Fuzzy C-Means Based Tissue Classification in The Presence of Noise and Field Inhomogeneity

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Introduction: Tissue differentiation/classification is important in many clinical applications and is a fundamental task of quantitative medical imaging, especially for MRI[1]. Generally, classification involving several tissue types relies more on intensity-based segmentation techniques than edge-based techniques. A major difficulty for intensity-based segmentation algorithms on MR images is their sensitivity to intensity variations, including field and RF inhomogeneity, noise, and partial volume effects. Fuzzy C-Means (FCM) clustering, a technique widely used in MR tissue characterization, proves to be problematic when classifying images that are deteriorated by intensity variations. The degraded performance can be attributed to the fact that no spatial information is used during the classification process. In the current study, we introduce a Map-Guided Intensity-Corrected FCM (MAGIC-FCM) algorithm that takes into consideration of both spatial constraint and inhomogeneity field characteristics to address the intensity variation problem.

Methods: If we may assume the inhomogeneity field is multiplicative, the corruption model of MR images is formulated as $I_{corrupted}=G*I_{origina}l+N$, where $I_{original}$ symbolizes the prototypical image, $I_{corrupted}$ is the acquired MR image, G is the smoothly changing inhomogeneity field and N is the noise. Since multiplication can be changed to addition by a simple logarithm transformation of intensities, we can assume an additive inhomogeneity field in the present study. To counteract the effect of the inhomogeneity field on the FCM technique, we introduce an adaptive surface that is able to reflect the low-frequency component of the corrupted image. Our proposed MAGIC-FCM has the following objective function:

$$J_{MAGIC-FCM} = \underbrace{\sum_{j=1}^{c}\sum_{i=1}^{n} M_{i,j}^{m}\left\|x_i - w_j - v_i\right\|^2}_{term1} + \underbrace{\alpha \sum_{j=1}^{c}\sum_{i=1}^{n} M_{i,j}^{m} \sum_{\substack{t=1\\ t\neq j}}^{c} \sum_{l\in Neighbor(i)} M_{l,t}^{m}}_{term2} + \underbrace{\eta \sum_{i=1}^{n}\left\|\nabla \underline{x_i} - \nabla v_i\right\|^2}_{term3} + \underbrace{\gamma \sum_{i=1}^{n}\left\|\Delta v_i\right\|^2}_{term4}$$

Here, i is a pixel index, j is a class index, c is the total number of classes, and n is the total number of pixels. $M_{i,j}$ is a membership function of pixel i to class j, m is the fuzzification factor, x_i is the intensity, w_j is the centroid, and v_i is the intensity adaptive factor for pixel i. Adaptive factors at all pixels comprise an adaptive surface that ameliorates the intensity variation problem. α is a positive constant that assigns weight to spatial information, η is a constant that restricts adaptive surface, and γ assigns the weighting of the smoothness in the adaptive surface. The first term of the function is a modified version of traditional FCM energy function. In this term, the adaptive factor v_i helps to counteract the intensity deviation from the expected value. The second term, introduced by Pham [2], reduces the membership function $M_{i,j}$ when the neighboring pixels of pixel i have a large sum of memberships in classes other than class j and makes the FCM more noise resistant. The third term constricts the gradients of the adaptive surface (delta w_i) to assemble the thresholded gradient field of the original image (delta $\underline{x_i}$). The last term in the objective function minimizes the Laplacian of the adaptive field. This term serves the purpose of making the adaptive field piecewise continuous.

In practice, we decomposed Equation (2) into two parts: 1) a MAGIC part representing the field correction (terms 3 and 4) and 2) a spatial penalized FCM (SPFCM) part (terms 1 and 2) and minimized them separately. The MAGIC procedure corrects intensity variations in MR image, and the SPFCM procedure gives the final clustering result. In our application of MAGIC-FCM classification, the fuzzification parameter m was set to 2; α was set to 10; η was set to 1; the smooth weighting γ was set to 0.01 for additive field estimation. For multiplicative estimation, the smoothness factor was set to zero in the additive field estimation; and 0.01 when retrieving the multiplicative field based on this additive field result.

For evaluation of methods, the MAGIC-FCM was applied to synthetic images and high resolution *ex-vivo* coronary plaque images and compared to classification without field correction and to correction by the N3 method, proposed by sled, et al. [3].

Results: Examples of MAGIC-FCM results on synthetic images and high resolution vessel wall images are shown in Fig. 1 and 2, respectively. In Fig. 1, a single MAGIC step was applied on a checker board image corrupted by the sinusoidal inhomogeneity. The MAGIC corrected result is shown in Fig. 1D. It can be seen that performing FCM classification on this image becomes a trivial task. In Fig. 2, we show a comparison of FCM classified results after MAGIC and N3 inhomogeneity correction on a high-resolution human coronary vessel wall image. The red arrows mark the misclassified regions outside the vessel in uncorrected and N3-corrected classification. These errors are not present in the MAGIC-corrected classification results.

Discussion: Although the MAGIC-FCM algorithm was only applied to two dimensional cases, the same idea can be applied to three dimensional and multi-contrast image classifications as well. Currently, the processing time for 181 by 217 images is about 1 minute for a MATAB implementation on Windows operating system installed on a 2.0GHz Intel Pentium 4 CPU with 512Mb ram. This situation may be ameliorated with better numerical schemes. The key factor in determining the convergence rate of MAGIC function is the size of the adaptive surface since every pixel on the surface depends on all other pixels. We anticipate that adding a limited number of control points in the adaptive surface, whose values can be fixed in MAGIC calculation, may be a feasible way to accelerate calculations.

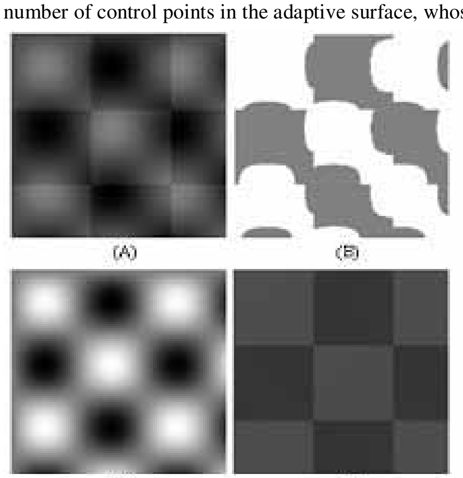

Fig. 1. Application of MAGIC-FCM on sinusoidal inhomogeneity corrupted check board image. (A) corrupted image (B) FCM classified result. (C) MAGIC estimated inhomogeneity field. (D) corrected image.

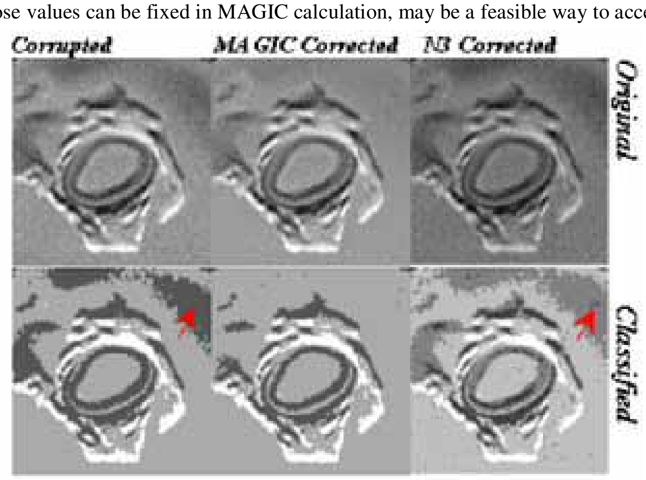

Fig. 2. Comparison of FCM, MAGIC-FCM and N3-FCM classification result on high resolution vessel wall images with intensity variation.

Conclusions: We have developed a novel MAGIC-FCM algorithm that mitigates misclassification due to intensity variations in traditional FCM algorithm. The algorithm can effectively suppress the intensity variations in medical images and can be easily implemented. Improved segmentation results were achieved using the proposed algorithm with fixed parameters compared to uncorrected classification or correction by existing methods.

Reference

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