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Original intensity preserved inhomogeneity correction and segmentation for liver magnetic resonance imaging

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ABSTRACT

Intensity inhomogeneity (IIH), also named as bias field, is an undesired phenomenon of liver magnetic resonance imaging (MRI) which severely affects the quantitative analysis of medical image and decreases the performance of subsequent computer aided diagnosis (CAD) of liver cirrhosis. Many algorithms have been proposed to reduce or eliminate IIH of MRI, and some notable achievements for brain MRI have been obtained. However, IIH correction of abdominal MRI receives less attention and is challenging because of the irregular structure and the wide intensity range of different tissues. In this paper, an automatic method based on the global intensity, the local intensity and the spatial continuity information is presented for reducing IIH of liver MRI. What should be noted is that the gray level should be preserved after correction since it is important for subsequent quantitative image analysis. Therefore, a constraint term is introduced based on the information of bias field intensity for appropriate IIH correction. In addition, the objective function introduces a fuzzy membership mask to remove the background noise and avoid misclassification. Our method is successfully applied to the clinical liver MRI and acquires desirable results. Compared with other approaches, our method obtains the best segmentation with Jaccard similarity (JS) = 0.88 ± 0.06, Dice index (DI) = 0.94 ± 0.03, and accuracy (ACC) = 0.99 ± 0.01.

1. Introduction

Magnentic resonance imaging (MRI) is an efficient non-invasive imaging technique which has been widely used for medical diagnosis, staging of disease and follow-up, especially for liver. However, it is time consuming to manually analyze MRI with such a large amount of data. Therefore, automatic computer analysis, such as precise segmentation, arouses and plays a crucial role in liver studies. However, it is challenging to segment liver from abdominal MRI because of the corruption caused by intensity inhomogeneity (IIH) [1,2].

IIH is a morbid phenomenon caused by various complex factors, such as the spatial variations of illumination or magnetic field and imperfections of imaging devices [3]. IIH causes slow intensity variations even in one tissue and blurs image details. Although it is not a serious problem for radiologist, the intensity variation caused by IIH has serious impact on subsequent computer aided diagnosis (CAD), such as segmentation, registration [4–6], or quantitative image analyses. Evaluating the segmentation obtained from corrected images can represent the performance of bias correction algorithm. Many image segmentation methods have been proposed [7–13], and Ma et al. [14,15] summarize the current segmentation algorithms used for medical images. Although, it is an essential step to eliminate or minimize the influence of IIH, the correction of IIH faces many difficulties as the inhomogeneities could change with different MRI acquisition parameters, from patients to patients and from slices to slices [16].

Rencent years, many IIH correction methods have been proposed and a comprehensive review is listed in [17]. The existing methods can be divided into prospective methods and retrospective methods [18]. Prospective methods can partly correct some of IIH caused by MR equipment. However, IIH still exists in MRI after prospective correction. Compared to prospective methods, retrospective methods have received widespread attentions. Retrospective methods focus on processing image itself and can

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effectively reduce or eliminate IIH which is caused by MR equipment or patient movement.

Currently, retrospective methods which can simultaneously compensate IIH and segment tissues have become a hot spot in IIH correction [19–22]. Li et al. [23] proposed a new energy minimization method based on coherent local intensity clustering (CLIC) for simultaneous bias field estimation and tissue classification of MRI. This algorithm only adopted local information of MRIs which might cause misclassification of boundary pixels especially in the regions with serious intensity inhomogeneous. Meanwhile, too many parameters reduced the robustness of the method. In order to overcome the drawback of CLIC, Ji et al. [24] proposed a modified possibilistic fuzzy c-means clustering algorithm which incorporated coherent local, global intensity and local spatial information to suppress the effect of noise and avoid misclassification. Tustison et al. [25] proposed the most popular and widely used N4 which used robust B-spline approximation routine and a modified hierarchical optimization scheme for bias field correction. However, most of these IIH correction algorithms are proposed for brain MRI. And as for abdominal MRI, IIH correction becomes challenging because of the irregular shape and the wide intensity range of abdominal organs.

In this paper, an automatic fuzzy c-means clustering algorithm with constraint term of bias filed is proposed to correct IIH of abdominal MRI. Our method can avoid misclassification and preserve the intensity and texture of blurred images. Furthermore, our method is insensitive to the initialization parameters and can be adopted to variousbias fields of clinical abdominal MRI. The results of experiment show that the gray level, boundary and texture of blurred images can be well preserved. And the gray histogram of the corrected images has obvious peaks and valleys, which indicates that our method successfully removes IIH.

The remainder of this paper is organized as follows. The related works are introduced in Section 2, including a brief review of classical algorithms. Section 3 introduces our proposed method. The results of experiment and discussion are given in Section 4. Finally, conclusions are summarized in Section 5.

2. Related work

The main purpose of bias field correction is to recover the original uncorrupted image. The bias field in a medical image (i.e. MRI, CT etc.) is usually regarded as a smooth spatially varying function, and can be modeled as a multiplicative field. The image blurred by bias field can be formulated as Eq. (1) [18]:

$$I = bJ + n \tag{1}$$

where I is the acquired image, J is the true image to be restored, b is the unknown multiplicative bias field, and n is the additive zero-mean gaussian noise which is considered completely independent of bias field. Our collected abdominal MRIs are clear and less affected by noise among the liver region, thus n is not considered for the whole image. The goal of IIH correction is to estimate bias field b from the acquired intensity I, and then the bias corrected images J can be obtained by I divided by the bias field b (I/b).

As mentioned above, Ji et al. [24] proposed a modified possibilistic fuzzy c-means clustering algorithm (MPFCM) for tissues segmentation and IIH correction for brain MRI. The objective function effectively introduced the weights of local spatial which combined with the local contextual information to overcome the influence of noise, acquired an optimal bias field and then achieved desirable classification. However, the gray level of corrected image will be greatly reduced compared with the acquired image. In order to preserve the gray level of corrected images, we proposed a novel energy constraint term.

3. Methods

Our algorithm contains two stages. First, the region-growing procedure with morphological operation is applied to get membership mask to remove the background noise. Second, an automatic method is proposed to estimate the bias field and conduct IIH correction. To effectively estimate the bias field, coherent local intensity, global intensity and spatial continuity information are all introduced into objective function. Meanwhile, a novel constraint term of bias field is defined to preserve the gray level of the corrected images. The parameters used in our method is set for guaranteeing desirable results, and it can be discovered from the following experiment that all parameters of pre-processing are insensitive and easy to be determined.

3.1. Background noise removal

There exist different levels of noise among the background of clinical abdominal MRI which will affect the subsequent analysis [26]. Therefore, a membership mask I_{mask} is constructed based on region growing to remove the background noise. Since the intensities of the background noise are much lower than those of abnormal boundaries, two top corners are sellected as regional seeds. The success of region growing relies on the predefined criteria formulized as Eq. (2) which is related to the intensity difference among neighborhood pixels. Based on region growing, mean μ_b and standard deviation σ_b of the background is estimated at first. Then the connected pixel whose intensity is less than $\mu_b + a\sigma_b$ is classified to the background. The algorithm stops while no more pixels fulfill this criterion.

$$\begin{cases} y_i < \mu_b + a\sigma_b, & m_i = 0, background \quad voxels \\ \mu_b + a\sigma_b < y_i < \mu_b + b\sigma_b, & m_i = \dfrac{y_i - \mu_b - a\sigma_b}{(b-a)\sigma_b} \\ \mu_b + b\sigma_b < y_i, & m_i = 1, tissue \quad voxels \end{cases} \tag{2}$$

The parameters $a = 2$ and $b = 4$ is set based on the intensity of noise of liver MRI. There are many small patches or holes in abnormal MRI. Then, the morphological opening operator is applied to reduce small artifacts and the morphological closing operator is applied to remove small holes. Lastly, original images multiply this mask I_{mask} to remove backgroud noise and then the intensity inhomogeneity of the new acquired images can be corrected by our method.

3.2. Inhomogeneity correction

A model based on coherent local, global intensity and spatial continuity information is proposed to reduce IIH of liver MRI. The objective function shows as Eq. (3):

$$\begin{aligned} J_m = & \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m [\sum_{s\in N_k} \omega_{ks} \cdot (\alpha \sum_{r\in\Omega} L_i(r) ||\tilde{I}_{ks} - b_r v_i||^2 \\ & + (1-\alpha)\sum_{r\in o_k} K(r-k)||\tilde{I}_{ks} - br_v||^2)] \\ & + \lambda \sum_{k=1}^{n} (1-b_k)^2 \end{aligned} \tag{3}$$

where Ω is the domain of the filtered image with the background noise removed and O_k is the local neighborhood of gray value of the kth pixel point in the image. $U = [u_{ik}]$ is the membership functions which represents the degree of pixels belonging to a cluster. Parameters $m > 1$. $\omega_{ks} \in [0, 1]$ is the local spatial continuity weight which effectively considers the influence of neighborhood pixels.