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Improved Spatial Rough Set Fuzzy Method of Precious Noisy Segmentation

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ABSTRACT

Image segmentation is an essential process in the visualization of human organs, particularly during clinical analysis of magnetic resonance (MR) images. In this paper, animproved rough-fuzzy c-means (RFCM) algorithm is presented for segmentation of brain MR images in noisy environment. The RFCM algorithm comprises a judicious integration of the rough sets, fuzzy sets, and c-means algorithm. While the concept of lower and upper approximations of rough sets deals with vagueness and incompleteness in the class definition of brain MR images, the membership function of fuzzy sets enables efficient handling of overlapping classes. The crisp lower bound and fuzzy boundary of a class for spatial data are introduced in the RFCM algorithm that enable efficient segmentation of brain MR images. Initial classes,which are defined based on maximization of class separability, is used to find new classes in RFCM. The effectiveness of the RFCM algorithm, along with a comparison with other related algorithms, is demonstrated on a set of brain MR images.

Keywords: Rough sets, fuzzy sets, medical imaging, segmentation, c-means algorithm.

1. INTRODUCTION

Medical imaging and analysis has become an important procedure in the diagnosis and treatment of the diseases caused in human beings. It is the process of viewing the body parts, organs, tissues and cells for performing clinical diagnosis, prescription, treatment and monitoring of diseases. Imaging techniques consist the fields of radiology, nuclear medicine and optical imaging and image-guided intervention. Radiological methods are very common that provide the anatomical and physiological detail of the human body at very high spatial and temporal resolution. This discipline covers methods such as ultrasound, CT, X-ray and MRI. The accuracy of analysing the radiological methods given above are made possible by adopting a technique called Segmentation.Medical Image Segmentation is the process of automatic or semi-automatic detection of boundaries and features within a 2D or 3D image. It is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics, control systems, Fingerprint recognition and Machine vision etc. It is mainly required to distinguish objects of the image from its background. Some of the practical applications of image segmentation include Medical imaging such as locating tumours and other pathologies, measuring tissue volumes, location of tumour in radiological images.

A major difficulty of medical image segmentation is the high variability in medical images, the human anatomy itself shows major variation modes. Possible applications are measurement of organs, cell counting, or differentiation based on the boundary and feature information extracted earlier. The different algorithms thatpresent in medical image segmentationare Feature-Space Based Techniques, Clustering methods such as K-means algorithm & Fuzzy k-means algorithm, Histogram thresholding, Image-Domain or Region

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Based Techniques that consist of Split-and-merge techniques, Region growing techniques, Neural-network based techniques, Edge Detection Technique, Fuzzy Techniques and Physics Based Approaches. Clustering technique has a wide and rich history of successful image information among all. The process of converting a dataset by clusters, which are the group of data points that belong together, is known as clustering.It is done by grouping the data in the form of their properties and characteristics. FCM is one of the major techniques used to perform medical image segmentation and it earns satisfactory results in many applications. Although the FCM is good at noise free images, it lags to blend some clear information about the features of the image like location, surface, etc. Due to this fact, it is required to provide a universal framework which can be used in many medical image applications.

The basic FCM segmentation method has been enriched with Rough set processing methods, which provide good results than the other systems. This theory is based on the object's discernibility and can handle uncertainty which is often phenomenal in medical images due to noise and poor acquisition quality. Additionally, it helps in reducing the feature space by introducing a new technique called granular knowledge that improves the performance of fuzzy algorithm to show better results. They also involve in the removal of noises present in the high risky medical images and classify the features present in them separately for further providing a clustered features describing the nature of diseased part or cells. The functioning of FCM in collecting and segmenting the medical images are thus improved by the proposed Rough set theory in them.

2. LITERATURE REVIEW

Mahmoud *et al.* [11] have implement brFCM algorithm that was a faster version of FCM algorithm, on two different GPU cards, Tesla M2070 and Tesla K20m. They comparedtheir brFCMwich was GPU-based implementation with its CPU-based sequential implementation. Additionally, they compared brFCM with conventional version of FCM algorithm. In experiments, they utilized lung CT and knee MRI images to do clustering. The outputs revealed that their implementation had a noteworthyenhancement over the conventional CPU sequential implementation. GPU parallel brFCM was 2.24 times quickerwith compared to its CPU implementation and 23.43 times quickerwith compare to a GPU parallel implementation of conventional FCM.

Bingquan *et al.* [12] have presented an enhanced FCMcombining mean shift algorithm to optimize segmentation visual effectsand efficiency of conventional FCM. At first, image segmentation carried out into several smallhomogeneous area by utilizing the mean shift algorithm. After that, image local entropy was taken into consideration todefine new nodes spatial and gray feature. At last, an exponential function which wascapable to well simulate human nonlinear visual reaction was utilized to compute similaritybetween the new node and the cluster centre node. The experimentationoutcome showed theefficiency and robustness of thesuggested FCM.

Ayuni Fateeha *et al.* [13] presented an automatic segmentation of brain lesions from diffusion-weighted imaging (DWI) by utilizing FCM algorithm. The lesions were acute stroke, tumour and chronic stroke. Pre-processing was applied to the DWI for intensity normalization, background removal and enhancement. After that, FCM was used for the segmentation process. The FCM delivereda well segmentation yield in hyperintensity and hypointensity lesions according to the high value of the area overlap, and low value of false positive and false negative rates. The average dice indices were 0.73 (acute stroke), 0.68 (tumour) and 0.82 (chronic stroke).These lesions were successfully segmented in this system by using this weighting technique due to their hypo intensity value properties.

Li Ma *et al.*[14] presented a hybrid artificial fish swarm algorithm (HAFSA). Itcombined artificial fish swarm algorithm (AFSA) with FCM whose benefits of global optimization searching and parallel computing ability of AFSA were utilized to find a good outcome. In the meantime, Metropolis criterion and noise reduction mechanism were also introduced to AFSA to enhance the convergence rate and antinoise capability. The artificial grid graph and Magnetic Resonance Imaging (MRI) were used in the experimentation.The test output showed that the proposed algorithm had stronger antinoise capability and higher accuracy. Numerous evaluation indicators also demonstrated that the effect of HAFSA was more superb than FCM and suppressed FCM (SFCM).

Pradipta Maji *et al*. [15] have presented a generalized hybrid unsupervised learning algorithm named as rough-fuzzy possibilistic C-means (RFPCM). It comprised a judicious integration of the principles of rough and fuzzy sets. It incorporated both probabilistic and possibilistic memberships simultaneously to avoid the problems of noise sensitivity of fuzzy C-means and the coincident clusters of PCM. Fundamental idea of crisp lower bound and fuzzy boundary of a class, which was introduced in the RFPCM, enabled efficient selection of cluster prototypes. Several quantitative indices were introduced on the basis of rough sets for the evaluation of performance of the proposed C-means algorithm. The efficiency of the algorithm, along with a comparison with other algorithms presented qualitatively and quantitatively based on a set of real-life data sets.

3. PROPOSED SYSTEM

Let $X = \{x_1, x_2, ...x_N\} \subset R^k$ in the k-dimensional space denotes the finite set of N objects, $Q = C \cup D$, where C is a set of condition at tributes, D is a set of decision attributes denotes a finite set of attributes, $f : X \times Q \to V$ denotes the information function (which designates the attribute value of each object x in X). Then a decision table knowledge representation system can be represented as

$$S =< X, Q, V, f > \tag{1}$$

This table may be unnecessarily large because it could be redundant at least in two ways. The same or indiscernible objects may be represented several times, or some attributes may be superfluous. The notion of equivalence relation is used to tackle this problem.

It determines the approximation space AS = (U, IND (A)) in set S. Assuming A $\subseteq$ Q and X $\subseteq$ U, lower/ upper approximate set of X can be defined as

$$A^{-}(X) = U\{Y|(Y \in U|IND(A) \wedge Y \cap X \neq \Phi)\} \tag{2}$$

$$A_{-}(X) = U\{Y|(Y \in U|IND(A) \wedge Y \subseteq X)\} \tag{3}$$

Here $A^{-}(X)$and $A_{-}(X)$constitute a dualistic group ($A^{-}(X), A_{-}(X)$), which is called rough set based on A. A positive domain of X is defined as POSA(X) = $A_{-}(X)$. Based on what mentioned above, knowledge reduction can be implemented by identifying equivalence classes.

Fuzzy c-means (FCM) is a scheme of clustering which allows one section of data to belong to dual or supplementary clusters. Main objective of fuzzy c-means algorithm is to minimizeeq. (4):

$$J_{FCM} = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} \| x_i - v_j \|^2, \tag{4}$$

In which c is a positive integer that is denoted as $(2 < c << N)$, $\|x_i - v_j\|$ be the Euclidean distance between the i[th] data and j[th] cluster centre. In eq. (1), u_{ij} be the membership value for each pixel i in j[th] cluster $(j = 1,2,....., c)$ in image I consisting a set of grayscales x_i at pixel $i(i = 1,2,....., N)$ at $X = \{x_1, x_2, ...x_N\} \subset R^k$ in k-dimensional space with the cluster centres $v = \{v_1, v_2, ...v_c\}$.

The noises and variations present in the image I can be removed with the addition of spatial parameters of surrounding pixels as,

$$J_{FCM} = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \| x_i - v_j \|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \Big(\sum_{r\in N_i} \| x_r - v_j \|^2\Big), \tag{5}$$

Where α a parameter to manage spatial information of neighbors N_i is the set of pixel and N_r is the cardinality of N_i in eq. (5).

The calculation of neighborhood pixel at each and every step can be minimized with the term $(1/N_R)\sum_{r\in N_R} \| x_i - v_j \|^2$ with $\| \overline{x_i} - v_j \|^2$ where $\overline{x}$ is the grayscale of a filtered image.

$$J_{FCM} = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \| x_i - v_j \|^2 + \alpha\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \| \overline{x_i} - v_j \|^2, \tag{6}$$

The eq. (6) can be rewritten as,

$$J_{FCM} = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \| x_i - v_j \|^2 + S, \tag{7}$$

Where, $S = \alpha\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \| \overline{x_i} - v_j \|^2$, the spatial parameter is denoted in the simplified form as S, which is calculated again once the kernel is added.

The function J_{FCM} is minimized by a famous alternate iterative algorithm. Now consider the proposed kernel fuzzy c-means (KFCM) algorithm. Define a nonlinear map as $\phi : x \rightarrow \phi(x) \in F$ where $x \in X$ and X denotes the data space and F is the transformed feature space with higher even infinite dimension. KFCM minimizes the following objective function given in eq. (7) by,

$$J_{KFCM} = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \| \phi(x_i) - \phi(v_j) \|^2 + S, \tag{8}$$

Where eq. (8) denotes the proposed Kernel FCM equation, denoted by J_{KFCM}. The kernel function is given by

$$\| \phi(x_i) - \phi(v_j) \|^2 = K(x_i, x_i) + K(v_j, v_j) - 2K(x_i, v_j) \tag{9}$$

Where $K(x_i, v_j) = \phi(x_i)^T \phi(v_j)$ is an inner product kernel function. If we adopt the Gaussian function as a kernel function, then the eq. (9) and (8) are combined and can be rewritten as,

$$J_{KFCM} = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} \big(1 - K(x_i, v_j)\big) + S \tag{10}$$

Given by the Gaussian formula $K(x_i, v_j) = \exp\left(-\|x_i - v_j\|^2 / \sigma^2\right)$, then $K(x_i, x_i) = 1$ respectively. The eq. (10) can be further minimized by adding an alternative optimization method membership function as,

$$u_{ij} = \frac{\big(1/\big(1 - K(x_i, v_j)\big)\big)^{1/(m-1)}}{\sum_{k=1}^{c}\big(1/\big(1 - K(x_i, v_j)\big)\big)^{1/(m-1)}}, \tag{11}$$

$$v_j = \frac{\sum_{i-1}^{N} u_{ij}^m K(x_i, v_j) x_i}{\sum_{i=1}^{N} u_{ij}^m K(x_i, v_j)}, \tag{12}$$

Where x_k is an optimization vector used for minimization given in eq. (11) and (12).

The FCM cluster centres sets can be reduced by adding Rough sets is described below, in which membership value of features are acquired first to further reduce it.

The initial cluster centres $v = \{v_1, v_2, ...v_c\}$ were generated by randomly choosing c points from an image point. $c \in [c_{\min}, c_{\max}], c_{\min} = 2$, $c_{\max} = \sqrt{n}$, where n is the image pixel number. Then the numeric image features are considered as $\{F_i, i = 1,2,...n\}$ for each cluster centres.

The feature F_i is described in terms of its fuzzy membership values corresponding to 3 linguistic fuzzy sets, namely, low(L), medium (M), and high (H), which characterized respectively by a π membership function.

$$\mu(F_i) = \begin{cases} 2\left[1 - \frac{|F_i - c|}{\lambda}\right]^2 & for\ \frac{\lambda}{2} \le |F_i - c| \le \lambda \\ 1 - 2\left[\frac{|F_i - c|}{\lambda}\right]^2 & for\ 0 \le |F_i - c| \le \frac{\lambda}{2} \\ & 0 \end{cases} \tag{13}$$

Where λ is the radius of the –membership function with c as the central point. To select the centre c and λ radius. Thus, the initial clustering centres set where each cluster centre is represented with the help of collecting fuzzy sets.

3.1. Constitution of a Decision Table for the Initial cluster Centres Set

1. Degree of similarity between two different clusterscentres is defined as mentioned in eq. (14),

$$\alpha = \frac{\sum_{i=1}^{n} \mu(F_i)}{n}, \tag{14}$$

   In which the value of similarity varies according to the cluster centres. It is high when the two cluster centres are closer.

2. In a same cluster centres set, if a cluster centre has a same similarity value to another one, then they are called redundant cluster centre each other.
   - If A and B are redundant cluster centre each other, B and C are redundant cluster centre each other, then A, B and C belong to a same redundant cluster centre.

$$\text{A} \leftrightarrow \text{B, B} \leftrightarrow \text{C} \Rightarrow \text{A} \leftrightarrow \text{B} \leftrightarrow \text{C} \tag{15}$$

   - Based on what mentioned above, taking initial cluster centres as objects, taking cluster centresfeatures F_i, the central point c and the radius λ as conditional attributes, taking degree of similarity between two different cluster centres as decision attribute by computing the π–membership function value, then a decision table for the initial cluster centres set can be constituted as follows:

$$T =< X, P \cup R, C, D > \tag{16}$$

- Where $X = \{x_i, i = 1,2,...m\}$, it denotes an initial cluster centres set. $P \cup R$ is a finite set of the initial cluster centre category attributes, where P is a set of condition attributes, R is a set of decision attributes. $C = \{p_i, i = 1,2,.... n\}$, where p_i is a domain of the initial cluster centre category attribute. $D : X \times P \cup R \rightarrow C$ is the redundant information mapping function, which defines an indiscernibility relation on X.

3.2. Eliminating redundant cluster centres from the initial cluster centres set

Assuming D(x) denotes a decision rule, D(x)|P (condition) and D(x)|R (decision) denote the restriction that D(x) to P and R respectively, i and j denotes two different cluster centres respectively, and other assumptions are as the same as what mentioned above. Based on what described above, the initial cluster centres set can be optimized by reduction theory according to the following steps:

1. Deducing the compatibility of each rule of an initial cluster centre set decision table.
   - If D(I)|P (condition)= D(j)|P (condition) and D(i)|R (decision)= D(j)|R (decision), then rules of an initial cluster centre set decision table are compatible;
   - If D(i)|P(condition)= D(j)|P(condition), D(i)|R(decision) ≠ D(j)|R(decision), then rules of an initial cluster centre set decision table are not compatible.
2. Ascertaining redundant conditional attributes of an initial cluster centre set decision table.
   - If an initial cluster centre set decision table are compatible, then when p∈P and Ind (P) = Ind (P-p), p is a redundant attribute and it can be leaved out, otherwise p can't be leaved out.
   - If an initial cluster centre set decision table are not compatible, then computing its positive region POS (P, R). If p∈P, when POS (P, R) =POS (P-p, D), then p can be leaved out, otherwise p can't be leaved out.
3. Eliminating redundant decision items from an initial cluster centre decision table. For each condition attribute p carries out the process mentioned above until condition attribute set does not change.

   As soon as redundant initial cluster centres in the initial cluster set is eliminated, a reduced cluster centre set is used as the FCM initial input variance for image segmentation.

   To evaluate the quality of clusters, the Xie-Beni index was used as the cluster validity index in this paper. The Xie-Beni index is expressed as:

$$XiB = \frac{\sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij} \left(1 - K\left(x_i, v_j\right)\right)}{\min_{ij} K\left(v_i, v_j\right)} \tag{17}$$

A smaller XB reflects that the clusters have greater separation from each other and are more compact. Based on what descript above, now the procedure for Rough Sets based FCM image segmentation method can be summered as follows:

1. Randomly initialize the number of clusters to c, where 2 ≤ c ≤ n and n is number of image points.
2. Randomly chooses c pixels from the image data set to be cluster centres.
3. Optimize the initial cluster centres set by Rough Sets.
4. Set step variable t=0, and a small positive numbers.
5. Calculate (at t=0) or update (at t>0) the membership matrix u_{ij} using eq. (11).
6. Update the cluster centres by equation (12).
7. Compute the corresponding Xie-Beni index using equation (17).

8. Repeat step 5-8 until $\left\| XiB^{(t+1)} - XiB^{t} \right\| < \varepsilon$.
9. Return the best XiB and best centre positions.

4. EXPERIMENTAL RESULTS

In this section, experimental results have been described in detailed. There are totally 7 algorithms used in these experiments, i.e.k-means, FCM, Kernel FCM, Particle Swarm Optimization-SFCM (PSO-SFCM), Artificial Bee Colony KFCM, AWKFCM and our proposed Spatial Rough set KFCM. They were also used as the parameter for FCM.

The Xie-Beni index value has been utilized to evaluate the quality of the classification for all algorithms. All experiments were implemented on PC with 1.8GHz Pentium IV processor using MATLAB (version 6.5).Every experiments were conducted with window size of 3 × 3 pixels. The accuracy of segmentation was measured using the Jaccard Similarity (JS) metric which was defined as the ratio between the intersection and union of segmented volume $S1$ and ground truth volume $S2$.

$$JS(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \tag{18}$$

The proposed Improved Rough set KFCM result in producing strong robustness and better performance over other existing algorithms. Estimation of spatial rough set theory leads to better kernel selection and clustering formation is also done in this paper. It shows good balance between smooth borders and preserving image details due to the addition of Rough set KFCM technology.

Many investigations have been carried out so far to enhance the quality of segmentation. The below mentioned figure analysis fig 1, 2, 3, 4, 5, 6, 7 clearly shows that the proposed algorithm performs well in medical image representation. A normal input image fig 1 is taken from Digital Imaging and Communications in Medicine (DICOM) studies and experiments are conducted with the above mentioned algorithms. The number of tissue classes in the segmentation was set to three, which corresponds to gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). Back-ground pixels are ignored in the computation. The application of Rough set fuzzy retains the picture details and displays a clear view of balance between smooth borders and edges, which can be visible from fig 7.

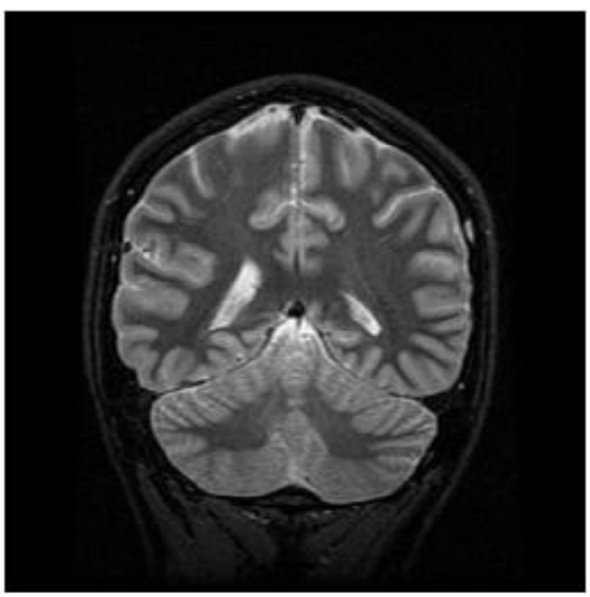

Figure 1: Input DICOM Image

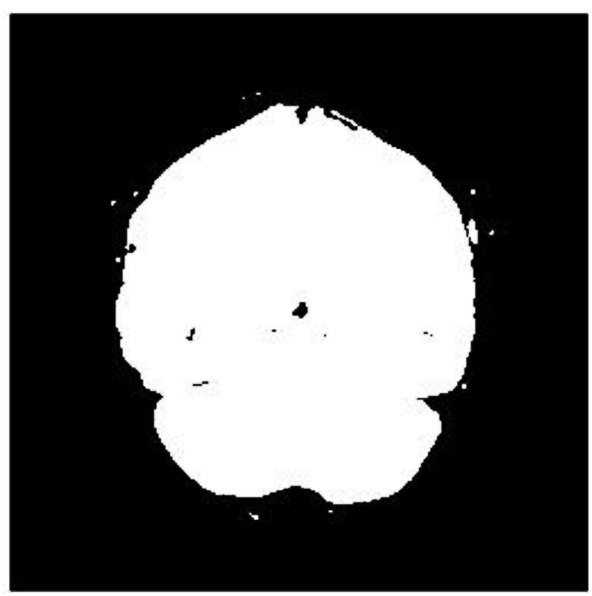

Figure 2: K Means Clustering

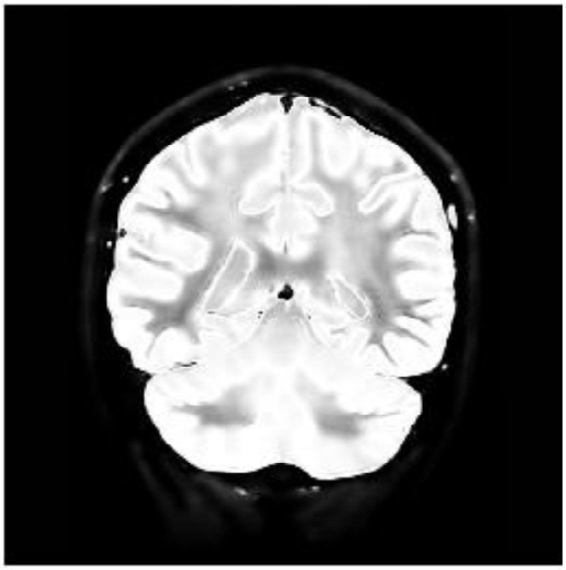

Figure 3: FCM Clustering

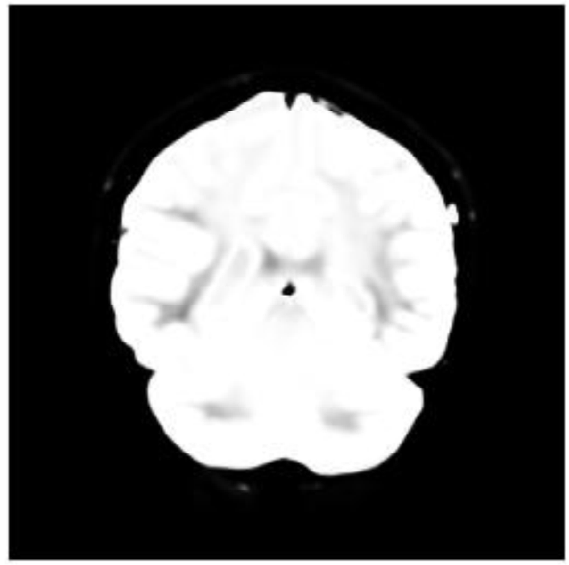

Figure 4: SFCM-MPSO Clustering

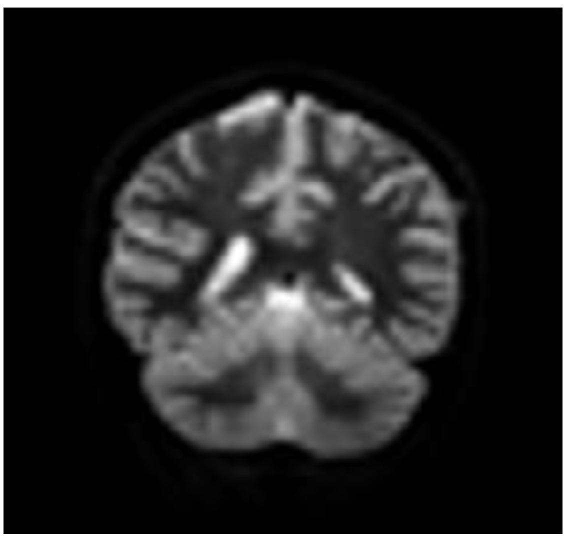

Figure 5: ABC-KFCM

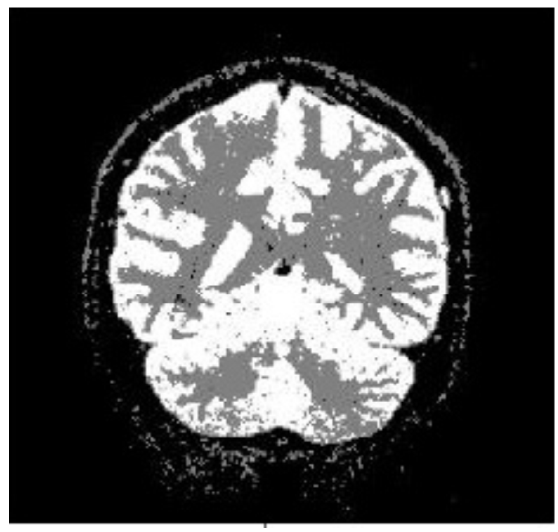

Figure 6: AWCKFCM

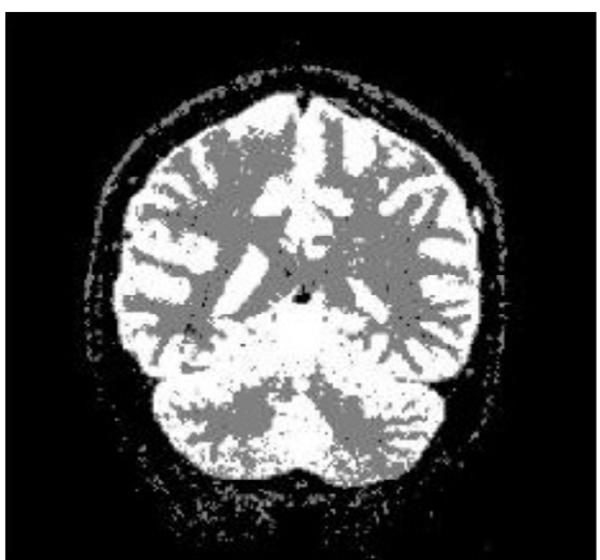

Figure 7: Rough set KFCM

The table 1 and table 2 denotes the ranges of the k-means, FCM, KFCM, PSO-SFCM, ABC-KFCM, AWCKFCM, Rough set KFCM by means of accuracy of segmentation. The centroid value represents the average accuracy of segmentation. It also calculates the pixel error value with the centroid, which is given in table 2.

Table 1
Comparison analysis of segmentation accuracy and pixel error for medical images

Method	*Pixel Error Count and Cluster Centers*				*Segmentation Accuracy*
	Centroids	*Error Pixel*	*Centroids*	*Error Pixel*	*Average Accuracy*
K-Means	6.6254, 98.6115	1195	6.4421, 77.6890, 125.2745	1201	91.68
FCM	6.7935, 101.1125	976	6.154, 76.2868, 123.0570	987	93.18
KFCM	6.2517, 99.9285	522	121.5948, 70.2040, 4.3013	548	96.28
PSO-SFCM	6.7106, 99.1261	437	76.2868, 6.1541, 123.0570	440	96.95
ABC-KFCM	6.2476, 99.9264	424	121.5908, 70.1984, 4.2976	429	97.03
AWCKFCM	6.2517, 99.9342	654	122.6012, 70.2531, 4.3013	673	96.88
Rough set KFCM	6.1889, 99.9970	619	109.6342, 67.8901, 4.8976	764	97.65

Table 2
Comparison analysis of segmentation accuracy and pixel error for medical images

Method	*Pixel Error Count and Cluster Centers*				*Segmentation Accuracy*
	Centroids	*Error Pixel*	*Centroids*	*Error Pixel*	*Average Accuracy*
K-Means	151.4870, 25.5933	63655	121.0076, 167.7719, 22.3747	63667	75.73
FCM	153.6055, 25.0161	59223	122.3355, 168.4849, 20.4672	59238	77.40
KFCM	23.5953, 154.3047	51236	18.3111, 168.1686, 121.3009	52656	80.18
PSO-SFCM	153.6055, 25.0161	48744	118.1560, 167.5352, 21.7026	48751	81.40
ABC- KFCM	23.5943, 154.2998	40589	18.3012, 168.1643, 121.2986	40899	84.45
AWCKFCM	23.5953, 154.4471	52387	18.3210, 168.1684, 121.2988	53664	81.02
Rough set KFCM	23.5953, P 154.4471	56745	18.5890, 168.7690, 121.2988	53986	82.67

5. CONCLUSION

A robust segmentation technique is presented in this paper by integrating the merits of rough sets, fuzzy sets, and c-means algorithm, for brain MR images. Some new measures are introduced, based on the local properties of MR images, for accurate segmentation. The method, based on the concept of maximization of class separability, is found to be successful in effectively circumventing the initialization and local minima problems of iterative refinement clustering algorithms like c-means. The effectiveness of the algorithm, along with a comparison with other algorithms, is demonstrated on a set of brain MR images.

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