G-017

脳の MRI 画像の領域分割のための改良ＫＦＣＭアルゴリズム
An Improved KFCM Algorithm in the Segmentation of Brain MRIs

徐 栄† 大谷 淳†
Rong Xu† Jun Ohya†

1. Introduction

Medical image segmentation is an important step for medical image processing, which is a complex and challenging task, especially in brain magnetic resonance images (MRIs) segmentation. A large number of approaches are available for MRIs segmentation [1-3]. However, for MRI images, there are many uncertain factors, such as noise, bias field effect and partial volume effect, which make MRI images essentially fuzzy [4]. Therefore, fuzzy clustering methods have been more widely used in MRIs segmentation.

The fuzzy c-means (FCM) algorithm [5] is a typical clustering algorithm, which uses Euclidean distance to measure similarity among image pixels, but it can only be effective in clustering 'spherical' data. In order to cluster more general dataset, a kernel-based fuzzy c-means (KFCM) algorithm [6] is proposed by inducting kernel function to measuring data's resemblance instead of Euclidean distance. However, the KFCM method is easily affected by noise owing to ignoring spatial information in images. Recently, kinds of methods [7-10] have been proposed by exploiting image spatial correlation to advance partition ability in the segmentation of low SNR images.

Herein, we introduce the priori probability of MRF model to propose a novel KFCM method via considering image spatial relativities for the sake of reducing the effect of noise. In experiments, the new method achieves more accurate results and has a better performance than the original method.

The chapters are organized as follows: Section 2 introduces the priori probability of MRF model. Section 3 proposes a novel KFCM algorithm based on priori probability. Section 4 sets out the experimental results in simulated brain MRIs segmentation. Finally, Section 5 gives our conclusions and some future works.

2. Priori Probability

In Markov Random Field (MRF) model, mutual influences among image pixels are characterizing by using MRF probabilities [11]. If $P(x_i \mid x_{S-\{i\}}) = P(x_i \mid x_{N_i})$, random field X is defined as a MRF correlated with neighborhood system N in image pixel set S, where neighborhood N_i is a site set bordered on site i. Then, the gray value of site i will be decided by the gray value of its neighborhood system N_i.

According to the Hammersley-Clifford theorem [12], the priori probability of MRF model meets Gibbs distribution and is defined as $P(x) = \exp(-U(x))/Z$, where $Z = \sum_{x \in X} \exp(-U(x))$ is normalizing constant, $U(x) = \sum_{c \in C} V_c(x)$ is energy function and $V_c(x)$ denotes the potential function of clique $c \in C$, which only depends on $N_i, i \in c$. C is the set of spatial second order cliques (i.e. doubletons).

If multi level logistic (MLL) model [13] is adopted and the dual potential function is only considered, the priori probability is defined as

$$p_{ki} = p(X_i = k \mid X_{N_i}) = \exp[\beta n_i(k)] / \sum_{l \in L} \exp[\beta n_i(l)] \tag{1}$$

Where $n_i(k)$ is the number of sites marked by k in N_i, L is a cluster set, the parameter β is to determine spatial correlation among dependent image pixels.

3. The Novel KFCM algorithm

The original KFCM algorithm [8] partitions a image into several distinct non-overlapped regions by minimizing the following objective function

$$J_m(U,V) = 2\sum_{k=1}^{L}\sum_{i=1}^{N} u_{ki}^m (1 - K(x_i, v_k)) \tag{2}$$

Where L is the number of clusters, N is the number of image pixels, u_{ki} is the membership of pixel i in class k, satisfying $\sum_{k=1}^{L} u_{ki} = 1$, $\{v_i, i = 1,2,\cdots,L\}$ are clustering centers, m is the quantity of controlling clustering fuzziness, generally $m = 2$, $K(x,y) = \exp(-\| x - y \|^2 / \sigma^2)$ is a Gaussian kernel function.

Here, $U = \{u_{ki}\}$ is only considered from single pixel's character, which easily leads to noise-sensitive. Therefore, we consider image spatial relativities by taking advantage of the priori probability p_{ki}, which figures the priori probability of pixel i in class k. Then, via importing p_{ki} and neighborhood controlling factor α, the membership degree matrix of KFCM is converted into $u'_{ki} = (1 - \alpha + \alpha \cdot p_{ki}) u_{ki}$, α is constant for controlling neighborhood effect, which is increasing with noise levels and $0 < \alpha < 1$. In that way, the new objective function is revised as

$$J_m(U,V) = 2\sum_{k=1}^{L}\sum_{i=1}^{N} ((1 - \alpha + \alpha \cdot p_{ki}) u_{ki})^m (1 - K(x_i, v_k)) \tag{3}$$

According to the constraint of u_{ki} and Lagrange multipliers, the new iterative equations are derived as

$$u_{ki} = \frac{(1 - \alpha + \alpha \cdot p_{ki})(1 - K(x_i, v_k))^{-1/(m-1)}}{\sum_{j=1}^{L} (1 - K(x_i, v_j))^{-1/(m-1)}} \tag{4}$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}^m K(x_i, v_k) x_i}{\sum_{i=1}^{N} u_{ki}^m K(x_i, v_k)} \tag{5}$$

† 早稲田大学大学院国際情報通信研究科
Graduate School of Global Information and Telecommunication Studies, Waseda University

4. Experiments

4.1 Misclassification Rate

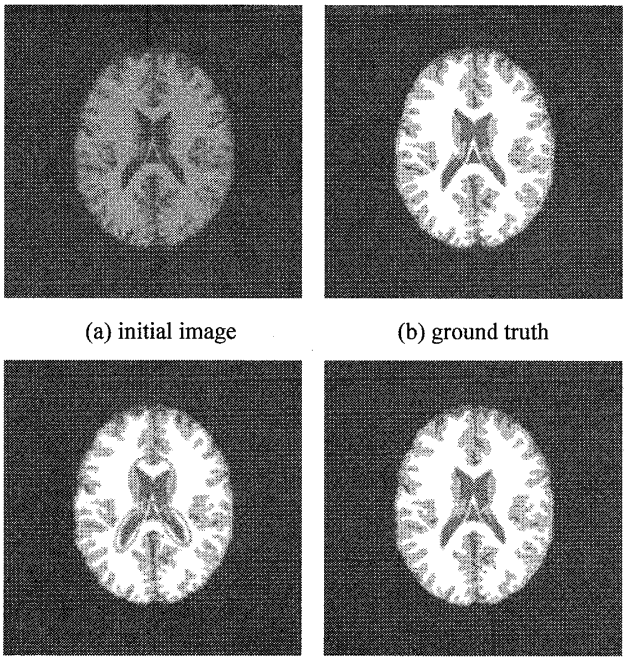
In order to verify the performance of new method, we apply the original KFCM algorithm and new method in experiments. For brain MRIs segmentation, the image will be divided into four regions: gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background (BG). In the interest of quantitatively evaluating image segmentation effect of the above algorithms, misclassification rate (MCR) is defined as:

$$MCR = \frac{the\ No.\ of\ misclassified\ pixels}{the\ No.\ of\ all\ pixels} \times 100\% \qquad (6)$$

Where $MCR \in [0,1]$. The smaller the $MCRs$, the better the segmentation performance. All experiments are operated by VS.Net 2003 in the PC of Intel® Core™2 CPU 6600 @ 2.40GHZ with 2GB memory.

4.2 Simulated Brain MRIs

In experiments, we use the simulated brain MRIs of Brainweb (http://www.bic.mni.mcgill.ca/brainweb/), which are called gold standard of image segmentation. Each data set is composed of $258*258$ pixels, thickness of layer is $1mm$, T_1 weighted. We use the image sequences of $Z = 16.5mm$.



(a) initial image (b) ground truth

(c) results of original KFCM (d) results of novel KFCM

Fig. 1. The results of two algorithms for simulated brain MRIs with 9% noise.

Fig.1 is a comparison of the segmentation results of two algorithms for simulated brain MRIs with 9% noise. Obviously in the area of circles of Fig.1.(c), there are much more misjudgments in the results of original KFCM compared with the results of novel KFCM. Therefore, the novel KFCM method achieves better segmentation results than the original KFCM.

Table 1. MCRs (%) of images with noise of different levels.

Noise Levels(%)	3%	5%	7%	9%
KFCM	4.88	5.65	6.64	8.19
Novel KFCM	4.75	5.38	6.02	6.82

Moreover, the data of Table 1 (These data also are average segmentation results of 20 images) indicate MCRs of novel KFCM for all simulated brain MRIs are lower than those of the original KFCM. In addition, the stronger the intensity of noise in image, the better the segmentation performance of the novel KFCM method.

5. Conclusions

In this paper, we propose a novel KFCM algorithm based on priori probability of MRF model by introducing image spatial influence. In the experiments of low signal-to-noise ratio image segmentation, the novel KFCM attain a better performance and the experimental results also testify the new method has stronger robustness for noise. In addition, this new method is simple and can be improved to apply into practical medical application, i.e., the segmentation of lesion in brain MRIs.

Reference

[1]Wells, W.M., Grimson, W.E.L., Kikinis R., Arrdrige, S.R. "Adaptive Segmentation of MRI Data". IEEE Trans. Med. Imag. 15, 429—442 (1996)

[2]Johnson,B., Atkins, M.S., Mackiewich, B., Andson, M. "Segmentation of Multiple Sclerosis Lesions in Intensity Corrected multispectral MRI". IEEE Trans. Med. Imag. 15, 154-169 (1996)

[3]Pham, D.L., Prince, J.L. "An Adaptive Fuzzy C-means Algorithm for Image Segmentation in the Presence of Intensity Inhomogeneities". Pattern Recognition Letters, 20(1), 57-68 (1999)

[4]Jayaram, K., Udupa, Supun, Samarasekera. "Fuzzy Connectedness and Object Definition: Theory, Algorithms, and Applications in Image Segmentation". Graphical Models and Image Processing, 58(3), 246-261 (1996)

[5]Bezdek, J.C. "Pattern Recognition with Fuzzy Objective Function Algorithms". Plenum Press, New York (1981)

[6]D.Q., Zhang, S.C., Chen. "Kernel Based Fuzzy and Possibilistic C-means Clustering". In: Proceedings of the International Conference Artificial Neural Network, pp. 122-125, Turkey (2003)

[7]A.W.C., Liew, Yan, H. "An Adaptive Spatial Fuzzy Clustering Algorithm for 3-D MR Image Segmentation". IEEE Trans. Med. Imag, 22(9), 1063-75 (2003)

[8]D.Q., Zhang, S.C., Chen. "A Novel Kernelized Fuzzy C-means Algorithm and Segmentation of MRI Data". Artificial Intelligence in Medicine. 32, 37-52 (2004)

[9]K.S., Chuang, H.I., Tzeng, S., Chen, et al. "Fuzzy C-means Clustering with Spatial Information for Image Segmentation". Computerized Medical Imaging and Graphics, 30, 9-15 (2006)

[10]X.F., Yu, B., Li, W.F., Chen. "A New Algorithm for Magnetic Resonance Image Segmentation based on Fuzzy Kernel Clustering". Journal of Southern Medical University, 28(4), 555-557 (2008)

[11]S.Z., Li. "Markov Random Field Modeling in Computer Vision". Springer, London (1995)

[12]Besag, J. "Spatial Interaction and the Statistical Analysis of Lattice Systems". Journal of the Royal Statistical Society, B(36), 192-236 (1974)

[13]H., Elliott, H., Derin, R., Cristi, D., Geman. "Application of the Gibbs Distribution to Image Segmentation". In: Proceedings of the International Conference on Acoustic, Speech and Signal Processing-84, pp. 32.5.1-32.5.4, San Diego (1984)