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Medical Image Segmentation and Detection of MR Images Based on Spatial Multiple-Kernel Fuzzy C-Means Algorithm

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Abstract**—**In this paper, a spatial multiple-kernel fuzzy C-means (SMKFCM) algorithm is introduced for segmentation problem. A linear combination of multiples kernels with spatial information is used in the kernel FCM (KFCM) and the updating rules for the linear coefficients of the composite kernels are derived as well. Fuzzy c-means (FCM) based techniques have been widely used in medical image segmentation problem due to their simplicity and fast convergence. The proposed SMKFCM algorithm provides us a new flexible vehicle to fuse different pixel information in medical image segmentation and detection of MR images. To evaluate the robustness of the proposed segmentation algorithm in noisy environment, we add 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 algorithm has better performance than those of other FCM based techniques for noisy medical MR images.

Keywords**—**Clustering, fuzzy C-means, image segmentation, MR images, multiple kernels.

I. Introduction

MEDICAL image segmentation and detection in Magnetic Resonance Imaging (MRI) has becoming an emergent research area in the field of computer vision and intelligent image analysis. Medical image segmentation aims at partitioning a medical image into its constituent regions or objects and isolating multiple anatomical parts of interest in the MR images [1]. Segmentation of medical images plays an important role in diagnosis and therapy of diseases. It can provide quantitative pathological information about diseases and help physicians to make decisions. Due to the inefficiency and the inter and intra expert variability residing in manual segmentation, accurate and robust automatic segmentation is highly desired. However, fully automatic segmentation of a structure of interest is still a challenging task because of the shape and appearance variations of the target structure in different medical MR images. There are lots of methods for automatic and semi automatic image segmentation [2]-[5], though, most of them fail in unknown noise, poor image contrast, and weak boundaries that are usual in medical images. Medical images mostly contain complicated structures and their precise segmentation is necessary for clinical diagnosis.

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The magnetic resonance imaging is one of the most popular techniques in medical imaging due to its high resolution and contrast. Besides all these good properties, MRI also suffers from three Considerable obstacles: noises, artifacts, and intensity in homogeneity. Due to these problems, classical approaches do not succeed to correctly segment these images [6]-[8]. Classification techniques, known from unsupervised artificial intelligence, fuzzy logic, probability and statistics, know a great success. Amongst the above said methods, in medical imaging research clustering based approaches perceived a great focus of interest. Clustering is a process for classifying objects or patterns in such a way that samples of the same cluster are more similar to one another than samples belonging to different clusters. There are two main clustering methods used in medical application. Those are hard clustering scheme and the fuzzy clustering scheme. K-means is one of the hard clustering methods [9]. The conventional hard clustering methods classify each point of the data set just to one cluster. As a consequence, the results are often very crisp, i.e., in image clustering each pixel of the image belongs just to one cluster. However, in many real situations, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity in homogeneity reduce the effectiveness of hard clustering methods [10]. Fuzzy set theory has introduced the idea of partial membership, described by a membership function. Fuzzy clustering is one of the soft segmentation methods have been successfully applied in image clustering and segmentation problem.

Among the fuzzy clustering methods, Fuzzy C-Means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods [11]. Although the conventional FCM algorithm works well on most noise-free images, it is very sensitive to noise and other imaging artifacts, since it does not consider any information about spatial context. To compensate this drawback of FCM, a pre-processing image smoothing step has been introduced. However, by using smoothing filters important image details can be lost, especially boundaries or edges. Moreover, there is no way to control the trade-off between smoothing and clustering. Thus, many researchers have incorporated local spatial information into the original FCM algorithm to improve the performance of medical image segmentation [12]. In addition to the incorporation of local spatial information, the kernelization of FCM has made an important performance improvement.

The kernel fuzzy c-means (KFCM) algorithm is an extension of FCM [13], [14], which maps the original inputs into a higher dimensional Hilbert space by some transform function. The kernel Fuzzy c-means clustering algorithm is used for spherical clusters only. Multiple kernel fuzzy c-means (MKFCM) algorithm is a new extension to the KFCM [15]. This multiple Kernel fuzzy c-means algorithm is used to provide a better analysis tool for pattern classification. It uses multiple kernels and automatic adjustment of kernel weights. It makes the kernels as less crucial. The proposed algorithm, especially with the spatial constraints is more robust to noise and outlier in image segmentation than the algorithms with the kernel substitution. Traditionally, fuzzy *C*-means clustering algorithm has been widely used for image segmentation. For improving its efficiency, multiple kernel trick and spatial constraints were adopted [16].

In this paper, multi-kernel based FCM algorithm with spatial information (SMKFCM) has been proposed using two Gaussian kernels in place of single kernel. Further, the membership values are modified by using their neighbors. The modified membership values are more robust noise images. The effectiveness of the proposed method is tested on Medical MR Images under different noise conditions and proved that the proposed algorithm is more robust as compared to FCM family algorithms.

The rest of this research paper is organized as follows. In Section II, FCM based algorithm and the proposed spatial multi-kernel FCM algorithm are described. Experimental results and comparison with existing segmentation algorithms are presented in Section III. Finally, conclusions followed by references come in Section IV.

II. 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.

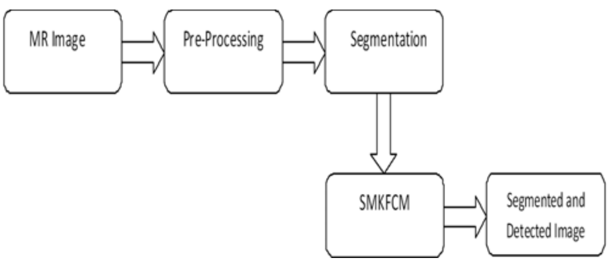

Fig. 1 Proposed medical image segmentation and detection model

A. Pre-processing

Pre-processing is the first step in medical image segmentation which includes enhancement in the way that finer details are improved and noise is removed from the medical MR image [17], [18]. Enhancement will result in more prominent edges and a sharpened image is obtained, noise will be reduced thus reducing the blurring effect from the image which is most suitable for segmentation. In addition to enhancement, edge detection will also be applied. This improved and enhanced image will help in detecting edges and improving the quality of the overall image. Edge detection will lead to detect the exact location of medical MR image. In this work mathematical morphological filter is used to sharpen as well as removed noise from the medical MR image.

B. Methodology

1. Fuzzy C-means (FCM) Algorithm

FCM is one of the well-known clustering techniques in the task of medical image segmentation due to their simplicity and fast convergence. In this technique clustering starts with the center point of the cluster. These cluster point will not be accurate, so FCM assigns membership rank for every cluster at every point. FCM iteratively moves the cluster to the correct place within a dataset. This iteration is based on minimizing an objective function that symbolizes the distance from any given data point [12]. To normalized the data point occurred in the images a gradient function using FCM is clustered, when pixels are close to the centroid of pixels assigned as 0,1 which optimize the objective function defined as

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m}\, d^2(x_j, v_i) \tag{1}$$

Here, u_{ij} is the membership of the data x_j belongs to the cluster v_i,m is the fuzzification coefficient of the system (m=2) and d is the Euclidean distance between the cluster center and pixel. The constraints on u_{ij} is $\sum_{i=1}^{c} u_{ij} = 1$, where c is the total number of clusters.

The Euclidean distance between the cluster center and pixel is given by

$$d^2\left(x_j, v_i\right) = \left\| x_j - v_i \right\|^2 \tag{2}$$

The membership values and cluster centers are updated as

$$u_{ij} = \frac{\left(d(x_j,v_i)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(d(x_j,v_k)\right)^{-1/(m-1)}} \tag{3}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{4}$$

The FCM iteration proceeds with the new membership that is incorporated with the spatial function. When the maximum difference between two cluster centers at two successive iterations is less than a threshold, the iteration is stopped. After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal.

2. Kernel Fuzzy C-means (KFCM) Algorithm

In KFCM the cluster centers in the kernel space are mapped from the original data space or the feature space [15]. The objective function is defined as

$$Q = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} \tag{5}$$

Here, $1 - K(x_j, v_i)$ is the robust distance measurement derived in the kernel space. By applying Gaussian kernels, we iteratively update the membership values and cluster centers as

$$u_{ij} = \frac{(1-K(x_j,v_i))^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1-K(x_j,v_k)\right)^{-1/(m-1)}} \tag{6}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m K(x_j,v_i)x_j}{\sum_{j=1}^{n} u_{ij}^m K(x_j,v_i)} \tag{7}$$

where, $i = 1,2 \ldots \ldots candj = 1,2 \ldots \ldots n$

3. Multiple Kernel Fuzzy C-means (MKFCM) Algorithm

MKFCM algorithm provides a new flexible vehicle to fuse different pixel information in image-segmentation problems. In this methodology composite or multiple kernels are used in the kernel FCM. If, K_1 and K_2 are two Mercer kernels [16] then their composite kernels (K_{com}) is defined as

$$K_{com} = K_1 + \alpha K_2 \tag{8}$$

Here, α is the learning parameter usually greater than zero. In machine learning community widely used composite kernel is the linear combination of several kernels is defined as

$$K_{com} = w_1K_1 + w_2K_{12} + w_3K_3 + \cdots w_iK_i \tag{9}$$

where, weights (w_i) are automatically adjusted in the kernels learning methods like multiple-kernel regressions and classifications. The membership values and cluster centers are update as

$$u_{ij} = \frac{(1-K_{com}(x_j,v_i))^{-1/(m-1)}}{\sum_{k=1}^{c}(1-K_{com}(x_j,v_k))^{-1/(m-1)}} \tag{10}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m K_{com}(x_j,v_i)x_j}{\sum_{j=1}^{n} u_{ij}^m K_{com}(x_j,v_i)} \tag{11}$$

4. Spatial Multiple Kernel Fuzzy C-means (SMKFCM) Algorithm

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 $x_j = [x_j, \overline{x}_j] \epsilon R^2$ and directly apply the MKFCM on these input data. Here,x_j is the intensity of pixel $j$and $\overline{x}_j$is the filtered intensity of pixel$j$, which represents the local spatial information and also $\overline{x}_j$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

$$K_{com} = K_1K_2 \tag{12}$$

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

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

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

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

III. Experimental Results

In this section, we compare the FCM based techniques and the newly proposed SMKFCM 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 [16], 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

$$S_{ik} = \frac{A_{ik} \cap A_{refk}}{A_{ik} \cup A_{refk}} \tag{16}$$

where, A_{ik} is the set of pixels belongs to class k that are found by algorithm i and A_{refk} is the set of pixels belongs to the class k in the reference segmented image. To evaluate the robustness of the 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.

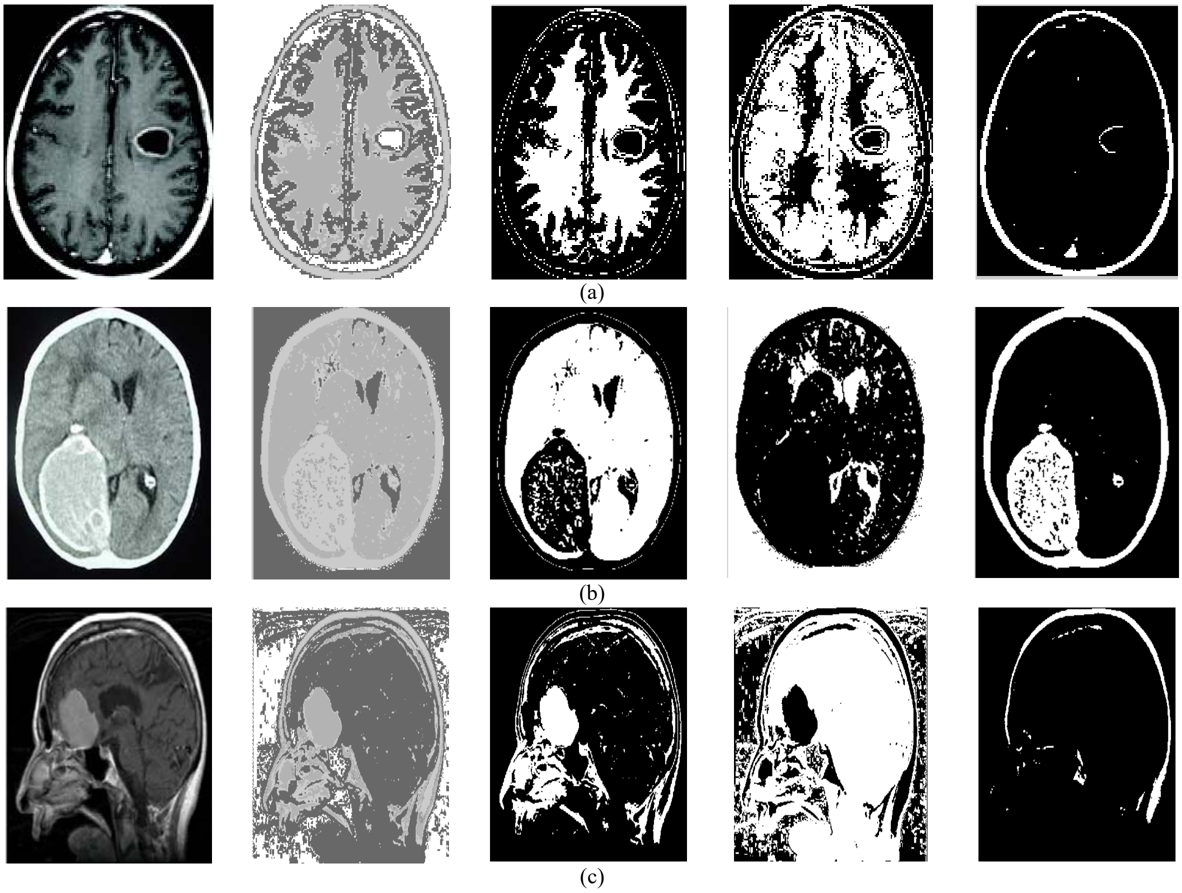

Fig. 2 Segmentation results of proposed method on medical MR images. (a)-(c) MR image with 5% noise and its correct segmentation. From left to right are the Original MR Image, Segmented MR image, the CSF, the GM, and the WM.

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

IV. CONCLUSIONS

This paper presented an SMKFCM 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 MKFCM 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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