G-017

An Improved KFCM Algorithm in the Segmentation of Brain MRIs

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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 inducing 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 characterized by using MRF probabilities [11]. If \( P(x_i | x_{i-1}) = P(x_i | x_{N_i}) \), 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 \( Z = \sum \exp(-U(x)) \) is normalizing constant, \( U(x) = \sum_{c} V_c(x) \) 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

\[
P_u = p(X_i = k | X_{N_i}) = \exp(\beta \eta(k)) / \sum \exp(\beta \eta(j))
\]

Where \( \eta(k) \) is the number of sites marked by \( k \) in \( N_i \), \( L \) is a cluster set, the parameter \( \beta \) 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

\[
J_u(U,V) = 2 \sum_{i=1}^{l} \sum_{k=1}^{K} u_{ik}^2 (1 - K(x_i, v_k))
\]

Where \( L \) is the number of clusters, \( N \) is the number of image pixels, \( u_{ik} \) is the membership of pixel \( i \) in class \( k \), satisfying

\[
\sum_{k=1}^{K} u_{ik} = 1, \quad \{v_i, i=1,2,\cdots,L\} \text{ are clustering centers, } m \text{ is the quantity of controlling clustering fuzziness, generally } m=2, \quad K(x_i, y_i) = \exp(-\|x_i - y_i\|^2/\sigma^2)
\]

is a Gaussian kernel function.

Here, \( U = \{u_{ik}\} \) 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 \( p_u \), which figures the priori probability of pixel \( i \) in class \( k \). Then, via importing \( p_u \) and neighborhood controlling factor \( \alpha \), the membership degree matrix of KFCM is converted into \( u_{ik} = (1 - \alpha + \alpha \cdot p_u) u_{ik} \), \( \alpha \) 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

\[
J_u(U,V) = 2 \sum_{i=1}^{l} \sum_{k=1}^{K} ((1 - \alpha + \alpha \cdot p_u) u_{ik})^2 (1 - K(x_i, v_k))
\]

According to the constraint of \( u_{ik} \) and Lagrange multipliers, the new iterative equations are derived as

\[
u_{ik} = \frac{(1 - \alpha + \alpha \cdot p_u) (1 - K(x_i, v_k))^{1/(m-1)}}{\sum_{j=1}^{K} (1 - K(x_i, v_j))^{1/(m-1)}}
\]

\[
u_k = \frac{\sum_{i=1}^{L} u_{ik}^2 K(x_i, v_k)}{\sum_{i=1}^{L} u_{ik}^2 K(x_i, v_k)}
\]
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:

\[ MCR = \frac{\text{the No. of misclassified pixels}}{\text{the No. of all pixels}} \times 100\% \tag{6} \]

Where \( MCR \in [0,1] \). The smaller the \( MCR \), 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 x 258 pixels, thickness of layer is 1mm, \( T \), weighted. We use the image sequences of \( Z = 16.5mm \).

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

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