Geometric Distance-Optimized Centroid with Membership-Constrained RFCM for Brain MRI Image Segmentation: Postprint

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Abstract

To address the issues of clustering complexity and insufficient segmentation accuracy in existing image segmentation algorithms, a medical image clustering segmentation algorithm combining geometric distance-optimized centroids with Rough Fuzzy C-Means (RFCM) is proposed. First, a pixel set represented by soft sets is established, and the distance between each pixel and the centroids is calculated; then, based on the minimum distance between pixels and centroids, pixels are assigned to clusters. To apply soft sets to Rough Fuzzy C-Means, a fuzzy soft set is defined, the input image is further converted into a binary image, and appropriate centroids are selected by calculating the geometric distance of connected regions. Finally, using these new centroids, the membership values of pixels are calculated and updated, thereby completing the fuzzy clustering partition. The performance of the proposed hybrid algorithm was evaluated on three medical databases including Allen Brain Atlas, and the obtained Jaccard coefficient and segmentation accuracy (SA) both outperform several comparison algorithms. Experimental results demonstrate that the proposed clustering segmentation algorithm exhibits favorable performance.

Full Text

A Brain MRI Image Segmentation Algorithm Based on Geometric Distance-Optimized Centroid and Membership Constraint RFCM

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Abstract

To address the problems of high clustering complexity and insufficient segmentation accuracy in existing image segmentation algorithms, this paper proposes a medical image clustering segmentation algorithm that combines geometric distance-optimized centroid with rough fuzzy C-means (RFCM). First, a pixel set represented by soft sets is established, and the distance between each pixel and the centroid is calculated. Pixels are then grouped into clusters based on their minimum distance to the centroids. To apply soft sets to rough fuzzy C-means, a fuzzy soft set is defined, the input image is further converted into a binary image, and appropriate centroids are selected by calculating the geometric distance of connected regions. Finally, the membership values of pixels are updated using these new centroids to complete the fuzzy clustering partition. The performance of the proposed hybrid algorithm was evaluated on three medical databases, including the Allen Brain Atlas. The obtained Jaccard' s coefficient and segmentation accuracy (SA) outperformed several comparison algorithms. Experiments demonstrate that the proposed clustering segmentation algorithm achieves good performance.

Keywords: image segmentation; soft set theory; centroid calculation; rough area; fuzzy C-means; membership constraint

0 Introduction

Image segmentation is a critical function in image analysis and processing, with significant applications in depicting anatomy, medical image diagnosis, tissue fluid extraction, pathology localization, treatment planning, partial volume correction of functional image data, and computer-integrated surgery [1-3]. Fuzzy sets and rough sets are effective tools for handling uncertainty and ambiguity in medical images and have been widely applied to medical image segmentation [4]. Soft set theory represents a new mathematical approach for dealing with uncertainty and vagueness [5].

The classical K-means clustering algorithm or hard C-means clustering algorithm is based on crisp sets [6], where each pixel belongs to only one cluster. Its fuzzy version, the fuzzy C-means clustering algorithm [7], has also received considerable attention. However, the fuzzy C-means method does not consider spatial and boundary conditions, making it sensitive to noise and insufficient data. To account for spatial and boundary regions, some studies have begun to incorporate soft set theory into the KM and FCM frameworks for image segmentation [5]. Several hybrid algorithms have been proposed in the literature: rough K-means [8], rough fuzzy possibilistic C-means [9], and shadowed C-means [10], among others. Reference [12] proposed a rough set algorithm that uses a threshold rather than a negative domain to find lower and upper approximations. However, since pixels absolutely belong to either the lower approximation, the upper approximation, or both, clustering does not eliminate pixels. Reference

[13] proposed soft rough sets to define lower and upper approximations without including a negative domain. However, this technique uses random initialization of cluster prototypes, which produces inaccurate results when poor choices are made. Reference [14] proposed a method for calculating the lower and upper approximations of fuzzy soft sets to effectively define boundaries. Nevertheless, these definitions are for crisp values and cannot handle boundary pixels, and the determination of rough regions is exceptionally complex. These rough set-based algorithms all involve complex instructions for calculating approximations and divide pixels into rough regions based on a single threshold. They attempt to calculate thresholds using the minimum and maximum membership degrees of pixels [11] based on the initial cluster centroids. Consequently, inappropriate initial centroids lead to inaccurate results. Additionally, reference [15] proposed a hybrid algorithm combining intuitionistic fuzzy sets with rough sets. These algorithms use ternary membership degrees, representing belonging to a cluster, not belonging to a cluster, and uncertainty about belonging to a cluster. Ternary membership degrees are used to calculate upper and lower approximations and regions, making these algorithms more computationally complex than rough set approaches.

This paper proposes the concept of using soft sets to represent images and defines the lower and upper approximations of image rough regions using soft fuzzy rough approximations. Unlike rough set algorithms, this clustering algorithm avoids the use of thresholds, weight parameters, and complex upper and lower approximations. The algorithm does not use a negative region, so all pixels can participate in clustering. Soft sets quantify uncertainty using similarity measures, which relate to the degree of similarity between the previous clustering and the current clustering.

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1 Rough Set Theory

Rough sets describe imprecise concepts through lower and upper approximations. Lower and upper approximations are used to approximate uncertain data. Let U denote the universal set, R be an equivalence relation, and $U/R = \{X_1, X_2, ..., X_n\}$ be a collection of n equivalence classes that form a partition in U. (U, R) is an approximation space. For a subset $X \subseteq U$, the lower and upper approximations can be expressed as:

$$\underline{R}X = \{x \in U \mid [x]_R \subseteq X\}$$

$$\overline{R}X = \{x \in U \mid [x]_R \cap X \neq \emptyset\}$$

where $[x]_R$ denotes the equivalence class of x under R. The lower approximation space represents objects that definitely belong to X, while the upper approximation space represents objects that possibly belong to X. The approximation space of X is classified into three distinct regions: positive domain, boundary domain, and negative domain.

Some studies have utilized rough set theory to propose hybrid algorithms such as rough K-means and rough fuzzy C-means. If a pixel belongs to all clusters, its membership degree is low. Including this pixel in clusters introduces noise, while removing it from clusters creates insufficient data. The incompleteness, uncertainty, and ambiguity in clustering can be defined using the lower and upper approximations of rough sets. The lower approximation of a cluster is the set of pixels that absolutely belong to the cluster, while the upper approximation is the set of pixels that possibly belong to the cluster. Pixels in the boundary region (between upper and lower approximations) are given a second chance so they can move to appropriate clusters in the next iteration. Therefore, rough sets can reduce clustering errors.

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2 Rough Fuzzy C-Means Clustering

The fuzzy C-means clustering algorithm evolves from the hard C-means clustering algorithm. It employs an iterative method to optimize the objective function to obtain fuzzy classification of datasets. The algorithm has good convergence properties and is one of the most widely used fuzzy clustering algorithms in practical applications. Reference [16] proposed a fuzzy C-means clustering method for magnetic resonance brain images, with its bias field model defined as shown in equation (3). The objective function for segmenting magnetic resonance brain images is given by:

$$J_{GFCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \| x_j - b_i C_i \|^2$$

where the membership values are calculated using the following equation with bias field [17]:

$$u_{ij} = \frac{\| x_j - b_i C_i \|^{-2/(m-1)}}{\sum_{k=1}^{c} \| x_j - b_k C_k \|^{-2/(m-1)}}$$

The positive domain $P(C_j)$ and boundary domain $B(C_j)$ are calculated based on two thresholds t_1 and t_2, defined as follows:

$$t_1 = \frac{1}{n} \sum_{i=1}^{n} d_{min}$$

$$t_2 = \frac{1}{n} \sum_{i=1}^{n} d_{max}$$

where d_{min} is the minimum distance between pixels and centroids, and d_{max} is the maximum distance between pixels and centroids. The weight parameter for each cluster is estimated as the percentage of the positive domain to the entire region, given by:

$$W_j = \frac{|P(C_j)|}{|P(C_j) \cup B(C_j)|}$$

The distance d_{ij} is given by:

$$d_{ij} = \arg\min_i \|x_j - C_i\|$$

The bias field b_i is approximated pixel-by-pixel through a linear combination of orthogonal polynomials:

$$b_i = \sum_{k=1}^{M} w_k g_k(i)$$

where M is the number of polynomials of degree D, and g_k is a linear combination of basis function sets G_k. The bias field for pixel i in region Ω_i is estimated and corrected using the energy function:

$$E = \sum_{i \in \Omega} \sum_{j \in N_i} \|x_j - b_i C_i\|^2$$

The energy is minimized with respect to W; this can be accomplished by solving:

$$\frac{\partial E}{\partial W} = 0$$

which yields:

$$W = A^{-1} V$$

where V is a multidimensional column vector given by:

$$V = \sum_{i \in \Omega} \sum_{j \in N_i} u_{ij}^m x_j C_i^T$$

and A is expressed as a linear equation:

$$A = \sum_{i \in \Omega} \sum_{j \in N_i} u_{ij}^m C_i C_i^T$$

The bias field can be estimated as $b_i = W^T G_i$. In this method, rough regions are defined by thresholds t_1 and t_2; pixels with distances greater than t_2 fall into the negative domain and are thus eliminated from clustering.

3.1.1 Rough Fuzzy C-Means Clustering

Fuzzy-based clustering allows overlapping clusters. To divide data into fuzzy clusters and improve the noise resistance of the FCM algorithm, we introduce spatial constraint relationships into the membership function of FCM's objective function. The new objective function is:

$$J' = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \|x_j - C_i\|^2 + \gamma \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \sum_{r \in N_j} \|u_{ij} - u_{ir}\|^2$$

where N_j represents the neighborhood region of pixel j, and the second term penalizes the difference between the membership degree of pixel j and its neighbors. To solve for the membership function, we establish the Lagrange function:

$$L = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \|x_j - C_i\|^2 + \gamma \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \sum_{r \in N_j} \|u_{ij} - u_{ir}\|^2 - \lambda \left(\sum_{i=1}^{c} u_{ij} - 1 \right)$$

which yields:

$$u_{ij} = \frac{\left(\|x_j - C_i\|^2 + \gamma \sum_{r \in N_j} \|u_{ij} - u_{ir}\|^2 \right)^{-1/(m-1)}}{\sum_{k=1}^{c} \left(\|x_j - C_k\|^2 + \gamma \sum_{r \in N_j} \|u_{kj} - u_{kr}\|^2 \right)^{-1/(m-1)}}$$

A threshold T is used to group elements into the lower approximation region $P(C_j)$ or boundary region $B(C_j)$. This threshold is calculated using the highest membership degree of element x_i to cluster centroid C_j. Rough fuzzy C-means uses the threshold defined in equation (17) to place pixels in either the lower or upper approximation.

3.1.2 Fuzzy Soft Set

A soft set maps parameters to the universal set. Let U be the universal set and A be the set of parameters, $A \subseteq E$. Then a soft set over U is given by (F, A), where F is a mapping $F : A \to P(U)$, and $P(U)$ denotes the power set of U, containing all subsets of U [28]. To apply soft sets to image segmentation, the pixel set in the observed image is first represented as $U = \{x_i \mid x_i \text{ is the value of the } i\text{-th pixel in the image}\}$. Let X be the observed image obtained from the true signal through bias field b and zero-mean Gaussian noise. Then let (F, A) be the soft set to be constructed, containing pixels belonging to clusters. Finally, the parameter set is taken as the clusters C_i to which pixels belong, $i = \{1, 2, 3, ..., k\}$.

Assume the pixel set in the image is given by $U = \{x_1, x_2, ..., x_n\}$, and the parameter set A is the clusters C_j to which pixels belong. The distance between each pixel and the centroid is calculated. Based on the minimum distance between pixels and centroids, pixels are grouped into clusters as follows:

$$F(C_j) = \{x_i \mid d_{ij} = \arg\min_i \|x_j - C_i\|\}$$

The soft set representation for the above example is:

$$F(C_1) = \{x_1\}, F(C_2) = \{x_2, x_3, x_4, x_5\}, F(C_3) = \{x_3, x_4, x_5, x_6\}$$

Table 1 shows the pixel set based on soft set representation. If $x_i \in F(C_j)$, its value is 1; otherwise, it is 0.

To apply soft sets to fuzzy values, a fuzzy soft set is defined: (F, A) is a parameter cluster of fuzzy value subsets of U. Therefore, $F(A)$ represents the fuzzy subset of U, which is the set of fuzzy value parameters: $F(A) = \{(\mu_{F(A)}(x)/x) \mid x \in U\}$. Thus, x belongs to $F(A)$ with membership degree μ as the parameter. The image is represented as a soft fuzzy set by considering each pixel’ s fuzzy membership degree to cluster centroids. A fuzzy soft set maps parameters to the universal set with fuzzy values. Therefore, to represent the fuzzy soft set, the membership degree values of pixels are calculated using equation (20). Assume the membership degree values of pixels to clusters are as follows:

$$F(C_1) = \{0.6/x_1, 0.1/x_2, 0.4/x_3, 0.7/x_4\}$$
$$F(C_2) = \{0.4/x_1, 0.2/x_2, 0.5/x_3, 0.1/x_4\}$$
$$F(C_3) = \{0.4/x_1, 0.3/x_2, 0.5/x_3, 0.2/x_4\}$$

The lower and upper approximations of the soft fuzzy set are calculated using equations (23) and (24). The tabular representation of the lower and upper approximations is given in Table 2 .

In the above definitions, no thresholds or weight parameters are used to calculate approximations; instead, simple AND and OR operations are employed. Using these approximations, the positive domain $P(C_j)$ can be determined through the following equation:

$$P(C_j) = \{x \mid \mu_{\overline{R}}(x) \geq 0.6\}$$

A pixel with a membership degree of 0.6 can be placed in the cluster. The value 0.6 is chosen to include pixels with at least 0.6 membership degree in the cluster. If it is less than 0.5, the clustering becomes more ambiguous and increases noise. The fuzzy rough lower and upper approximations for soft sets are given by:

$$\underline{R}(F, A) = \{(x, \mu_{\underline{R}}(x)) \mid \mu_{\underline{R}}(x) = \bigwedge_{y \in U} [(1 - \mu_F(x, y)) \vee \mu_A(y)]\}$$

$$\overline{R}(F, A) = \{(x, \mu_{\overline{R}}(x)) \mid \mu_{\overline{R}}(x) = \bigvee_{y \in U} [\mu_F(x, y) \wedge \mu_A(y)]\}$$

3.1.3 Geometric Distance Optimization Centroid

Initial cluster centroids play a crucial role in segmentation. Clustering algorithms such as K-means or hard C-means are used in the initial membership function. Poorly chosen centroids may lead to local minima and inaccurate results. The input image is converted to a binary image, and the corresponding gray levels are selected as initial cluster centroids. The algorithm for geometric distance optimization centroid proceeds as follows:

a) Convert the input image to a binary image

b) Find all connected regions through connected component labeling algorithm and label them separately

c) Apply the geometric distance calculation algorithm to each connected region to obtain centroids

d) Draw the connected regions and centroids with different colors, and further output the processed results

The geometric moment for a connected region is calculated as:

$$M_{ab} = \int \int x^a y^b f(x, y) \, dx \, dy$$

Using these new centroids, the membership degree values of pixels are updated. Since the clustering algorithm is iterative, the soft set-based clustering algorithm iterates using the similarity between clusters formed in the previous iteration and the current iteration.

4.1 Method Implementation

The performance of the proposed hybrid algorithm was evaluated on three medical databases: (i) Brain Perfusion Database [18]; (ii) Allen Brain Atlas [19]; (iii) BRATS database [20]. The number and size of images selected from these databases for simulation are shown in Table 3 . All three databases are classic brain image databases with suitable image quantities and sizes for simulation experiments in this paper. These images were converted to MATLAB-readable format. As a preprocessing step, non-brain tissues were removed from the images using MIPAV (Medical Image Processing, Analysis, and Visualization) software before segmentation. The proposed algorithm was implemented in MATLAB 2012a on a 4.2GHz Intel i7 7700K processor. Figure 1 [Figure 1: see original paper] shows sample images from the Allen Brain Atlas.

In all brain image experiments, the number of clusters was set to $c = 4$ (corresponding to GM, WM, CSF, and background). Segmentation results were calculated using quantitative comparison with actual segmentation boundaries, evaluated using Jaccard' s Coefficient (JC) and Segmentation Accuracy (SA). The JC between two datasets is the result of dividing the number of attributes common to both datasets by the total number of attributes.

$$Jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where A is the segmentation image obtained by the proposed method and B is the ground truth image. A Jaccard coefficient above 70% indicates good segmentation results. SA is another common metric used to compare similarity between segmented and ground truth images. To calculate segmentation accuracy, four parameters were computed for each segmentation result:

a) True Positive (TP): Correct pixels in the ground truth image correctly detected as segmented pixels

b) True Negative (TN): Incorrect pixels in the ground truth image correctly detected as segmented pixels

c) False Positive (FP): Correct pixels in the ground truth image not found in the segmented region

d) False Negative (FN): Incorrect pixels in the ground truth image not present in the segmented region

$$SA = \frac{TP + TN}{TP + TN + FP + FN}$$

The first experiment was conducted on the Brain Perfusion Database, which contains 2D axial views of 10 T1-weighted simulated brain images with 90 slices, 1mm thickness, different intensity non-uniformities (INU = 0 and INU = 20), and noise levels (0%, 1%, 3%, 5%, and 9%). Since the typical noise level in magnetic resonance brain image data is around 3%, synthetic brain MR images with 3% noise and 0% INU were selected. For validation, other images with 9% noise level were also selected.

4.2 Performance Evaluation

The performance of many clustering algorithms is affected by initial cluster centroids. The histogram-based centroid optimization method proposed in this paper addresses the problem of random centroids. Histogram-based optimized centroids achieve high efficiency in finding starting points close to the true centroids, thereby obtaining reliable brain image segmentation results. Table 4 presents the SA results of the algorithm, and Table 5 provides the JC values. The results show that the proposed new algorithm performs very well even in the presence of noise.

Magnetic resonance brain images are often divided into White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). Effective extraction of these regions is crucial for quantitative analysis. Several methods have been developed for segmenting MR brain images. Magnetic resonance brain images are shown in Figure 2 [Figure 2: see original paper].

Although the method in reference [12] requires little evaluation time, it does not work for pixels in boundary regions (unidentifiable), thus increasing clustering errors and reducing SA and JC values. While K-means clustering or hard C-means clustering algorithms can handle ambiguity by defining membership degrees, they cannot properly cluster indiscernible cases. Consequently, increasing SA and JC values for one tissue reduces them for another tissue. Rough sets can effectively handle indiscernible pixels in clustering by providing a buffer region. Pixels in the buffer are given a second chance before cluster assignment to reduce clustering errors and achieve good SA and JC results, as shown in Table 4, Table 5 , and Figure 3 [Figure 3: see original paper]. Methods in references [13-15] divide pixels into rough regions based on a single threshold, attempting to calculate the threshold using the minimum and maximum membership degrees of pixels based on initial cluster centroids. Therefore, inappropriate initial centroids lead to inaccurate results.

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5 Conclusion

This paper proposes a magnetic resonance brain image clustering segmentation algorithm based on rough fuzzy C-means with membership constraints. By applying soft sets to fuzzy sets and rough sets, a hybrid algorithm and its application in medical image segmentation are presented. The proposed algorithm offers several advantages: it uses parametric tools to define upper and lower approximations to handle uncertainty, reduces clustering errors, and achieves rapid convergence using soft set similarity coefficients. The algorithm produces accurate results. The performance of the proposed algorithm was evaluated using synthetic data and simulations, demonstrating accurate brain image segmentation. Future work aims to further refine the proposed method.

Soft sets facilitate effective design of upper and lower approximations through parametric tools. Soft sets also use similarity coefficients, assigning a quantity to a pair of soft sets representing the degree of equality. Similar to many clustering algorithms, soft set-based algorithms are iterative. However, since soft sets use parametric tools and similarity coefficients, they can reach convergence very quickly. To handle indiscernible pixels and reduce time, combining rough sets with soft sets proves to be a better solution. A comparison of execution times for various algorithms is shown in Figure 4 [Figure 4: see original paper].

Due to the use of parameterization and similarity coefficients, the proposed method avoids threshold calculation, thereby reducing time complexity to $O(nk)$, where n is image size and k is the number of clusters. In contrast, methods in references [12-15] all require threshold calculation. Therefore, the proposed method converges faster than other literature methods. While reducing computational complexity, the rough regions of MR brain images defined using soft sets maintain segmentation accuracy.

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Note: Figure translations are in progress. See original paper for figures.