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Performance Improved Modified Fuzzy C-Means Algorithm for Image Segmentation Applications

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Abstract. Fuzzy C-Means (FCM) algorithm is one of the commonly preferred fuzzy algorithms for image segmentation applications. Even though FCM algorithm is sufficiently accurate, it suffers from the computational complexity problem which prevents the usage of FCM in real-time applications. In this work, this convergence problem is tackled through the proposed Modified FCM (MFCM) algorithm. In this algorithm, several clusters among the input data are formed based on similarity measures and one representative data from each cluster is used for FCM algorithm. Hence, this methodology minimizes the convergence time period requirement of the conventional FCM algorithm to higher extent. This proposed approach is experimented on Magnetic Resonance (MR) brain tumor images. Experimental results suggest promising results for the MFCM algorithm in terms of the performance measures.

Key words: fuzzy C-means, segmentation, pre-processing, distance measures and computational complexity.

1. Introduction

Image segmentation is one of the important applications in the medical field especially for tumor size detection in abnormal brain images. The volumetric analysis of the tumor portion in the abnormal brain image is highly necessary to evaluate the nature of the treatment and for further treatment planning. Abnormal brain images are usually segmented using an automated system into several clusters with the tumor portion corresponding to a single cluster. The accuracy of the automated system must be sufficiently accurate to group all the tumor pixels in a single cluster. Several automated systems have been developed for this specific application.

Among the automated systems, fuzzy based techniques have been widely used for computational applications due to its high accuracy. FCM technique is one of the prime fuzzy based automated systems used for medical image segmentation. Literature survey reveals the usage of FCM technique for medical imaging applications (Winder *et al.*, 2008; Sikka *et al.*, 2009; Chen and Zhang, 2004; Balafar *et al.*, 2010). But one of the major

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drawbacks of the FCM algorithm is the requirement for huge computational time period. In order to tackle this problem, modifications on the conventional FCM algorithm must be performed in such a manner that the convergence rate is improved without any compromise in the accuracy. Several modified FCM algorithms have been proposed in the literature for medical imaging applications.

Cheng *et al.* (1998) have used the multistage sampling technique to speed-up the FCM algorithm. A fuzzy rule set was generated based on this technique for performance enhancement of FCM algorithm. An adaptive FCM algorithm for image segmentation is framed in Pham and Prince (1999). In this approach, the objective function is suitably modified to make the system adaptive. The emphasis of this approach is on improving the accuracy and this method is more suitable for noisy medical images. Khalighi *et al.* (2011) have developed an improved MRI segmentation technique by incorporating the spatial constraints in the conventional FCM algorithm. The convergence rate problem of the conventional FCM algorithm is tackled by Kolen and Hutcheson (2002). In this technique, the two update equations are merged into a single update equation. This technique minimizes the mathematical operations which ultimately improves the convergence rate of the algorithm. Liew and Yan (2003) have framed an adaptive spatial fuzzy clustering algorithm for 3-D MR images. A detailed comparative analysis is reported in this work to show the superior nature of the proposed approach in terms of segmentation efficiency.

A fast and accurate fuzzy clustering algorithm is implemented by Eschrich *et al.* (2003). This approach involves the concept of data reduction to reduce the iterative time period of the conventional FCM algorithm. Juang *et al.* (2007) have implemented self-organizing Sugeno model fuzzy systems for improving the accuracy of image classification applications. A time efficient Expectation Maximization (EM) algorithm for MR brain image segmentation is proposed by Yong and Huang (2006). This system is a hybrid approach involving the prior knowledge for image segmentation. An extensive analysis is also given in this report. Few high speed FCM algorithms are reported in Murugavalli and Rajamani (2006), Hemanth *et al.* (2011). Few modified fuzzy approaches are also used for decision making problems such as the classification applications (Meng and Chen, 2014; Zeng *et al.*, 2013). This technique minimizes the time period required for selection of cluster centers. This method employs two parallel processors for reducing the computational time period.

In this work, a novel methodology (MFCM) is adopted to speed-up the conventional FCM algorithm. The methodology consists of two phases: (a) data reduction and (b) conventional FCM algorithm. In the data reduction phase, the pixel intensities are initially converted to binary form. Then, the distance between two pixel intensities is determined based on the similarity in the bit positions. Several distance measures are estimated and all those pixels which shows low distance measure values (based on threshold value) are grouped in the same cluster. Several clusters are formed using the same procedure. Further, one representative (input pixel) from each cluster is selected and a new data set is formed whose size is very much lesser than the original dataset. In the second phase, conventional FCM algorithm is implemented using the reduced dataset. At the end of the FCM algorithm, the membership value of the representative pixel is assigned to the remaining pixels in the same cluster. This approach is experimented on brain image segmentation applications. Experimental results show promising results for the proposed approach in terms of convergence rate, segmentation efficiency, sensitivity and specificity.

2. Materials and Methods

The automated system consists of two major parts: (a) Conventional FCM based MR brain image segmentation and (b) Modified FCM based MR brain image segmentation. A comparative analysis is performed between these two approaches to show the superior nature of MFCM. In this work, real time abnormal MR images are used for testing the automated systems. These images are collected from M/s. Devaki Scan Centre, India. These images are gray scale images of size 256×256. A sample brain image is shown under Section 6.2.

Initially, the entire input dataset is given as input to the conventional FCM algorithm and the performance measures are calculated. Then, the modified FCM technique is tested with the reduced input dataset. In this modified system, an approach of data reduction of the input vector size is adopted to minimize the convergence time period of conventional FCM. This data reduction is achieved through the concept of distance metrics estimation. The distance measures used in this work are 'Matching' and 'Dice' (Finch, 2005). All the pixels whose distance measures are lesser than the specified threshold value are grouped under one cluster. Further, one pixel from each cluster is selected and used as input for the FCM algorithm. Finally, the membership values are shared among the corresponding cluster members. The performance measures of the conventional FCM and the modified FCM are further compared to prove the superior nature of the proposed system.

The rest of this paper is organized as follows: Section 3 covers the Conventional FCM algorithm, Section 4 deals with the Modified FCM algorithm in detail and Section 6 deals with the Experimental results and discussions.

3. Conventional FCM Based MR Brain Image Segmentation

Fuzzy C-means (FCM) is a method of clustering which allows one pixel to belong to two or more clusters (Yang *et al.*, 2005). The FCM algorithm attempts to partition a finite collection of pixels into a collection of "C" fuzzy clusters with respect to some given criterion. Depending on the data and the application, different types of similarity measures may be used to identify classes. Some examples of values that can be used as similarity measures include distance, connectivity, and intensity. In this work, distance is used as the similarity measure. Fuzzy C-means algorithm is based on minimization of the following objective function:

$$J = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2}, \tag{1}$$

u_{ij} is between 0 and 1, c_i is the centroid of cluster I, d_{ij} is the Euclidean distance between i_{th} centroid and j_{th} data point, $m \in [1, \infty]$ is a weighting exponent.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown in Eq. (1), with the update of membership u_{ij} and the cluster centers c_i by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left[\frac{d_{ij}}{d_{kj}}\right]^{2/(m-1)}}, \qquad c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}}, \tag{2}$$

where x = input feature set.

The entire algorithm can be summarized as follows:

Step 1: Initialize the membership matrix U.
Step 2: Calculate the center vectors c_i with u_{ij} at k_{th} number of iteration.
Step 3: Update the membership matrix u_{ij} for the k_{th} step and the next step.
Step 4: If the difference in membership values of two successive iterations is less than the specified error value (0.01), then STOP, otherwise return to step 2.

In the above algorithm, the entire image (all pixel feature values) is supplied as input for image segmentation. The number of clusters used in this work is 4 which correspond to Gray Matter (GM), White Matter (WM), Cerebro Spinal Fluid (CSF) and Tumor region. The images are of size 256×256 (65536 pixels) which is significantly high. This large dataset is one of the reasons for the inferior convergence rate of the conventional FCM. Also, several parameters such as the number of initial clusters, initial membership values, and number of iterations (or) error threshold value are randomly initialized and the parameter convergence is highly iterative in nature which consumes huge computational time period. This huge requirement for time period significantly limits the practical applications of the FCM algorithm. This drawback of computational complexity is eliminated in the modified FCM.

4. Modified FCM (MFCM) Based MR Brain Image Segmentation

In this proposed approach, the computational complexity problem of the conventional FCM is tackled by reducing the size of the input dataset. The data reduction is achieved through a sequence of steps which involved the concept of distance metrics. The reduced dataset is then given as input to the conventional FCM algorithm. Thus, the convergence is achieved quickly for the Modified FCM. The dimensionality reduction for faster convergence is achieved without compromising for segmentation efficiency. Thus this modified FCM yields accurate results within less time period. The step by step procedure of the Modified FCM is explained below.

4.1. *Algorithm*

The MFCM algorithm consists of two phases: (1) Data Reduction and Representative selection and (2) Conventional FCM algorithm and membership value assignment.

Table 1
General response table format.

Subject 1	Subject 2	
	‘1’	‘0’
‘1’	a	b
‘0’	c	d

Phase 1: Data Reduction and Representative Selection

Step 1: Initially, all the pixel intensity values are converted to binary representation. Since the intensity value ranges from 0 to 255, 8 bits are used to represent each pixel. For example, the intensity value ‘0’ is represented by 00000000 and ‘255’ is represented by ‘11111111’.

Step 2: The distance metrics between the first pixel and the rest of the pixels are determined in a sequential manner. For example, let us assume that the distance between the two pixels with values ‘93’ and ‘147’ are to be estimated. A pixel with the value ‘93’ is represented as ‘01011101’ and a pixel with value ‘147’ is represented as ‘10010011’. The distance measures are estimated by forming another table called as Response Table. Table 1 shows the general format for forming the Response Table.

Table 1 shows a 2×2 Response Table since only two subjects ‘1’ and ‘0’ are involved in the binary representation. Using this table , the distance measures such as ‘Matching’ and ‘Dice’ can be determined.

Step 3: In Table 1 ‘a’ corresponds to the number of times ‘11’ combination occurred in the same bit position for the two input pixels, ‘b’ corresponds to the number of times ‘10’ combination occurred in the same bit position, ‘c’ corresponds to the number of times ‘01’ combination occurred in the same bit position and ‘d’ corresponds to the number of times ‘00’ combination occurred in the same bit position. For the above mentioned example, the values of ‘a’, ‘b’, ‘c’ and ‘d’ are 2, 3, 2 and 1 respectively. Using these values, the distance measures are calculated.

Step 4: Two distance measures are used in this work. Initially, the parameters ‘Matching’ (M) and ‘Dice’ (D) are estimated and further the distance is calculated using (1-M) and (1-D) values. The parameter ‘Matching’ is estimated using the following formula:

$$\mathrm{M} = \frac{a+d}{a+b+c+d}. \tag{3}$$

This parameter is also called as ‘Matching Coefficient’ which involves the attributes which has a perfect match in the bit positions (‘11’ and ‘00’ combinations). Hence, higher the value of M better is the similarity between the two pixels. Another parameter ‘Dice’ is determined using the following formula:

$$\mathrm{D} = \frac{2a}{2a+b+c} \tag{4}$$

‘Dice’ corresponds to weighted distance measure for attributes with mutual agreement (‘11’ combination). The final distance measure through Dice Coefficient is determined by calculating (1-D). Hence, higher the value of D better is the similarity between the two pixels.

Step 5: The final distance measure through 'Matching' is determined by calculating (1-M) and the distance measure through 'Dice' is determined by calculating (1-D). For the sample input values, the parameter 'M' yields a value of 3/8 and 'D' yields a value of 4/9. Hence, the values of (1-M) and (1-D) are 5/8 and 5/9 respectively. The distance measure values range from 0 to 1. If the distance measure values are low, then the similarity between the pixels are high.

Step 6: The measure of closeness (or) similarity between the two pixels can be determined by comparing these values with a specified threshold value. Since two subjects (1 and 0) are involved in the binary representation, the threshold value is set to 0.5 in this work. Higher value of threshold results in less number of clusters. In this case, the probability of the non-neighboring pixels grouped under the same cluster is high. This leads to inaccurate segmented results. On the other hand, if the threshold value is too low, then the number of clusters increase which results in computational complexity. In this case, at one point of time, MFCM converges to FCM. The threshold value in this work is 0.5. The selection of threshold value is extremely important for the proposed approach. If the threshold value is too high, then the accuracy gets affected. If the threshold value is too low, then the computational complexity gets affected. Hence, an average value of 0.5 (between 0 and 1) is used in this work. All the pixels whose (1-M) and (1-D) values are lesser than 0.5 are grouped under the same cluster. The values in the specified example do not belong to the same cluster since their distance measure values are greater than the specified threshold value. Using the threshold value, the pixels are grouped into different clusters.

Step 7: The number of clusters is noted down and one representative from each cluster is selected. Mode is used to determine the representative pixel from each cluster. Mean also can be a choice but averaging yields decimal values which again require a quantization process. Hence, mode is used as the tool for selecting the representative pixel from each cluster. Thus, the new dataset consists of pixels equal to the number of clusters which is lesser than 65536 (original input dataset).

Phase 2: Conventional FCM Algorithm and Membership Value Assignment

Step 8: The conventional FCM algorithm discussed under Section 3 is repeated with the reduced dataset (representative pixels). At the end of the iterative process, the membership values are obtained for the representative pixels.

Step 9: Since the whole image is considered for segmentation, the remaining pixels (other than the representative pixels) also require membership values to complete the process. To fulfill this requirement, the membership value of the representative pixels is assigned to its cluster members. Since the representative and the cluster members are of same nature, the membership assignment methodology does not affect the segmentation efficiency. Thus, the membership values of the entire image are obtained with less number of iterations since the data set size is small.

From the above procedural steps, it is evident that the computational complexity of modified FCM is significantly better than the conventional FCM. The accuracy of the proposed approach is also guaranteed. Thus, the proposed approach proved to be a better alternative for conventional FCM algorithm. The concepts discussed in this section are verified by the experimental results.

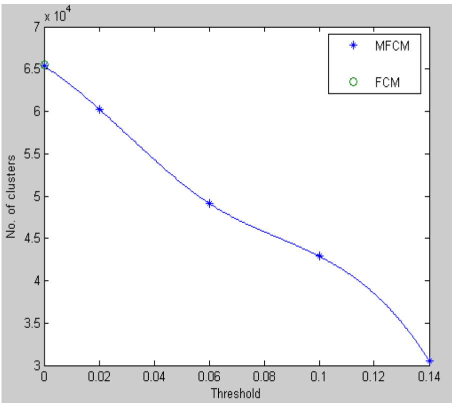
5. Experimental Results and Discussions

The proposed approach is tested with 260 real time MR images from four abnormal brain tumor categories. The experiments are carried out on an stockticker IBM PC Pentium with processor speed 1 GHz and 2 GB stockticker RAM. The software used for the implementation is MATLAB (version 7.0) (MATLAB, 1994-2002). The experiments are performed with the conventional FCM algorithm and the modified FCM algorithm. The performance measures used in this work are convergence time period and segmentation efficiency. Both qualitative and quantitative analysis is reported in this work. The rest of this section is organized as follows: Section 5.1 shows the analysis on distance metric calculation of modified FCM, Section 5.2 deals with the qualitative and quantitative analysis of segmentation results and Section 5.3 shows the comparative analysis between the two techniques in terms of performance measures.

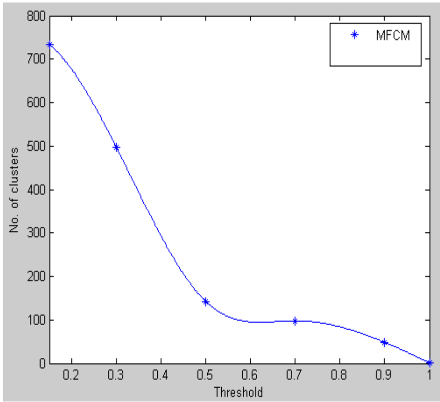
5.1. *Distance Metric calculation of Modified FCM*

The first step of the modified FCM algorithm is the distance metric calculation which is followed by clustering the pixels based on the threshold value (0.5). The calculation of distance measures between various pixels is an additional step of the modified FCM algorithm over the conventional FCM algorithm. Since the emphasis of the proposed approach is on convergence time period, the time taken for this extra procedure is extremely important to analyze the efficiency of the proposed approach. The time requirement for modified FCM must be minimal which also depends on the threshold value. The average convergence time is 2.1 s, 1.7 s, 1.1 s, 0.5 s and 0.2 s for threshold values of 0.15, 0.3, 0.5, 0.7 and 0.9 respectively. The time taken for clustering the pixels is inversely proportional to the threshold value. If the threshold value is maximum, then the number of grouping operations required is very less which minimizes the time period. If the threshold value is minimum, more number of clusters is to be formed which results in increased clustering operations. The threshold used in this work is 0.5. The number of clusters and the time taken also depend on the dispersion of intensity values in the input image. In any case, the maximum possible time period required is very less when compared with the convergence time required for conventional FCM.

After clustering into different groups, the representative pixels are selected. The time taken for representative pixel selection is very minimal. Hence, the results are not shown in this report. Thus, a new dataset is formed whose size is very much lesser than the original dataset. The number of clusters formed is approximately 142 for a threshold value of 0.5 and thus the reduced data set consists of only 142 pixels instead of 65536 pixels. The image segmentation is then performed with the original dataset (conventional FCM) and



(a)



(b)

Fig. 1. (a) Analysis of Threshold vs. number of clusters for threshold values between 0 and 0.14. (b Analysis of Threshold vs. number of clusters for threshold values between 0 and 1.

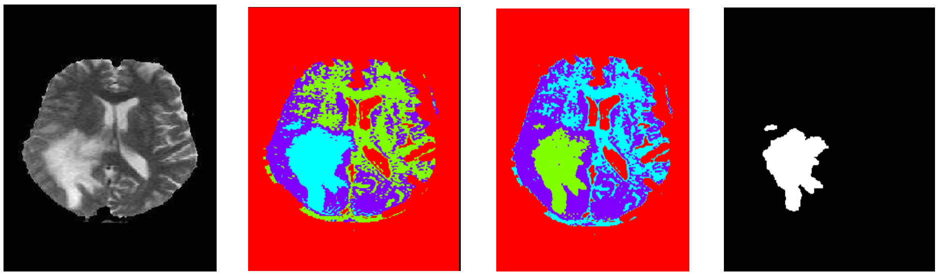
the reduced dataset (modified FCM). A graphical representation between the number of clusters and the Threshold values for the MFCM is shown in Fig. 1.

In the proposed MFCM, the number of clusters gradually increases with reduced threshold value. If the threshold value is 1 (maximum), then all the pixels are grouped under the same cluster which results in a single cluster. If the threshold value is 0.15, the number of clusters is 733. If the threshold value is reduced beyond 0.15, then the number of clusters drastically increases and slowly the proposed MFCM approximately converges to FCM. This concept is represented separately in Fig. 1(b). If the threshold value is 0 in MFCM, then the number of clusters is 65328. It may be noted that concept of threshold is not used in FCM and hence the number of clusters is 65536 (each pixel is considered as an individual cluster). The small difference in the number of clusters for MFCM and FCM with threshold value of 0 is because of the presence of more than one pixel with the same intensity value. In MFCM, these pixels are grouped under same cluster but they are treated separately in FCM. The experimental results are analyzed in terms of segmentation efficiency and convergence time period. A comparative analysis is also presented to show the superior nature of the proposed method.

5.2. *Image Segmentation Results*

Initially, image segmentation is performed with the modified FCM and then the results are compared with the conventional FCM. A qualitative analysis of the segmented image using the modified FCM is shown in Fig. 2.

Figure 2(a) shows the input MR brain image and Fig. 2(b) shows the clustered output of modified FCM technique. The threshold used for the images in Figure 2 is 0.5 and the number of groups formed during the pre-clustering process is 142. Representatives from these groups are observed and the conventional process of FCM clustering is performed with these representative pixels only. However, the objective is to cluster the image into 4 clusters corresponding to WM, GM, CSF and tumor region. The presence of abnormal



(a) (b) (c) (d)

Fig. 2. Segmented output of sample MR image: (a) Input image. (b) MFCM clustered output. (c) FCM clustered output and (d) Ground truth image.

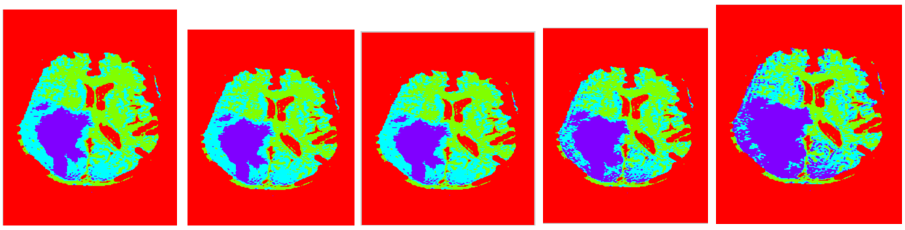
Table 2
Summarized performance measures of the modified FCM.

Technique	Threshold	Average segmentation efficiency (%)	Average convergence time (s)	Number of clusters
Modified FCM algorithm (MFCM)	0.15	95.9	190	733
	0.3	95.8	142	497
	0.5	95.5	78	142
	0.7	73	52	101
	0.9	56	34	52

tumor region (blue color) in one of the clusters is evident from Fig. 2(b). The conventional FCM clustered output is shown in Fig. 2(c). It is very difficult to compare the MFCM and FCM clustered outputs since both looks similar except for the change in colors. However, a careful observation shows that some of the tumor pixels are missed (numerous blue dots seen in green tumor portion) in Fig. 2(c). The results also show that the ground truth image closely resembles the tumor region in Fig. 2(b) than in Fig. 2(c). Thus, the efficiency of the proposed approach in terms of segmentation efficiency is verified qualitatively. The same process is repeated for all the images but only a sample is shown in Fig. 2.

A quantitative analysis is also performed to estimate the convergence rate and the segmentation efficiency numerically. Segmentation efficiency is the ratio of the number of correctly classified pixels to the total number of ground truth pixels. In this work, 260 images are used in the experiment. A variance of 1.3 is achieved for the segmentation efficiency and a variance of 42.4 is achieved for the convergence time with the 260 input images. These results are obtained with the threshold value of 0.5 in the MFCM algorithm. Table 2 illustrates the summarized performance measure analysis of MFCM.

From the above table, it is evident that the segmentation efficiency and the convergence time are inversely proportional to the threshold values. If the threshold value is very large, then all the pixels are grouped under the same cluster. This will result in a single representative pixel for the FCM segmentation. Such a method of segmentation leads to highly inaccurate results since all the pixels are shared with the same membership values. If the threshold value is small, a comparable number of clusters are formed which yield a set of representative pixels for image segmentation. But, if the threshold value is too small, the efficiency again decreases which is evident from Table 2.



(a) (b) (c) (d) (e)

Fig. 3. Modified FCM output with (a) 0.15 threshold, (b) 0.3 threshold, (c) 0.5 threshold, (d) 0.7 threshold and (e) 0.9 threshold.

In terms of convergence rate, selection of higher threshold values results in an exceedingly lower convergence time period for the automated system and a lower threshold value makes the system comparatively slower. The reason is that the number of representative pixels is more for a lower threshold value and low for a higher threshold value. Since there is no compromise on segmentation efficiency, threshold value of 0.5 must be adopted. Thus, for convergence, an average time period of 78 s is required for the modified FCM. This increases to approximately 136 s when the time taken for the distance calculation is also included. Thus, it is evident that the proposed FCM is highly efficient in terms of convergence rate and segmentation efficiency.

5.2.1. *Effect of Threshold Values on Performance Measures*

An extensive analysis is also performed to prove that the threshold value of 0.5 is better than the higher threshold values (0.5–1) in terms of segmentation efficiency. The qualitative analysis of an image with various threshold values is shown in Fig. 3.

The clustered output of MFCM algorithms for threshold values less than 0.5 is almost same without any major deviations. The segmentation efficiency of the image shown above is 95.2%, 95.4% and 95.5% respectively for threshold values of 0.15, 0.3 and 0.5. However, when the threshold value increases beyond 0.5, the change in the shape of the clustered tumor region is seen clearly in Figs. 3(d) and 3(e). A sample image is shown here but the same case persists for all the input images. Hence, it can be concluded that a threshold value beyond 0.5 is not suitable for MFCM specifically for segmentation efficiency. However, if a threshold value less than 0.5 is chosen (e.g. 0.3), then the computational complexity increases significantly. The computational complexity is directly proportional to the number of clusters. Hence, even though a lower threshold value yields a marginal improvement in segmentation efficiency, 0.5 is preferred to gain advantage in terms of both performance measures. It may be noted that the deviation in the efficiency values for threshold vales less than 0.5 is only in the range of (0.3%–0.1%).

5.3. *Comparative Analysis*

The same experiment is performed using the conventional FCM algorithm and the results are compared with the modified FCM algorithm. An extensive comparative analysis is shown in Table 3.

Table 3
Comparative Analysis of the proposed approaches.

Parameters/technique	Conventional FCM	Modified FCM (0.5 threshold value)
Input dataset size	256×256	$< 256 \times 256$
Average segmentation efficiency (%)	95.8	95.5
Average convergence time period (s)	1650	136

Table 4
Comparative analysis with other works in terms of segmentation efficiency.

Techniques/authors	Segmentation efficiency (%)	Convergence time (s)
Suppressed FCM/Hung *et al.* (2006)	90	3300
Alternative FCM/Hung *et al.* (2006)	73	255
Modified FCM/Winder *et al.* (2008)	75–80	–
FCM/Fletcher-Heath *et al.* (2001)	75–79	–
Fast FCM/Eschrich *et al.* (2003)	80	285
Modified FCM/Hemanth *et al.* (2011)	77	168
Proposed MFCM	95.5	136

The input dataset size used for the modified FCM is significantly less when compared with the conventional FCM. The extent of data reduction depends on two factors: (a) selection of the threshold value while calculating the distance measures and (b) dispersion of intensity values in the image.

In terms of segmentation efficiency, there is no significant difference between the modified FCM and the conventional FCM. Emphasis must be on the selection of threshold values since the segmentation efficiency depends on the threshold value. The segmentation efficiency of conventional FCM and modified FCM (with 0.5 threshold) are almost similar. Since the emphasis of this work is on convergence rate, the segmentation efficiency results are tolerable even though it is not higher than conventional FCM.

The significant results of this work are the reduction of convergence time period of conventional FCM which is evident from Table 3. The time taken for convergence of the modified FCM is exceedingly lower than the conventional FCM. Average speed-up factor of up to 12 is achieved with the modified FCM. This shows that the modified FCM is significantly faster than the conventional FCM. Another important fact is that even though the algorithm is implemented in a much faster processor, the MFCM always requires lesser time period than the conventional FCM. A comparative analysis with other research works is shown in Table 4. All these works have concentrated on improved versions of FCM algorithm.

From the comparative analysis, it is evident that the proposed approach yields better results in comparison with other works. However, it may be noted that the environment of the research works mentioned above may not be similar. Thus, this work has highlighted a suitable alternative to conventional FCM algorithm for real time applications.

6. Conclusions

In this work, a modified FCM algorithm is proposed for MR brain image segmentation applications. The proposed algorithm is based on the clustering technique which involves distance metrics calculation ('Matching co-efficient' and 'Dice co-efficient'). Average speed up factors of 12 is achieved through the proposed approach over the conventional FCM algorithm without any compromise in the segmentation efficiency. Thus, this work highlights a practically feasible FCM algorithm for real-time applications where convergence time period is extremely significant. Several other distance measures may be implemented to enhance the performance of the proposed approach.

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Našesnis modifikuotasis neraiškiųjų C-vidurkių algoritmas skirtas vaizdų segmentavimo taikymams

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Neraiškiųjų C-vidurkių (NCV) algoritmas yra vienas iš labiausiai taikomų vaizdams segmentuoti neraiškiųjų algoritmų. Nors šis algoritmas yra pakankamai tikslus, tačiau atliekamų skaičiavimų sudėtingumas neleidžia NCV algoritmo naudoti realaus laiko uždaviniuose. Šiame darbe, sprendžiant algoritmo greitesnio konvergavimo problemą, pasiūlytas modifikuotasis neraiškiųjų C-vidurkių (MNCV) algoritmas. MNCV algoritme, remiantis panašumo matais, įėjimo duomenys suskirstomi į telkinius ir toliau NCV algoritmu apdorojami tik telkinių centrų duomenys. Toks sprendimas sąlygoja žymiai greitesnį algoritmo konvergavimą. Siūlomas segmentavimo būdas išbandytas su galvos smegenų vėžiu sergančių pacientų magnetinio rezonanso tomografijos vaizdais. Gauti palyginamieji MNCV algoritmo našumo eksperimentiniai rezultatai atskleidžia jo privalumus.