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Optimized Rough Intuitionistic Fuzzy C- Means for Magnetic Resonance Brain Image Segmentation

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ABSTRACT : *Accurate segmentation of human brain image is an essential step for clinical study of magnetic resonance imaging (MRI) images. However, vagueness and other ambiguity present between the brain tissues boundaries can lead to improper segmentation. Possibilistic fuzzy c-means (PFCM) algorithm is the hybridization of fuzzy c-means (FCM) and possibilistic c-means (PCM) algorithms which overcomes the problem of noise in the FCM algorithm and coincident clusters problem in the PCM algorithm. A major challenge posed in the PFCM algorithm for segmentation of ill-defined MRI image with noise is to take into account the ambiguity in the final localization of the feature vectors due to lack of qualitative information. This may lead to improper assignment of membership (typicality) value to their desired cluster. In this paper, we have proposed the possibilistic intuitionistic fuzzy c-means (PIFCM) algorithm for Atanassov's intuitionistic fuzzy sets (A-IFS) which includes the advantages of the PCM, FCM algorithms and A-IFS. Real and simulated MRI brain images are segmented to show the superiority of the proposed PIFCM algorithm. The experimental results demonstrate that the proposed algorithm yields better result.*

Keywords: Possibilistic c-means algorithm ,fuzzy c-means algorithm, A-IFS ,intuitionistic fuzzy c-means algorithm, magnetic resonance imaging ,image segmentation**.**

1. INTRODUCTION

Segmentation of brain magnetic resonance images (MRIs) into non-overlapping regions of white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) is essential for studying anatomical structure changes and brain quantification and for building tumor growth models. Due to existence of noise, bias field, and partial volume effect, brain MRI segmentation faces several challenging issues. Existing methods still suffer from a lack of robustness to outliers, a high computational cost, the needs for manual adjustment of crucial parameters, a limited segmentation accuracy in the presence of high level noise, and a loss of image details.

One promising approach to MRI segmentation is the soft clustering, an unsupervised learning, that groups similar patterns into clusters that have soft boundaries. By assigning each pixel to each cluster with a varying degree of membership, this approach is able to account for the uncertainty. Several soft clustering methods have been proposed for MRI segmentation, including the well-known fuzzy C-means (FCM) clustering, mixture modeling, and some hybrid methods based on the former two methods. Although the accuracies of these soft clustering algorithms are good in the absence of image noise, they are sensitive to noise and other imaging artifacts.

Recently, several methods have been proposed to improve the FCM clustering on noise tolerance by representing clusters as intuitionistic fuzzy sets (IFSs). Aruna et al. presented a modified intuitionistic fuzzy C-means (IFCM) clustering algorithm, which adopts a new IFS generator and the Hausdorff distance. Verma et al. presented an improved intuitionistic fuzzy C-means (IIFCM) algorithm, which takes the local spatial information into consideration. IIFCM is able to tolerate noise and does not require any parameter tuning. However, these algorithms are still based on Euclidean or Hausdorff distance among pixels. As a result, these algorithms can only find linearly separable clusters and the clustering results are depending on the initial choice of centroids.

It is well-known that kernel functions can be used to find clusters that cannot be linearly separated. However, the performance of those kernel-based methods is highly sensitive to the choice of kernel parameters. Although several methods have been proposed to estimate the optimal values for kernel parameter, the problem has not been completely solved.

We believe that by applying kernel functions to find the IFS-based FCM clustering, we can have a robust method for MRI segmentation. Using this approach, the segmentation problem can be transformed into an optimization problem: finding the optimal kernel parameters that lead to optimal noise-tolerant fuzzy clusters.

The DNA genetic algorithm, based on DNA computing and the Genetic Algorithm (GA), have been recently introduced to solve complex optimization problems in many areas, such as, chemical engineering process parameter estimation, function optimization , clustering analysis , and membrane computation . This technique can be used to solve the aforementioned optimization problem.

Motivated by the previous discussion, we formulate an MRI segmentation problem as a kernel-based intuitionist fuzzy C-clustering problem and provide a DNA-based genetic algorithm for solving this problem. Specifically, our contributions in this paper are as follows.

We formulate an image segmentation problem as a kernel-based intuitionistic fuzzy C-means (IFCM) clustering problem by specifying a new parametric objective function. This formulation includes a new measure for pixel local noise, a method to model fuzzy clusters as intuitionistic fuzzy sets instead of conventional fuzzy sets, and an adaptation of a kernel trick to improve performance.

We propose a new DNA-based genetic algorithm to learn the IFCM clustering. This algorithm uses a DNA coding scheme to represent individuals (i.e., potential solutions) and a set of improved DNA genetic operator to search through the solution space for optimal solutions. Each individual encodes a set of values of the modeling parameters, including kernel parameters. While the algorithm searches for optimal set of model parameters, it also obtains the optimal IFS based fuzzy clusters.

We perform empirical study by comparing our method with six existing state-of-the-art fuzzy clustering algorithms using a set of UCI data mining data sets, a set of synthetic MRI data, and a set of clinical MRI datasets. Our preliminary results show that our algorithm outperforms the compared algorithms in both the clustering metrics and computational efficiency.

1.1. LITERATURE SURVEY

Fuzzy C-Mean (FCM) groups data into predefined clusters according to membership grade and
Information it provides better than hard clustering methods. ROI detection using FCM proposed by Jianchao et al. A new fuzzy level set algorithm has been proposed for medical image segmentation where different imaging modalities wereconsidered and the efficiency and robustness of thealgorithm have been compared with other standardalgorithms. Kernelized FCM (IFCM) with spatial constraints has been proposed for optimal and automatic medical image segmentation where Gaussian radial basis function classifier is replaced with Euclidean distance. A novel robust kernel induced distance is used for clustering image pixels in Magnetic Resonance (MR) images. The experiments were executed on the noisy images and the superiority of the proposed method was compared with basic FCM and IFCM. The same metric is applied on corrupted images by replacing Euclidean norm in standard FCM to segment homogeneous groups and its effectiveness is proven with FCM and its variants.
The performance of a novel algorithm with kernel induced distance is better than FCM and is robust for noise. A fast clustering segmentation algorithm has been proposed to improve the clustering performance of basic FCM. A generalized rough FCM algorithm is proposed for accurate and reliable segmentation of brain images and is more robust to initialization and noise. The effect of otsu thresholding and morphological reconstruction has been demonstrated to segment breast cancer images and results have been compared with other standard methods.

II. BACKGROUND

FUZZY SET AND INTUITIONISTIC FUZZY SET

Fuzzy sets are designed to manipulate data and information possessing non-statistical uncertainties [24]. A fuzzy set is represented by Zadeh [19] as follows,

$$FS = \{\langle x, \mu_{FS}(x)\rangle | x \in X\}$$

Where, μFS: X → [0, 1] and νFS: X → [0, 1] and νFS(x)=1 – μFS(x). Here μFS is the membership value and νFS is the non-membership value.
An Intuitionistic Fuzzy Set proposed by Atanassov [26] can be symbolized as below :

$$IFS = \{\langle x, \mu_{IF}(x), \nu_{IF}(x)\rangle | x \in X\}$$

where, μIF: X → [0, 1] and νIF: X → [0, 1] define the degree of membership and non-membership, respectively and πIF(x) = 1 – μIF(x) – νIF(x) such that 0 < μIF(x) + νIF(x) < 1 where, πIF is the hesitancy value used to represent the uncertainty.

III. INTUITIONISTIC FUZZY C-MEANS CLUSTERING

The first task for IFCM algorithm is to convert crisp data into fuzzy data which in turn would be converted to Intuitionistic fuzzy data. This process involves the task of fixing the lambda value which is a value that varies for each dataset. The value of lambda is chosen as the one which maximizes the entropy value. Entropy is the amount of fuzziness present in any given dataset and it is calculated as,

$$IFE = \frac{1}{N \times M} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \frac{2\mu_i(d_j)\nu_i(d_j) + \pi_i^2(d_j)}{\pi_i^2(d_j) + \mu_i^2(d_j) + \nu_i^2(d_j)} \qquad (1)$$

Where, N and M are the rows and columns of the dataset. The crisp data is converted into fuzzy data using the following Eq.(2)

$$\mu_i(d_j) = \frac{d_{ij} - \min(d_j)}{\max(d_j) - \min(d_j)} \qquad (2)$$

Where, dij is the current cell of the matrix under consideration and min(dij) indicates the minimum value in the dataset matrix and max(dij) indicates the maximum value in the dataset matrix. Then the fuzzy data is converted to Intuitionistic fuzzy data as follows:

$$\mu_i(d_j;\lambda) = 1 - (1 - \mu_i(d_j))^{\lambda} \qquad (3)$$

$$\nu_i(d_j;\lambda) = 1 - (1 - \mu_i(d_j))^{\lambda(\lambda+1)} \qquad (4)$$

where, $\lambda \in [0,1]$

The intuitionistic fuzzification converts the intermediate fuzzy dataset to intuitionistic fuzzy dataset. The hesitancy factor is calculated by summing up the membership and non-membership degrees and subtracting the sum from one. The clustering procedure given by [19] is followed. The distance matrix is calculated based on the Intuitionistic fuzzy Euclidean distance. Then, the membership matrix is calculated as follows :

$$U_{ij} = \frac{1}{\sum_{r=1}^{C} \left(\frac{dis(d'_j, v_i)}{dis(d'_j, v_r)} \right)^{\frac{2}{m-1}}}, 1 \le i \le C,\ 1 \le j \le n,\ m = 2 \qquad (5)$$

Where, C is the number of clusters, n is the number of instances and m is the fuzziness parameter. This membership value is used to calculate non-membership and hesitancy values. Using these values, the mass (weight) factor given to each attribute t is calculated as follows,

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$$ma_i(k+1) = \left\{ \frac{u_{i1}(k)}{\sum_{j=1}^{n} u_{ij}(k)}, \frac{u_{i2}(k)}{\sum_{j=1}^{n} u_{ij}(k)}, \ldots, \frac{u_{in}(k)}{\sum_{j=1}^{n} u_{ij}(k)} \right\}, 1 \le i \le C \quad (6)$$

where, k indicates the previous iteration.

Using these mass values, the new centroids are calculated as

$$V_i = \left\{ \left[d_s, \sum_{j=1}^{n} ma_j \mu_{A_{ij}}(d_s), \sum_{j=1}^{n} ma_j v_{A_{ij}}(d_s) \right], 1 \le s \le n \right\}, 1 \le i \le C \quad (7)$$

where, d_s is the attribute value in the original dataset.

The objective function of IFCM can be given as

$$J_m(x, y) = \sum_{i=1}^{c} \sum_{j=1}^{n} U_{ij}^m X_j' - C_i, \; 1 \le m \le \infty \quad (8)$$

where, U_{ij} indicates the membership matrix and the term $\|..\|$ denotes the distance matrix.

This objective function should be minimized so that the bondage between the objects of same cluster is high and the intercluster distance between objects of various clusters is low. The iterations are continued till two consecutive iterations produce same value for the objective function.

IV.PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) [2][28] is a populationbased stochastic optimization technique inspired by bird flocking and fish schooling which is based on iterations/generations. Each particle has an initial position and it moves towards a better position with a velocity. The positions represent the solutions for the problem. Initially, the position and velocity matrices are assigned random values. Consider the population or swarm size as m and the particle dimension as n. Let velocity be represented as Veloi = {v1, v2 ,…, vn} and position be represented as Xposi ={x1, x2,…, xn} where i = 1 to n. For every iteration, these two vectors are updated using the following Eq.(9)-Eq.(10).

$$Velo(k+1) = wt \cdot Velo(k) + (c_1 \cdot rand_1) \cdot (p_{best}(k) - Xpos(k)) + (c_2 \cdot rand_2) \cdot (g_{best}(k) - Xpos(k)) \quad (9)$$

$$Xpos(k+1) = Xpos(k) + Velo(k+1) \quad (10)$$

Where, c1 and c2 are user-defined constants, wt denotes the inertia weight, rand1 and rand2 are the random values from 0 to 1. The fitness is evaluated by calculating the objective function for each particle in the swarm. The individual best performance is termed as pbest and it is updated by comparing fitness values of each iteration with that of the previous iteration. The overall best position attained by any particle with the overall minimum fitness (in case of minimization problems like clustering) is chosen as the gbest. The inspiring feature of PSO is that it exempts the possibility of the solution getting stuck in the local optima and tries to reach the global optima by converging in less number of iterations.

V. PROPOSED TECHNIQUE

The proposed technique for the segmentation and detection of medical MR images consists of the following processes as shown in Fig. 1. Pre-processing, FCM based segmentation algorithm and resulting in the segmented and detected image. We now discuss the above mentioned steps in detail.

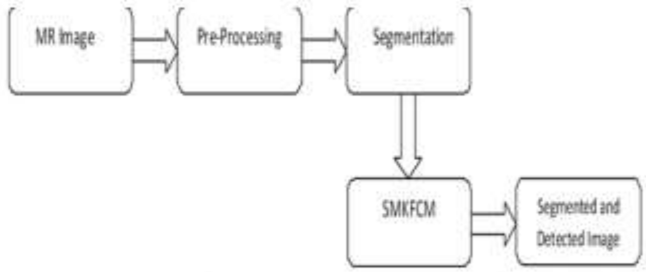

Fig. 1 Proposed medical image segmentation and detection model

The optimization property of MKFCM is improved when it is combined with spatial information. In order to combine the local spatial information of pixels into the MKFCM based image-segmentation algorithms, we select input data $x_j (j = 1,2, \ldots, n)$ as $x_j = [x_j, \bar{x}_j] \epsilon R^2$ and directly apply the MKFCM on these input data. Here, x_j is the intensity of pixel j and $\bar{x}_j$ is the filtered intensity of pixel j , which represents the local spatial information and also $\bar{x}_j$ is the mean or the median filtered intensity defined in a 3×3 window centered at pixel j. If, K_1 is the Gaussian kernel and K_2 is another Gaussian kernel for local spatial information then their composite kernels (K_{com}) is defined as

$$K_{com} = K_1 K_2 \qquad (12)$$

By adding the local spatial information in the objective function, cluster centers and membership functions, the new objective function, cluster centers and membership functions for the proposed method becomes

$$Q = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \left(1 - K_{com}(x_j, v_i)\right) + \alpha \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \left(1 - K_{com}(\bar{x}_j, v_i)\right) \qquad (13)$$

$$u_{ij} = \frac{\left(\left(1-K_{com}(x_j,v_i)\right)+\alpha\left(1-K_{com}(\bar{x}_j,v_i)\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(\left(1-K_{com}(x_j,v_k)\right)+\alpha\left(1-K_{com}(\bar{x}_j,v_k)\right)\right)^{-1/(m-1)}} \qquad (14)$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m}\left(K_{com}(x_j,v_i)x_j+\alpha K_{com}(\bar{x}_j,v_i)\bar{x}_j\right)}{\sum_{j=1}^{n} u_{ij}^{m}\left(K_{com}(x_j,v_i)+\alpha K_{com}(\bar{x}_j,v_i)\right)} \qquad (15)$$

VI.EXPERIMENTAL RESULTS

In this section, we compare the FCM based techniques and the newly proposed IFCM image segmentation algorithm on several noisy medical brain tumor images; all patients have ages ranging from 18 to 96.Their MRI scans were stored in database of images in JPEG format. The proposed algorithm is tested on a large database consisting of 70 tumor images. The algorithm proposed in this paper is able to detect the brain tumor successfully with 98.57% accuracy in various age groups. Table I shows the comparison of proposed algorithm with existing FCM based techniques.

TABLE I
COMPARISON OF PROPOSED ALGORITHM

Image set	SMKFCM	MKFCM	KFCM	FCM
MR brain Tumor Images (Noisy)	69/70	67/70	66/70	64/70
Success rate (%)	98.57	95.71	94.28	91.42

The performance of the proposed algorithm and other FCM based techniques are compared with the optimal segmentation accuracy, which is defined as the sum of the correctly classified pixels divided by the sum of the total number of pixels. The segmentation accuracy of I on class K is calculated as

$$S_{ik} = \frac{A_{ik} \cap A_{refk}}{A_{ik} \cup A_{refk}} \qquad (16)$$

Proposed segmentation algorithm in noisy environment, we add different amount of noise in medical brain tumor MR images. The segmentation accuracy results for the three clusters corresponding to Cerebrospinal Fluid (CSF), Gray Matters (GM) and White Matters (WM) by using FCM based techniques and the proposed algorithm is shown in Table II. The segmentation results of the proposed algorithm with 5% noise applying on three medical tumor MR images are shown in Fig. 2. However, from Table II, we proved the algorithm proposed in this paper have better performance than those of other FCM based techniques.

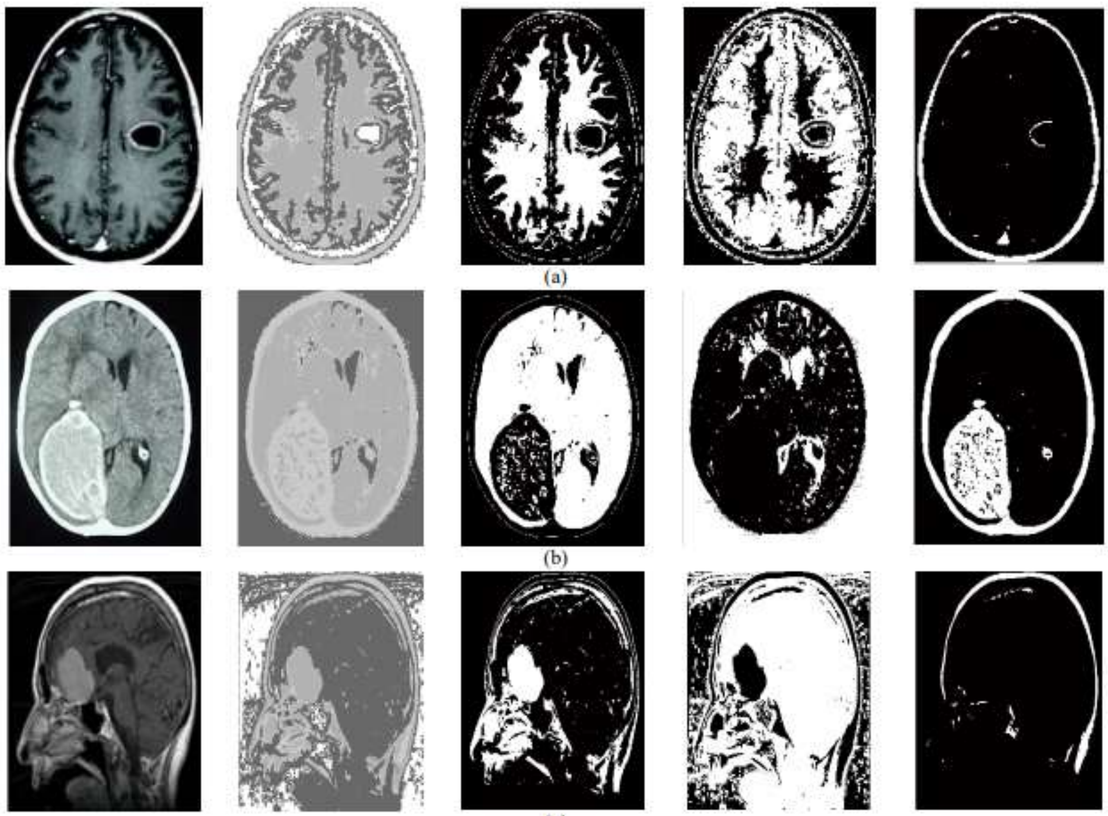

Fig. 2 Segmentation results of proposed method on medical MR images. (a)-(c) MR image with 5% noise and its correct segmentation. From left to right are the Original MR Image, Segmented MR image, the CSF, the GM, and the WM.

TABLE II
COMPARISON OF SEGMENTATION ACCURACY FOR THE CLUSTER OF CSF, GM AND WM

CLUSTERS	SMKFCM	MKFCM	KFCM	FCM
CSF	0.78	0.71	0.68	0.58
GM	0.88	0.82	0.81	0.71
WM	0.71	0.62	0.51	0.43

VII. CONCLUSIONS

This project presented an IFCM algorithm for the segmentation and detection of medical MR images, where the kernel function is composite by multiple kernels. These kernels are selected for different spatial information of image pixels. Considering the image-segmentation problems under the MIFCM framework, the proposed algorithms provide a significant flexibility in selecting and combining different kernel functions. More importantly, a new information fusion method is obtained, where the information of the image from multiple heterogeneous or homogeneous data sources is combined in the kernel space. To evaluate the robustness of the proposed segmentation algorithm in noisy environment, we add 5% noise in medical brain tumor MR images and calculated the success rate and segmentation accuracy. From the experimental results it is clear that the proposed method have better performance than FCM based techniques for noisy medical MR images.

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