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Multi-Spectral MRI Brain Image Segmentation Based On Kernel Clustering Analysis

Xiao-li Jin[1, 2] Tu-sheng Lin[1] Liang Liao[3] and Teng Wang[2]

[1]School of Electronic and Information Engineering, South China University of Technology, Guangzhou, P.R. China

[2] School of Computer Science, South China Normal University, Guangzhou, P.R. China

[3] School of Electronic and Information Engineering, Zhongyuan University of Technology, Zhengzhou, P.R. China

jinxl@scnu.edu.cn (X. L. Jin)

Abstract. Recently, kernel-clustering analysis has been an important tool in medical image segmentation algorithms. In this paper, a multi-spectral magnetic resonance imaging (MRI) brain image segmentation algorithm based on kernel clustering analysis was proposed. The algorithm, called multi-spectral kernel based fuzzy c-means clustering (MS-KFCM), first filtered the T1-weighted and T2-weighted MRI brain image and selected the features as the input data. Then the input data are mapped to a high dimensional feature space (kernel space) in order to improve the separability of the input data. And the initial clustering center of MS-KFCM comes from the output of FCM (fuzzy c-means) clustering. The experimental results show that our proposed algorithm has better segmentation performance than traditional single-channel FCM and KFCM algorithms.

Keywords: Magnetic Resonance Imaging (MRI); Fuzzy C-means Clustering; Kernel Clustering Analysis

1. Introduction

Medical image segmentation refers to the process of partitioning observed image data to a serial of non-overlapping regions [1]. These regions denote different human tissue structures and decide the performance of some advanced medical image processing and the accuracy of clinical diagnosis. These advanced medical image processing include feature registration, anatomy structure analysis, 3D reconstruction, movement analysis, and etc. Image segmentation plays an important pole in these processing.

For MRI brain image segmentation, the brain tissue is often divided into white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). The precise measurement of WM, GM and CSF is important for quantitative pathological analyses and so becomes a goal of lots of methods for segmenting MRI brain image data. Among these methods, fuzzy clustering analysis has proven to be an effective tool in image analyses [2]. Because of the imperfections of imaging scanner, imaging techniques and etc., obtained medical images will inevitably be affected by some corruption factors including random additive noises, partial volume effect and intensity bias field. For improving segmentation performance, many different strategies, for example, Mercer Kernel techniques, Filtering techniques and etc., can be adopted. The basic idea of the Mercer Kernel technique is to implicitly map input patterns to a higher dimensional feature space (kernel space), and then apply traditional algorithms in kernel space [2]. Multi-spectral image information has also contributed to the improvement of image segmentation performance [3]. Multi-spectral image information includes T1-weighted, T2-weighted, and PD-weighted MRI brain image data. Improving single channel image processing algorithms forms the multi-spectral image processing algorithms. The performance of these algorithms is generally better than that of the single channel image processing algorithms. Combined with kernel technique analysis, there are many other algorithms, such as kernel-based support vector machines [4], kernel clustering [5], kernel-based support vector clustering [6], kernel principle component analysis [7], kernel fisher discriminant [8] and etc. According to the different applications, these algorithms have their own characteristics. In this paper, a new image segmentation algorithm called multi-spectral MRI brain image segmentation is described. Based on kernel clustering analysis, it pre-processes the multi-spectral image data and improves the initial clustering center of the traditional KFCM. Finally, it leads to a better segmentation result than the traditional FCM and KFCM.

2. Background

In kernel-based clustering algorithm, Mercer kernel has the following forms, the Gaussian Kernel, Radial Basis Function Kernel, Hyperbolic Tangent Kernel, Sigmoid Kernel and Polynomial Kernel. Mercer Kernel function denotes as $K(x_i, y_i)$. According to Mercer theorem [9], Kernel functions meet formula (1).

$$K(x_i, y_i) = \Phi(x_i)^T \Phi(y_i) \tag{1}$$

Where K is the real symmetric function, corresponds to the dot product of a definition in a feature space. The sample data $X = \{x_1, \cdots, x_N\}$ can be mapped to feature space (kernel space) by Φ .

All forms of Mercer Kernel meet positive definite conditions. And they are all used in clustering algorithms to transform non-linear problem into a linear problem for improving the separability of the input data.

The traditional KFCM maps input data to kernel space and uses FCM in kernel space for data classification. The target of KFCM is to minimize the objective function defined as formula (2) [1,2].

$$J(U, V) = \sum_{i=1}^{C} \sum_{k=1}^{N} \mu_{i,k}^{m} \left\| \Phi(x_k) - v_i^{\Phi} \right\|^2 \tag{2}$$

Where C is the category of the data and N is the number of samples. The membership function $\mu_{i,k}$ can be formulated as formula (3). And the cluster center function v_i^{Φ} denotes as formula (4) [1].

$$\mu_{i,k} = \frac{\left\| \Phi(x_k) - v_i^{\Phi} \right\|^{-2/(m-1)}}{\sum_{j=1}^{c} \left\| \Phi(x_k) - v_j^{\Phi} \right\|^{-2/(m-1)}} \tag{3}$$

$$v_i^{\Phi} = \frac{\sum_{k=1}^{N} \mu_{i,k}^{m} \Phi(x_k)}{\sum_{k=1}^{N} \mu_{i,k}^{m}} \tag{4}$$

Combined Eq.(1), Eq.(2), Eq.(3), Eq.(4) with the specific expression of Mercer Kernel, the minimum of Eq.(2) can be found and the input data can be classified.

Based on KFCM algorithm, there are many improved algorithms which are mostly concentrated in the selection of input features [1], the set of the initial value of membership function, the set of the initial value of cluster centers, the choice of optimization algorithm, the simplify of the calculation equivalent [2], and so on. In this paper, the proposed algorithm (MS-KFCM) focuses on the selection of the input feature data and the set of the initial value of cluster centers in the improvement based on the traditional KFCM.

3. The Proposed Algorithm (Ms-Kfcm)

3.1 Pre-image technique and input features selection

The brain MRI includes Transverse, Coronal and Sagittal MRI slices map in three directions. Among them, the transverse slice map has three modes, T1-weighted image, T2-weighted image and PD-weighted image. Usually T1 weighted MRI image has high contrast and low noise characteristics. So there are more T1-weihted image segmentation algorithms. Multi-spectral images composed by different modes are usually able to provide richer anatomy information, so the accuracy of the multi-spectral image segmentation can often be higher than that of the single-channel image segmentation. But because the different modes have their own unique characteristics and different processing methods, so the multi-spectral image processing algorithms are usually more complex than the single-channel image processing algorithms. In this paper, the multi-spectral images only include T1-weighted brain MRI image and T2-weighted brain MRI image as shown in Fig.1 and Fig.2.

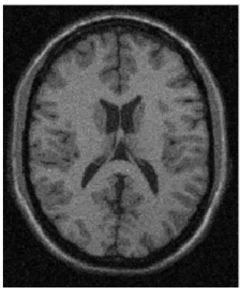


Fig.1 T1-weighted image

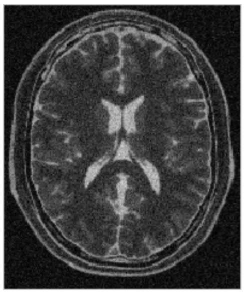


Fig.2 T2-weighted image

Brain tissue segmentation needs to remove some areas in the extra-cranial part of the brain in this paper. In this respect, there are many ways, such as watershed-based approach [10], morphology-based approach [11], hybrid method [12] and so on. To simplify this algorithm, we remove the extra-cranial part by hand directly.

Because the MRI image most likely contains a lot of noise, so this algorithm contains the filtering process including the mean filtering, the median filtering and the wavelet denoising. Then, T1-weighted image, T2-weighted image, their mean filtering results, median filtering results, and wavelet denoising results form a feature matrix as the input data of the clustering.

3.2 Fuzzy clustering and image segmentation based on kernel

In this paper, we use FCM Cluster centers v_{Fi}^{Φ} as the initial cluster centers of MS-KFCM for enhancing the stability of MS-KFCM. The Gaussian Kernel is used in MS-KFCM. It is denoted as equation (5) below.

$$K(x_i, y_i) = \exp(-\sigma^{-2}\|x_i - y_i\|^2) \tag{5}$$

Where the Gaussian Kernel parameter $\sigma \in R$ and $\sigma \neq 0$. When the σ value is different, the cluster performance is different. Where $\sigma = 150$.

The Gaussian Kernel meets equation (6) by the above equation (5).

$$K(x_i, x_i) \equiv 1 \tag{6}$$

The membership function $\mu_{i,k}$ and cluster centers v_i^{Φ} can be calculated by equation (3) and (4). The membership matrix exponential m usually equals to 2. Here the exponential m is 2.

$\|\Phi(x_k) - v_i^{\Phi}\|^2$ can be expanded as follows.

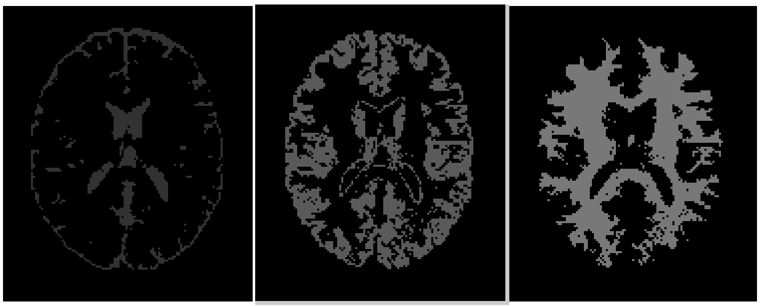
$$\begin{aligned}\|\Phi(x_k)-v_i^{\Phi}\|^2 &= (\Phi(x_k)-v_i^{\Phi})^T(\Phi(x_k)-v_i^{\Phi}) = \Phi(x_k)^T\Phi(x_k)+(v_i^{\Phi})^T(v_i^{\Phi})-2\Phi(x_k)^T(v_i^{\Phi}) \\ &= K(x_k, x_k)+\sum_{k1=1}^{N}\sum_{k2=1}^{N}\alpha_{i,k1}\alpha_{i,k2}K(x_{k1}, x_{k2})-2\sum_{k1=1}^{N}\alpha_{i,k1}K(x_k, x_{k1})\end{aligned} \tag{7}$$

Where the initial matrix $\mu_{i,k}$ is a random array, the sum of its each column is 1. $\alpha_{i,k}$ is defined as follows.

$$\alpha_{i,k} = \left(\sum_{k=1}^{N}\mu_{i,k}^{m}\right)^{-1}\mu_{i,k}^{m} \tag{8}$$

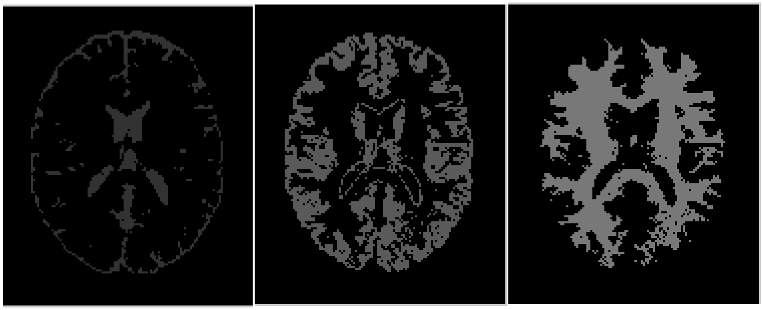
For the target of the minimum value of equation (2), after several iterations, we can get the resulting data including background, CSF, GM and WM.

In order to measure the performance of this algorithm (MS-KFCM), the segmentation results of FCM and KFCM on T1-weighted image will be given. Three kinds of algorithms for segmentation results are shown in Fig.3, Fig.4 and Fig.5.



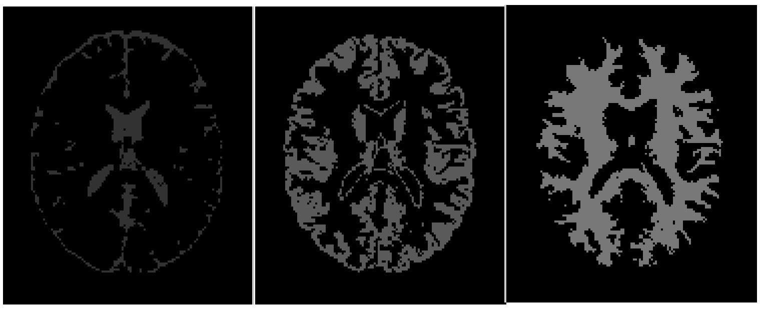
(a) CSF (b) GM (c) WM

Fig.3 FCM segmentation results



(a) CSF (b) GM (c) WM

Fig.4 KFCM segmentation results



(a) CSF (b) GM (c) WM

Fig.5 MS-KFCM segmentation results

From the subjective point of view, the segmentation effects in Fig.3 and Fig.4 are the same. Fig.5 has less holes and stray points.

3.3 The effect of Gaussian kernel parameters σ on the clustering result

In the kernel-clustering algorithm, Gaussian kernel parameter σ has an important impact on the clustering results. The segmentation accuracy of MS-KFCM with the different σ is shown in Fig.6. From Fig.6, we can see that when the Gaussian kernel parameter $\sigma < 100$, the segmentation accuracy is low and easy to get into local minima. When the Gaussian parameter σ reaches approximately greater than 100, the segmentation accuracy of MS-KFCM basically remains unchanged and maintains a high level. In this paper, the value of the Gaussian kernel parameter is 150. This makes the proposed algorithm has high performance and difficult to get into local minima.

4. Results And Discussion

The image data in this paper comes from McConnell Brain Image Center in Montreal Neurological Institute. It is 3D data with 217 × 181 × 181 pixels. It has provided the segmentation ground truth for quantitatively comparing segmentation accuracy and also permits controlled evaluations on different noise and bias field conditions. In this paper, we use the transverse slice map, the slice thickness is 1mm, and the size is 217 × 181 pixels.

For the performance evaluation of MS-KFCM, the quantitative indicators are the segmentation accuracy s_1 and the segmentation similarity S_2^i in this article, which is defined as equation (9) and (10) [1,2].

$$S_1 = \frac{\sum_{i=1}^{C} A_i \cap A_{std,i}}{N} \tag{9}$$

$$S_2^i = \frac{A_i \cap A_{std,\ i}}{A_i \cup A_{std,\ i}} \quad i \in \{1, 2, \cdots, c\} \tag{10}$$

Where A_i is the i-th area of the segmentation results, $A_{std,\ i}$ is the i-th area of the standards segmentation, C is the categories, and N is the total number of pixels.

The quantitative indicator s_1 is the ratio of the correct segmentation pixel number and the total pixel number. It shows the whole segmentation performance, the larger value of s_1, the higher segmentation performance of the algorithm.

The quantitative indictor S_2^i reflects the segmentation indicator of the specific classification (the i-th classification), the larger value of S_2^i, the better segmentation performance of the algorithm.

For comparing the performances of relevant algorithms, we apply FCM, KFCM and M-KFCM on input data respectively, which include original, mean-filtered, median-filtered, and Wavelet denoising images. The segmentation results under different degenerated condition are shown in Table 1. From the view of segmentation accuracy S1 and segmentation similarity S2, with the change of the degenerated condition, the segmentation results of FCM and KFCM are similar, but the performance of MS-KFCM is better obviously. (The symbol pnXrfY means that the experiment data have been corrupted by X% noise and Y% bias field.)

In addition, when Gauss nuclear parameter σ is different, the image division accuracy is also different. In the same degradation condition pn9rf40, the segmentation accuracy curve S_1 is shown as Fig.6.

It can be seen from Fig.6 that FCM segmentation accuracy is independent of the Gaussian parameter σ, and its segmentation accuracy remains unchanged. It is because the FCM algorithm does not contain the Gaussian parameter σ. While the segmentation accuracies of the KFCM and the MS-KFCM algorithm are related to the Gauss parameter σ, therefore their division accuracies change along with the Gauss parameter. When σ is greater than 50, the segmentation accuracy of the KFCM algorithm is equivalent to that of the FCM algorithm. When σ is greater than 100 approximately, the MS-KFCM division accuracy is higher than the FCM division accuracy and the KFCM division accuracy. So in this paper, the Gauss parameter σ equals to 150.

Table.1 The performance of FCM, KFCM and MS-KFCM

Corruption Condition	FCM				KFCM				MS-KFCM			
	S1	S2-CSF	S2-GM	S2-WM	S1	S2-CSF	S2-GM	S2-WM	S1	S2-CSF	S2-GM	S2-WM
Pn0rf40	0.9415	0.8749	0.8415	0.9153	0.9411	0.8749	0.8409	0.9144	0.9405	0.8339	0.8700	0.9429
Pn1rf40	0.9416	0.8736	0.8419	0.9160	0.9420	0.8759	0.8427	0.9160	0.9416	0.8425	0.8692	0.9410
Pn5rf40	0.9293	0.8524	0.8173	0.8986	0.9298	0.8554	0.8185	0.8986	0.9419	0.8462	0.8537	0.9237
Pn7rf40	0.9119	0.8227	0.7874	0.8729	0.9114	0.8206	0.7862	0.8729	0.9324	0.8356	0.8351	0.9086
Pn9rf40	0.9021	0.8029	0.7671	0.8622	0.9021	0.8029	0.7671	0.8622	0.9254	0.8458	0.8160	0.8920

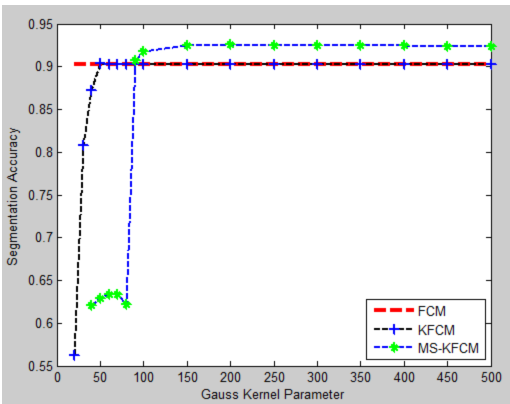


Fig.6 Segmentation Accuracy Curves

5. Conclusions

In this paper, a new multi-spectral MRI brain image segmentation algorithm based kernel clustering analysis has been proposed. The proposed algorithm uses the kernel clustering and the input patterns of multi-spectral images for improving the segmentation performance. The experiment has shown that the proposed algorithm is superior to the traditional FCM algorithm and KFCM algorithm so long as the parameter is well-tuned. (In the proposed algorithm, the Gauss parameter evaluates to 150)

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