is presented with much depth in the following study.

MATERIALS AND METHODS

The proposed MRI brain image segmentaion method: The proposed system is focused on improving the quality of the image segments for accurate diagnosis of the disease, for example identification of the brain tumor from the MRI brain image. The image segments formed using any clustering method may not lead to 100% efficiency. In order to improve the quality of the image segments formed, the optimal multi-objective adaptive fuzzy C means clustering algorithm is used for image segmentation. Prior to segmentation, the MRI brain image is preprocessed for removing the noise using Gaussian filter which results in an image of better quality free from noise. Segmentation is performed on the preprocessed image using the optimal MAFCM clustering method which results in optimized image segments which help physicians to identify the abnormalities in the human brain and provide the correct treatment. The method of preprocessing and segmentation for improving the quality of the resulting image segments is described below. In Fig. 1, the block diagram of the proposed medical image segmentation technique is shown.

Preprocessing using Gaussian filter: Noise is termed as unwanted signal, that is unwanted information which decreases the quality of the image. For example, random changes in the brightness or color of the image are considered as noise. The sources of noise in medical

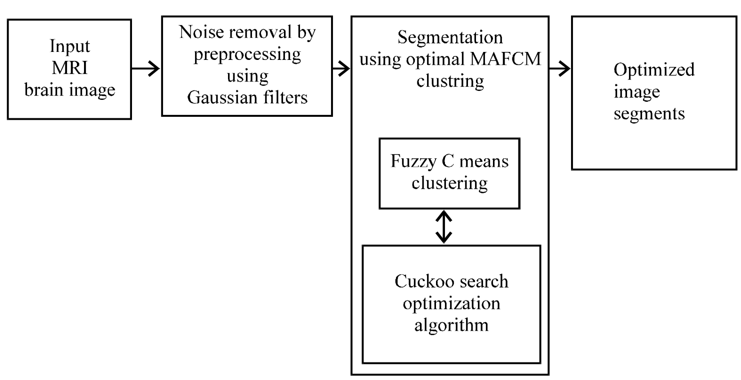

Fig. 1: Block diagram of the proposed image segmentation method using Optimal MAFCM clustering

images are bit error during transmission and capturing in MRI, non uniform intensity of color or gray level and spreading of regions over boundaries. Therefore, preprocessing is required for de-noising and equalization of the image. In the proposed method, preprocessing is performed using Gaussian filters because it best supports the optimal MAFCM segmentation method that is done after filtering of the noise.

Filtering aims at reducing noise in images. Segmentation is a post processing task which benefits by noise reduction. The value of the filtered image at a given location is a function of the values of the input image in a small neighborhood of the same location. In Gaussian low pass filtering, a weighted average of the pixel values in the neighborhood is calculated. Here, the weights will decrease with the distance from the respective neighborhood center. This method is found to show good results for filtering in the case of medical images. Images have the property of varying over space so, pixels nearby have similar values and it is better to average them. This is because, there is mutually less correlation in the noise values corrupting the nearby pixels than the signal values. So, noise is averaged and signal is protected.

In Gaussian filtering, the smoothing operator is a 2D convolution operator which blurs the images and removes detail and noise. The Gaussian function in 1D is given by:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

where, σ is the standard deviation of the distribution. The distribution is assumed to have a mean of 0. When working with images, 2D Gaussian function must be used and it is given by:

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

The properties of the Gaussian filter are as follows. The Gaussian filter is a non-uniform low pass filter. The kernel coefficients decrease with increasing distance from the centre of the kernel. Pixels at the centre have more weighting than those on the border. Larger values of σ produce blurring to a greater extent. For maintaining the Gaussian nature of the filter, kernel size must increase with increasing σ. Gaussian kernel coefficients depend on the value of σ. At the edge of the mask, coefficients must be close to 0. The kernel is rotationally symmetric with no directional bias. The separable nature of the Gaussian kernel allows for faster computation. Gaussian filter is better than a mean filter because, it provides gentler smoothing and preserves edges. The greatest advantage of using a Gaussian filter for smoothing is its frequency response.

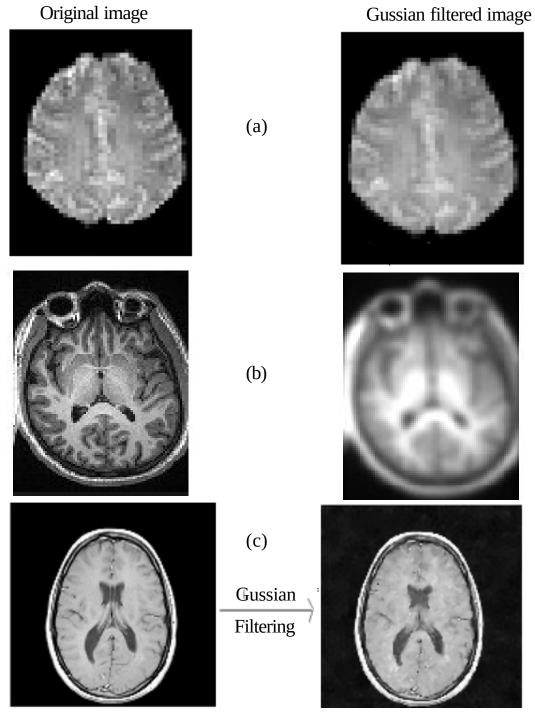

Fig. 2: a-c) Gaussian filtering performed on various MRI brain images

These factors have motivated the use of Gaussian filtering to be performed on the MRI brain image before performing segmentation using the optimal multi-objective adaptive fuzzy C means method. Figure 2a-c shows the effect of performing Gaussian filtering on different MRI brain images.

Gaussian filtering is more effective at smoothing images. It has been found that in the human visual perception system, neurons create a similar filter when visual images are processed.

Optimal multi-objective adaptive fuzzy C means clustering: Segmentation partitions an image into regions which can be semantically interpreted. The partitions of an image are non-overlapping, the union of which is the entire image. Segmentation meaningfully decomposes an image into parts with respect to the application under consideration. In the proposed system, segmentation is performed by the optimal multi-objective AFCM clustering method on the MRI brain image which has been filtered using Gaussian filtering for removing the noise and smoothing it. The clustering method for segmentation is described as follows.

With an eye on achieving competent image segments, the combined cuckoo search and FCM method is employed. FCM is identical to the K-means classifier which permits one image pixel essential belonging to multiple clusters. A class membership value is indicated to each pixel essential, in accordance with the similarity of the pixel essential to a particular class relation to other classes. Cuckoo search algorithm is a meta-heuristic algorithm which is motivated by the breeding character of the cuckoos and it is simple to execute. In Cuckoo search, a number of nests are available. Each egg signifies a solution and an egg of cuckoo represents a fresh solution. The fresh and superior solution substitutes, the worst solution in the nest. The procedure of segmentation is furnished as follows: Initiate the population of host nest hn_i, $I \in 1, 2, \ldots, s$ randomly. Here, s is the dimension of the population. The $s = 2 \times Q$ where Q-represent number of segments.

Choose a cuckoo arbitrarily and create a fresh solution by means of levy flights. Subsequently, assess the created cuckoo by means of the objective function for assessing the quality of the solutions. Evaluate, the fitness Function (F) of all the nests by means of Eq. 3:

$$F = \{\max(J_1), \max(J_2), \max(J_3), \max(J_4)\} \tag{3}$$

Where:

$$J_1 = \sum_{i=1}^{N} \sum_{j=1}^{ce} me_{ij}^{m} \| x_i - Ce_j \|^2 \tag{4}$$

Where:

me_{ij} = Membership of the ith pixel to the jth segment
x_i = The ith pixel
Ce_j = Centroid of the jth segment
N = Number of pixel points

$$J_2 = \sum_{i=1}^{N} |A_i - B_i| \tag{5}$$

Where:

J_2 = City block distance
A_i, B_i = The ith pixel points of the segment A and B

$$J_3 = \max_i |A_i - B_i| \tag{6}$$

Where, J_3 Chebyshev distance:

$$J_4 = \left(\sum_{i=1}^{N} \frac{1}{S_i^2} \left(|A_i - B_i| \right) \right)^{1/2} \tag{7}$$

Where:

J_4 = Seuclidean distance
S_i^2 = Standard deviation

The quality of the solution is assessed and a nest is chosen among s randomly. If the quality of the fresh solution in the chosen nest is superior to the previous solutions, it will be substituted by the fresh solution (Cuckoo). Or else, the preceding solution is maintained as the best solution.

Abandon the worst nests in accordance with their probability p_α values and create fresh ones. Subsequently, grade the best solutions according to their fitness function. Thereafter, recognize the best solutions and label as optimal solutions. Continue till the maximum iteration is achieved. At last, the best segmented image is achieved.

The multi-objective nature of the segmentation process leads to placing the pixels in segments in an optimal manner which leads to better quality segments than the segments formed by AKFM and OEFKCM methods. This helps in efficient identification of the abnormalities in the human brain. The following experimental results section accounts for the efficiency of the proposed method in comparison with the existing segmentation methods.

RESULTS AND DISCUSSION

Experiments have been performed on the MRI brain images obtained from the medical centre by preprocessing them using Gaussian filtering for noise removal and smoothing the image. The preprocessed image is given as input for segmentation by using the optimal MAFCM Clustering algorithm. The images obtained after preprocessing and segmentation are displayed in Fig. 3.

Figure 3a and b display the original and Gaussian filtered image of image1respectively. Figure 4a and b show the segmented image on application of AFKM and OEFKCM clustering respectively on the original image of image 1. Whereas, Fig. 4c shows the segmented image on application of the optimal MAFCM clustering after performing Gaussian filtering on image 1. Similarly, Fig. 5a and b display the original and Gaussian filtered image of image 2, an image of the brain with tumor, respectively. Figure 6a and b show the segmented image on application of AFKM and OEFKCM clustering, respectively on the

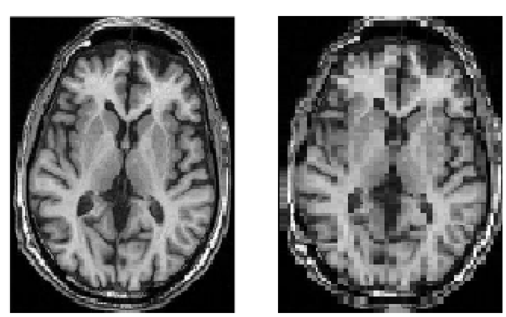

Fig. 3: a) Original image; b) Gaussian filtered image of image 1

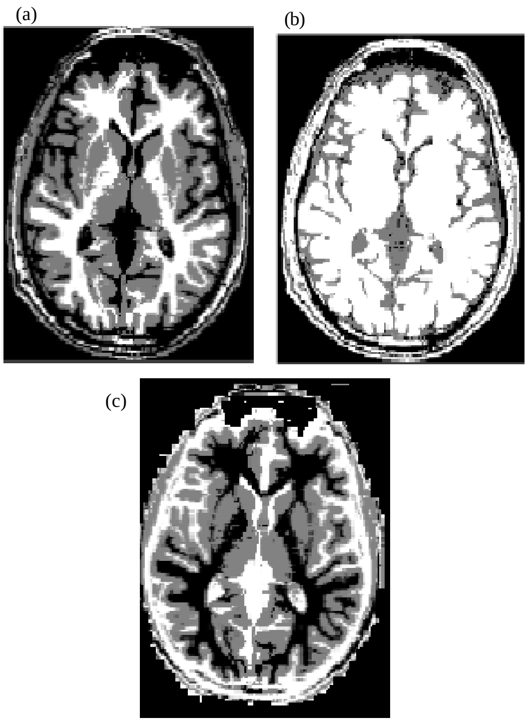

Fig. 4: Segmentation on image 1: a) AFKM clustered image; b) OEFKCM clustered image; c) Optimal MAFCM clustered image after filtering

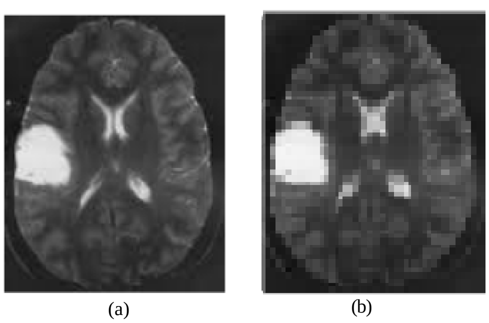

Fig. 5: a) Original image; b) Gaussian filtered image of image 2 (an image of a brain with tumor)

original image of image 2. Whereas, Fig. 6c shows the segmented image on application of the optimal MAFCM clustering after performing Gaussian filtering on image 2. From these images, it is found that the proposed method of segmentation leads to better quality and optimal clusters when compared to the existing AFKM and OEFKCM methods. This is justified by computing the following performance measuring parameters for the proposed and existing methods.

Performance evaluation

Structural similarity index measure: The Structural Similarity (SSIM) Index Method measures the presence of

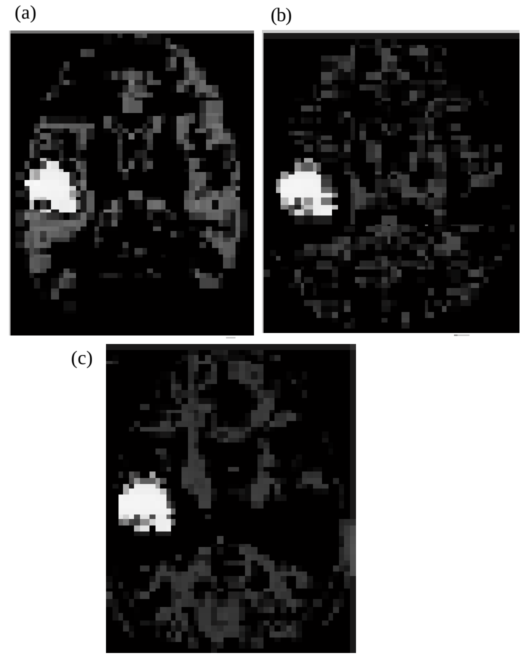

Fig. 6: Segmentation on image 2 (an image of a brain with tumor): a) AFKM clustered image; b) OEFKCM clustered image; c) Optimal MAFCM clustered image after filtering

similarity between two images. The SSIM index is a quality measure which measures the quality of one image by comparing, it with another image of perfect quality. Considering the case of two non negative images being compared, the mean intensity is given by:

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{8}$$

Standard deviation is given by:

$$\sigma_x = \left(\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2\right)^{\frac{1}{2}} \tag{9}$$

Contrast comparison c(x, y) is denoted by the Eq. 10:

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 C_2} \tag{10}$$

Luminance comparison is represented by:

$$\iota(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 C_1} \tag{11}$$

where, C1 and C2 are constants. Structure comparison is denoted by s(x, y) and is performed on normalized signal represented by:

$$\left(x-\mu_x\right)/\sigma_x \text{ and } \left(y-\mu_y\right)/\sigma_y \quad (12)$$

Finally, structural similarity index which involves the above mentioned parameters is given by:

$$\mathrm{SSIM}(x,y)=\left[l(x,y)\right]^{\alpha}\times\left[c(x,y)\right]^{\beta}\times\left[s(x,y)\right]^{\gamma} \quad (13)$$

That is:

$$\mathrm{SSIM}(x,y)=\frac{\left(2\mu_x\mu_y+C_1\right)\left(2\sigma_{xy}+C_2\right)}{\left(\mu_x^2+\mu_y^2+C_1\right)\left(\sigma_x^2+\sigma_y^2+C_2\right)} \quad (14)$$

where, α, β and γ are parameters which vary the relative importance of the three vital components for the computation of SSIM.

Structural content: Structural Content (SC) plays a vital role in assessing the quality of the segmented image and it is given by:

$$SC=\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(y(i,j)\right)^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x(i,j)\right)^2} \quad (15)$$

Where:

x(i, j) = The original (reference) image
y(i, j) = The modified (segmented) image
M and N = The matrix rows and columns, respectively.

Better quality is exhibited with smaller values of structural content.

Mean square error: Mean Square Error (MSE) is a measure of the amount of errors present in the image and it is denoted by:

$$MSE=\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x_{ij}-y_{ij}\right)^2 \quad (16)$$

Where:

x = The original image
y = The distorted image
M and N = The width and height of an image

A less value of MSE denotes less number of errors. MSE = 0 denotes absence of errors.

Peak signal to noise ratio: It is denoted by:

$$PSNR=10\log_{10}\frac{L^2}{MSE} \quad (17)$$

Where:

x = The original image
y = The distorted image
M and N = The width and height of an image
L = The dynamic range of the pixel values and MSE is the mean square error

Table 1: Performance evaluation for the proposed and existing methods

Image	Method	SSIM	SC	MSE	PSNR
1	AFKM	0.356	3.55	6.475	10.125
	OEFKCM	0.568	2.45	5.955	10.505
	MAFCM	0.835	1.05	3.125	12.992
2	AFKM	0.225	6.56	8.565	08.885
	OEFKCM	0.453	4.08	6.483	10.185
	MAFCM	0.674	1.14	3.335	12.954

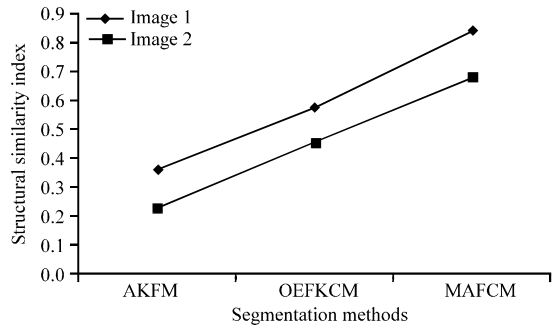

Fig. 7: Structural similarity index measure for two images for existing and proposed segmentation methods

PSNR calculates the peak signal to noise proportion between two images in the form of decibels. This is a feature measurement percentage between two images. Higher PSNR denotes better quality of the segmented image. Table 1 displays performance evaluation results for the existing and proposed segmentation methods for two images computed based on different performance metrics such as structural similarity index measure, structural content, mean square error, peak signal to noise ratio.

It is found from Table 1, that the different performance evaluation parameters display better results for the proposed method when compared to that of the existing methods with respect to two different MRI brain images, image 1 and 2. The result with respect to each of the parameters is displayed in the form of a graph in Fig. 7-10.

From Fig. 7, it is found that the value for SSIM is the highest for the proposed optimal MAFCM method in the case of both the images when compared to the existing methods denoted by AFKM and OEFKCM.

From Fig. 8, it is found that the value for SC is the lowest for the proposed optimal MAFCM method in the case of both the images when compared to the existing methods denoted by AFKM and OEFKCM.

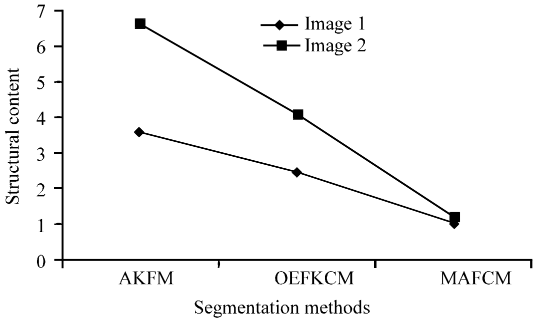

Fig. 8: Structural content for two images for existing and proposed segmentation methods

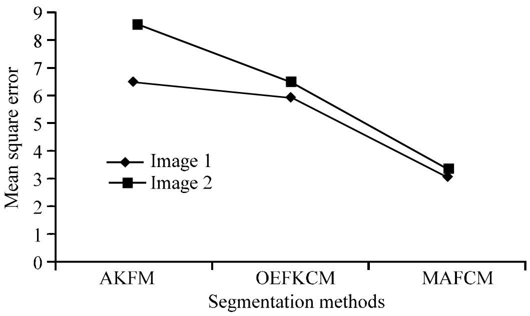

Fig. 9: Mean square error for two images for existing and proposed segmentation methods

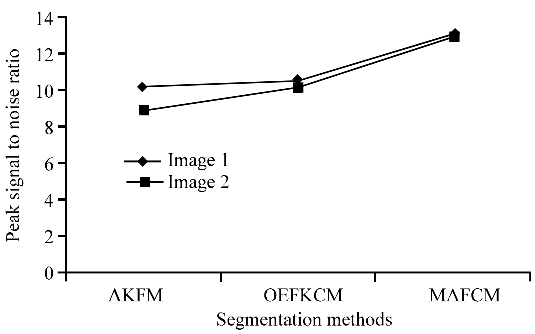

Fig. 10: Peak signal to noise ratio for two images for existing and proposed segmentation methods

From Fig. 9, it is found that the value for MSE is the lowest for the proposed optimal MAFCM method in the case of both the images when compared to the existing methods denoted by AFKM and OEFKCM.

From Fig. 10, it is found that the value for PSNR is the highest for the proposed optimal MAFCM method in the case of both the images when compared to the existing methods denoted by AFKM and OEFKCM.

From Fig. 7-10, it is found that the segments resulting from the proposed method are of better quality than those resulting from the existing methods. The performance

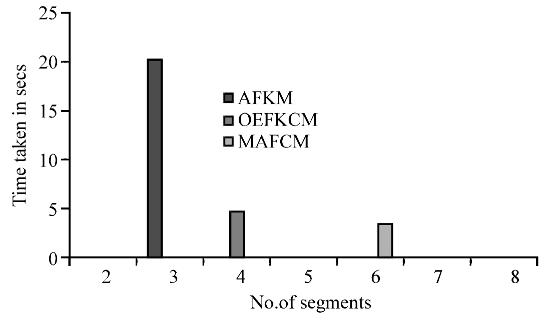

Fig. 11: Computation time for image 1 with respect to the existing and proposed segmentation methods for varying number of segments

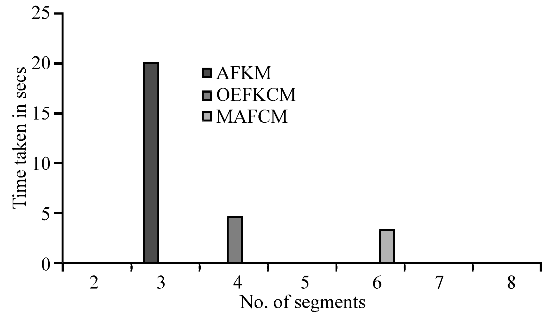

Fig. 12: Computation time for image 2 with respect to the existing and proposed segmentation methods for varying number of segments

Table 2: Image 1 segmentation results

Method	No. of segments	Time taken(s)
AFKM	3	20.252
OEFKCM	4	04.568
MAFCM	6	03.372

Table 3: Image 2 segmentation results

Method	No. of segments	Time taken(s)
AFKM	4	24.567
OEFKCM	6	06.053
MAFCM	8	05.532

of the existing and proposed segmentation methods are also assessed in terms of computation complexity and time complexity, the results of which are shown in Table 2 and 3.

The time taken by the proposed method is less when compared to the existing segmentation methods and also even in the case of more number of segments the amount of computations performed is less in the case of the proposed system which leads to less computation complexity and less time complexity. This is displayed in the form of a graph in Fig. 11 and 12, respectively for the two different MRI brain images, image 1 and 2.

Image 2 is the MRI image of a brain affected by tumor. The proposed segmentation method helps in identifying the tumor efficiently which is made possible by the resulting better quality and optimal segments.

CONCLUSION

In the proposed optimal multi-objective AFCM segmentation method, preprocessing is performed prior to segmentation using Gaussian filtering which removes noise and smoothens the image. Also, the multi-objective model of the objective function of the proposed method decreases the computation complexity and time complexity. Thus, the proposed segmentation method for the MRI brain image is very effective in producing optimal and better quality segments which leads to efficient identification of tumor and other abnormalities in the human brain. The results produced by the optimal MAFCM method are found to be 40 and 25% higher than those produced by the existing AKFM and OEFKCM methods, respectively. This is proved from the results obtained for the various performance evaluation parameters.

RECOMMENDATIONS

Further, this method of segmentation can be still improved by improving the quality of the input image by considering better methods of filtering which may still improve the quality of the image segments obtained.

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