



Rough Set based MRI Medical image segmentation using optimized initial centroids

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Abstract: Medical image segmentation plays a vital role in image processing due to the catering needs of the medical images in automating, delineating anatomical structures and diagnosis. Very often the medical images contain uncertain, vague, and incomplete data definition. The concepts of lower and upper approximations of rough sets effectively handle this data. In this paper, rough sets based clustering is analyzed with respect to K-means and Fuzzy C-means algorithms for MRI images of BrainWeb database and the centroids are optimized using local maxima of histogram. The performance of proposed Rough K-means(RKM) and Rough Fuzzy C-means (RFCM) is evaluated and compared with classic k-means (KM) and fuzzy C-means (FCM)

Keywords: segmentation; k-means; C-means; Rough k-means; Rough fuzzy C-means

I. I. Introduction

Images acquired through the techniques like Magnetic Resonance Imaging (MRI), Ultra sound imaging, Computed Tomography (CT), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), and functional MRI (fMRI) are studied and analyzed by interception and perception of the radiologists [9]. There is the need for segmentation algorithms for delineating of anatomical structures and other region of interest for assisting and automating radiologist's tasks. There exist numerous biomedical imaging applications based on segmentation algorithms such as the extracting tissue volumes, diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data, and computer integrated surgery [1].

In this paper, Medical image segmentation & rough sets are briefly discussed in section II. Optimized centroid algorithms for Rough k-means and Rough fuzzy C-means are presented in section III. Experimental results are presented in section IV. Concluding remarks are given in section V.

II. Medical Image segmentation using Rough sets

A. Medical image segmentation

There exist many approaches to image segmentation such as histogram based methods, edge detection, region growing, split and merge methods, PDE based methods and clustering methods[3]. However, in this paper clustering techniques are considered where each image pixels is assigned to a cluster such that all members in the same cluster are similar. In Classical K-means clustering, each object must be assigned to exactly one cluster. On the other hand, fuzzy C-means allows object to belong to a cluster to a degree of memberships [2, 5, 12]. Fuzzy C-means cannot recover from noise and outliers. A possibilistic clustering approach by Krishnapuram and Keller [6, 7] was proposed which uses possibilistic type of membership function to describe the degree of membership. Possibilistic C-means generates coincident clusters [11]. To handle the uncertainty and vagueness in images Rough set theory, developed by Z Pawlak (1981) [10] gained lot of interest. Lingras and West introduced a new clustering method, called rough C-means, which describes a cluster by a prototype (center) and a pair of lower and upper approximations [8].

B. Rough sets

Definition: Let U be the universe and an indiscernible relation $A \subseteq U \times U$. Let X be a subset of U . Then the rough set over the approximation space $\langle U, A \rangle$ is given by $\langle \underline{A}(X), \overline{A}(X) \rangle$.

$$\underline{A}(X) = \bigcup_{X_i \in X} X_i;$$

$$\bar{A}(X) = \bigcup_{X_i \cap X \neq \emptyset} X_i;$$

- The lower approximation $\underline{A}(X)$ of a set X is the set of all elements that definitely belong to X with respect to A .
- The upper approximation $\bar{A}(X)$ of a set X is the set of all objects which can be possibly belong to X with respect to A .
- The boundary region of a set X is the set of all objects, which can belong to X or does not belong to X with respect to A .
- Set X is crisp, if the boundary region of X is empty.
- Set X is rough, if the boundary region of X is nonempty.

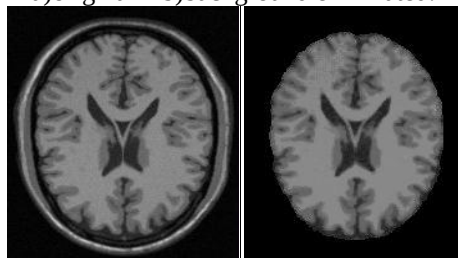
Rough sets when applied to clustering, Let $\underline{A}(V_j)$ and $\bar{A}(V_j)$ be the lower and upper approximations of cluster V_j , and boundary for cluster V_j is denoted by $B(V_j) = \{\underline{A}(V_j) - \bar{A}(V_j)\}$. Then the object X_i can obeys the properties :

- An object X_i can belong to at most one lower approximation.
- An object X_i belonging to $\underline{A}(V_j)$ also belongs to $\bar{A}(V_j)$
- An object X_i is not part of any lower approximation then X_i belongs to two or more upper approximation.

C. Roughsets for image segmentation.

The process involves three step preprocessing, choosing optimized centroids and then clustering the image into segments. In preprocessing, as the BrainWeb dataset images are in MINC format which are to be converted to MATLAB readable format which is achieved by MIPAV software[17] and then the brain images are processed to eliminate the background of the images. Figure 2.1 show the preprocessing of the images. Then find out the initial centroids of the image as per presented in section III A. Apply the clustering techniques as described in section III B and III C.

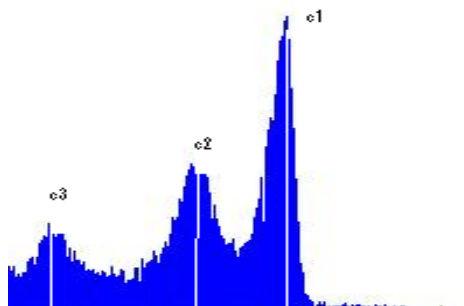
Figure 2.1 Phantom t1 weighted images
a)original b)background eliminated.



III. Rough K-Means And Rough Fuzzy C-means

A. Optimization of centroids using histogram based method.

Initial centroid play a great role in the segmentation using clustering algorithms like kmeans and fuzzy for initial membership function. The main idea is to find the peaks in the histogram and choose the corresponding gray levels for initial cluster centers of the K-means, Fuzzy C-means, Rough K-Means and Rough Fuzzy C means.



Steps in Algorithm:

1. Find the histogram of the image.
2. Identify the local maximum of peaks in the histogram.
3. Choose the global maxima as first centroid and find other local maxima or corresponding gray levels and find the centroids.

These optimized centroids V_j are used as the initial cluster centroids for KM, FCM, RKM and RFKM to find the cluster distances. The Fuzzy membership values initially can be calculated using the equation 1 based on these optimized centroid V_j using the below equation.

$$U_{ij} = \frac{1}{\sum_{j=1}^c \sum_{k \neq j}^c \left(\frac{X_i - V_j}{X_i - V_k} \right)^{\frac{2}{m-1}}} \quad \dots (1)$$

B. Rough K-Means

Incorporating rough sets into K-Means is to add the concept of lower and upper approximation which acts as an interval of rough sets for each cluster [7, 13]. The image pixel that definitely belong to the cluster are kept in lower approximations and the elements neither nor belong to the cluster are kept in the upper approximations and further, calculations are done to move the boundary region elements to clusters hence, reducing the no of computations.

Let d_{ij} be minimum similarity distance of an element X_i to clusters, by dividing all other distances d_{ik} , if the result is less than threshold then X_i belongs to $\underline{A}(V_j)$ and $\bar{A}(V_j)$ and X_i cannot be a member of any lower approximation belongs to $\bar{A}(V_j)$ such that d_{ij} is minimum over the k clusters.

Let

$$T = \{j: d_{ik}/d_{ij} \leq \text{threshold and } i \neq j\} \quad \dots (2)$$

Then we get:

If $T \neq \Phi$ then at least one other centroid is close to the element.

If $T = \Phi$ then no other centroids are similarly close to the element.

if $(T \neq \Phi)$

then $X_i \in \bar{A}(V_j)$ and $X_i \in \bar{A}(V_k), \forall X_i \in T$

else $X_i \in \bar{A}(V_j)$ and $X_i \in \underline{A}(V_j)$

Hence, the centroid calculation is modified to include the effects of lower as well as upper approximation. The value of centroid is given by:

$$V_j = \left\{ \begin{array}{l} P, \text{ if } \underline{A}(V_j) \neq \phi \text{ and } \bar{A}(V_j) - \underline{A}(V_j) = \phi, \\ Q, \text{ if } \underline{A}(V_j) = \phi \text{ and } \bar{A}(V_j) - \underline{A}(V_j) \neq \phi \\ W_{lower} \times P + W_{upper} \times Q, \text{ if } \underline{A}(V_j) \neq \phi \text{ and } \bar{A}(V_j) - \underline{A}(V_j) \neq \phi \end{array} \right\} \quad \dots (3)$$

Where

$$P = \frac{\sum_{x \in (\bar{A}(V_j) - \underline{A}(V_j))} X_i}{|\bar{A}(V_j) - \underline{A}(V_j)|} \quad \dots (3.1)$$

$$Q = \frac{\sum_{x \in (\bar{A}(V_j) - \underline{A}(V_j))} X_i}{|\bar{A}(V_j) - \underline{A}(V_j)|} \quad \dots (3.2)$$

Wlower is the weights for lower approximation and Wupper is the weights for Upper approximation.

Algorithm for Rough K-Means:

Input: image data(X); number of cluster K, threshold, last_Cj(Image clusters), new_Cj(Image clusters), Wlower, Wupper, stop criterion ε (here $\varepsilon = 0.001$, threshold =2, Wlower=0.5 and Wupper=0.5).

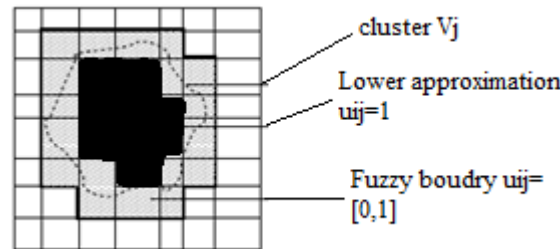
Output: new_Cj(segmented image data).

1. Chose initial centroids as described in section III.A.
 $V_j; 1 \leq j \leq k$; for the k clusters.
2. Calculate the similarity distance between the data point X_i to all cluster means V_j . Update the last_Cj with the data points X_i which belong to same clusters.
3. Let d_{ij} be the distance from V_j to X_i data point and d_{ik} be the distance between the X_i and the V_k .
4. Determine the nearest centroid for X_i let it be d_{ij} .
5. Check for other centroid closer to the nearest centroid using equation 1:
 - a. if ($T \neq \Phi$)
 - b. then $X_i \in \bar{A}(V_j)$ and $X_i \in \bar{A}(V_j), \forall X_j \in T$
 - c. else $X_i \in \bar{A}(V_j)$ and $X_i \in \underline{A}(V_j)$
6. Compute new centroids V_j based on equation 2.
7. Calculate the similarity distance between the data point X_i to all cluster means V_j . Update the new_Cj with the data points X_i which belong to same clusters.
8. Repeat step 2 to 6 until $|\text{last_Cj} - \text{new_Cj}| \leq \text{stop criteria}$.
9. Stop.

C. Rough Fuzzy C-means

Rough K-means assign an object definitely to a cluster based on the interval of lower and upper approximation where as Rough Fuzzy C-means follows a membership function for the degree of belonging of object to a cluster based on the boundary of rough set. The membership value for the objects belonging to the lower approximations is 1 and the objects belonging to boundary region has a membership of [0,1]. Figure 3.1 presents the details.

Figure 3.1 shows the membership values at lower and boundary approximation



The membership of the objects present in the boundary is defined by membership function [15].

$$U_{ij} = \left\{ \begin{array}{l} 1, \text{ if } x_j \in \underline{A}(V_j) \\ \frac{1}{\sum_{j=1}^c \sum_{k \neq j}^c \left(\frac{X_i - V_j}{X_i - V_k} \right)^{\frac{2}{m-1}}}, \text{ if } x_j \in \bar{A}(V_j) - \underline{A}(V_j) \end{array} \right\} \quad \dots (4)$$

The centers of the fuzzy C-means is calculated using the

$$V_j = \frac{1}{n} \sum_{i=1}^c \sum_{x_j \in X} \|x_i - v_j\|^2 (U_{ij})^m \quad \dots (5)$$

The rough fuzzy C-means partition the objects into clusters by minimizing the objective function. The objective function is given by equation 5.

$$J_{RF} = \left\{ \begin{array}{l} P_1, \text{ if } \underline{A}(V_j) \neq \phi \text{ and } \bar{A}(V_j) - \underline{A}(V_j) = \phi, \\ Q_1, \text{ if } \underline{A}(V_j) = \phi \text{ and } \bar{A}(V_j) - \underline{A}(V_j) \neq \phi \\ W_{lower} \times P_1 + W_{upper} \times Q_1, \text{ if } \underline{A}(V_j) \neq \phi \text{ and } \bar{A}(V_j) - \underline{A}(V_j) \neq \phi \end{array} \right\} \quad \dots (6)$$

where

$$P_1 = \sum_{i=1}^c \sum_{x_j \in \underline{A}(x)} \|x_i - v_j\|^2 \quad \dots (6.1)$$

$$Q_1 = \sum_{i=1}^c \sum_{x_j \in \bar{A}(V_j) - \underline{A}(V_j)} \|x_i - v_j\|^2 (U_{ij})^m \quad \dots (6.2)$$

Let U_{ij} be maximum membership, by dividing all other memberships U_{ik} , if the result is less than threshold then X_i belongs to $\underline{A}(V_j)$ and $\bar{A}(V_j)$ and X_i cannot be a member of any lower approximation belongs to $\bar{A}(V_j)$ such that U_{ij} is maximum over the k clusters.

$$T = \{j: U_{ij} / \max(U_{ij}) \leq \text{threshold and } i \neq j\}. \quad \dots (7)$$

Then we get:

If $T \neq \Phi$ then at least one other centroid is close to X_i .

If $T = \Phi$ then no other centroids are close to the X_i .)

IF $(T \neq \Phi)$

Algorithm for Rough Fuzzy C-means:

Input: image data(X_i); number of cluster k , threshold, W_{lower} , W_{upper} , stop criterion ϵ . (here $\epsilon = 0.001$, threshold = 0.5, $W_{lower} = 0.5$ and $W_{upper} = 0.5$)

Output: segmented image data

1. Chose initial centroids as described in section III.A.
 $\leq j \leq k$; for the k clusters.
2. Compute U_{ij} using equation 1 for k clusters and X_i objects.
3. Calculate the new centroid using equation 5.
4. Update the last_Cj with the data points X_i which belong to same clusters based on the U_{ij} .
5. Determine the nearest centroid for X_i based on maximum U_{ij} .
6. Check for other centroid closer to the nearest centroid using equation 7:
 if $(T \neq \Phi)$
 then $X_i \in \bar{A}(V_j)$ and $X_i \in \bar{A}(V_k), \forall X_i \in T$
 else $X_i \in \bar{A}(V_j)$ and $X_i \in \underline{A}(V_j)$
7. Calculate U_{ij} using equation 4.
8. Compute the objective function JRF based on equation 6.
9. Repeat step 3 to 8 until $| \text{last_JRF} - \text{new_JRF} | \leq \epsilon$ (stop criteria).
10. stop

IV. Experimental results

This section presents a set of experiments to validate the performance of proposed algorithms. The experiment datasets are collected from the BrainWeb database [16] for MRI image. The BrainWeb images are in MINC format which are to be converted to MATLAB readable format which is achieved by MIPAV software[17].

The BrainWeb contains different anatomical structures ground truth images for T1 weighted images among which we consider white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). The performance is

evaluated on normal t1 weighted images with 1mm thickness of phantom, subject04, subject05, subject08, subject20 from BrainWeb. The phantom, subject04, subject05 normal t1 weighted images are presented in figure 4.1. The extracted WM, CSF, GM segmentation results for phantom image are presented in figure 4.2 and for subject 04 image are presented in figure 4.3.

The evaluation of segmentation results are calculated using the quantitative comparison with the ground truth. A number of similarity coefficients methods [4] are used to specify how well segmentation 'A' matches a referenced ground truth 'B'.

$$\text{Jaccard coefficient} = \frac{(A \cap B)}{(A \cup B)}$$

The jaccard coefficient is above 70% means that the segmentation result is good. Performance of the algorithm can be also measured using other criteria [14]. The average results of phantom, subject04, subject05, subject08, subject20 results are presented in table 4.1 to table 4.5. Figure 4.1 shows the chart for similarity index.

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{FP+TN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Segmentation Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

The proposed algorithms are implemented in MATLAB 10.1 on 1.8 GHz Intel core 2 Duo processor.

Figure 4.1. (a) Ground truth original phantom Image, (b) Ground truth original Subject04 Image, (c) Ground truth original Subject05 Image.

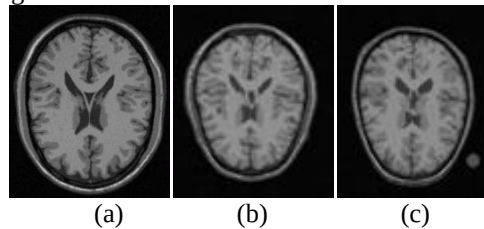
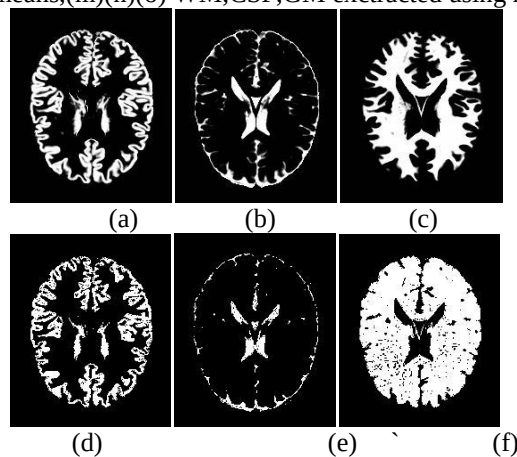


Figure 4.2. Segmentation results for Phantom normal T1 weighted image of 1mm thickness. (a) Ground truth WM of Phantom, (b) Ground truth CSF of Phantom, (c) Ground truth GM of Phantom, (d)(e)(f) WM, CSF, GM extracted using K-means, (g)(h)(i) WM, CSF, GM extracted using Rough K-means, (j)(k)(l) WM, CSF, GM extracted using Fuzzy c-means, (m)(n)(o) WM, CSF, GM extracted using rough Fuzzy c-means.



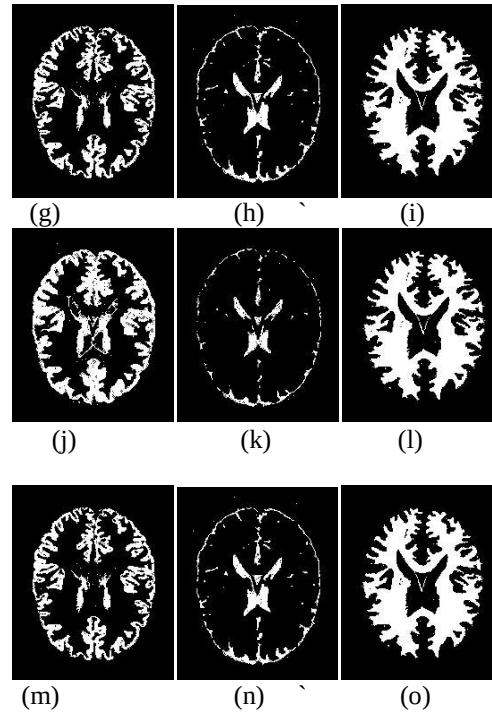
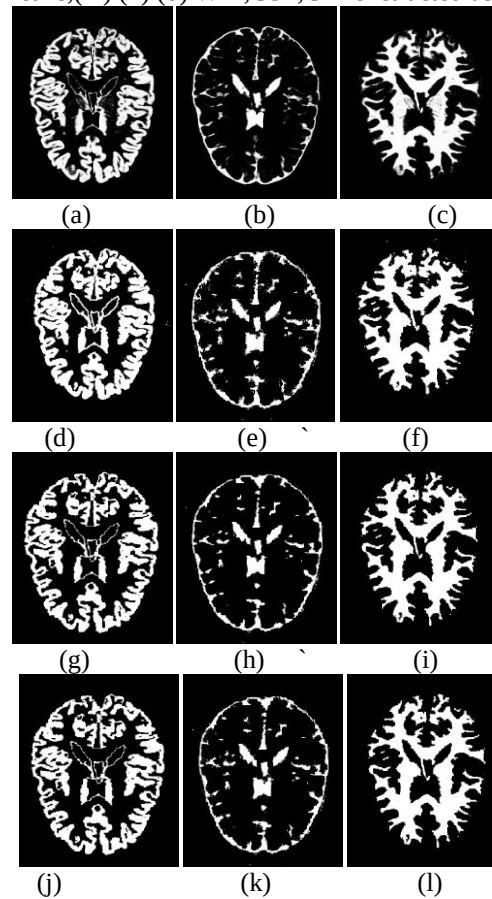


Figure 4.2. Segmentation results for Subject04 T1 weighted image of 1mm thickness. (a) Ground truth WM of Subject04, (b) Ground truth CSF of Subject04, (c) Ground truth GM of Subject04, (d) (e) (f) WM, CSF, GM extracted using K-means, (g) (h) (i) WM, CSF, GM extracted using Rough K-means, (j) (k) (l) WM, CSF, GM extracted using Fuzzy C-means, (m) (n) (o) WM, CSF, GM extracted using rough Fuzzy c-means for Subject04.



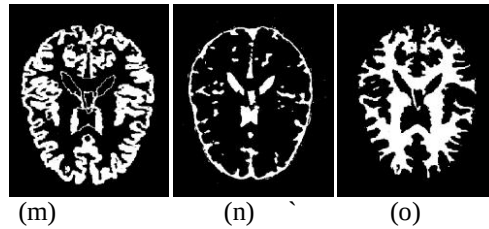


Table 4.1 Performance measure by Similarity index using Jaccard Coefficient.

Type	GM %	CSF %	WM %
K-means	74.47	71.69	85.38
Rough K-means	79.92	72.16	91.52
Fuzzy C-means	74.56	72.27	91.38
Rough Fuzzy C-means	80.01	74.99	91.52

Table 4.2 Performance measure by Segmentation Accuracy

Type	GM %	CSF %	WM %
K-means	95.29	96.90	91.23
Rough K-means	96.23	96.94	97.26
Fuzzy C-means	95.30	96.58	93.23
Rough Fuzzy C-means	96.23	96.62	97.26

Table 4.3 Performance measure by Precision

Type	GM%	CSF%	WM%
Kmeans	98.48	97.44	90.55
Rough K-means	96.95	97.24	90.50
Fuzzy C-means	98.40	97.95	90.55
Rough Fuzzy C-means	96.92	97.49	90.50

Table 4.4 Performance measure by Specificity.

Type	GM%	CSF%	WM%
Kmeans	95.68	96.38	11.13
Rough K-means	88.06	96.01	09.66
Fuzzy C-means	95.45	97.62	11.13
Rough Fuzzy C-means	87.90	96.99	09.66

Table 4.5 Performance measure by sensitivity.

Type	GM	CSF	WM
Kmeans	13.81	4.39	24.24
Rough K-means	14.91	4.44	24.27
Fuzzy C-means	13.83	4.04	24.24
Rough Fuzzy C-means	14.92	4.10	24.27

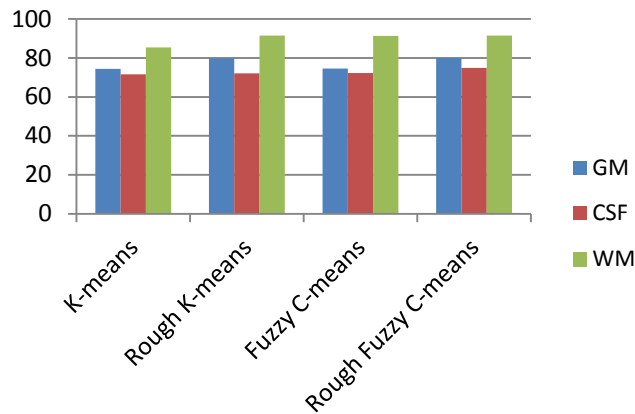
Table 4.6 Performance measure by Execution time

Type	No of iterations	CPU time in sec
K-means	12	6.9
Rough K-means	12	5.5
Fuzzy C-means	48	130.6
Rough Fuzzy C-means	27	74.62

Table 4.6 Performance measure by number of Iterations

Type	No of iterations with random	No of Iteration with Optimized centers
K-means	45	12
Rough K-means	45	12
Fuzzy C-means	67	48
Rough Fuzzy C-means	54	27

Figure 4.1 Chart for similarity Index



V. Conclusion Remarks

In this work the segmentation frame work based on Rough sets is proposed and the results show significant improvement in accuracy for segmenting complex MR images of brain.

The experimentation on MR images prove the efficiency of proposed method compared to classic models such as k-means and Fuzzy C-means. The performance is evaluated by visual perception and quantitative measurements of sensitivity, specificity, precision, accuracy and similarity. However, the results depend on the initial centroids for K-means and initial membership values for fuzzy c-means. The random initialization of centroid leads to uncertain clusters and increase computation time. In this work the optimization of the centroids and member ship values using histogram local maxima based method provide accuracy and closer proximity of centroids to ground truth.

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