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Local region statistics combining multi-parameter intensity fitting module for medical image segmentation with intensity inhomogeneity and complex composition

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ABSTRACT

It is difficult to segment medical image with intensity inhomogeneity and complex composition, because most region-based modules relay on the intensity distributions. In this paper, we propose a novel method which uses local region statistics and multi-parameter intensity fitting as well. By replacing the original local region statistics with the novel local region statistics after bias field correction, the effect of intensity inhomogeneity can be eliminated. Then we devise a maximum likelihood energy function based on the distribution of each local region. Segmentation and bias field estimation can be jointly obtained by minimizing the proposed energy function. Furthermore, in order to characterize the features of each local region effectively, two parameters are used to fit the average intensity inside and outside of the counter, respectively. This can well handle the medical images with complex composition, such as larger gray difference even in the same region. Comparisons with several representative methods on synthetic and medical images demonstrate the superiority of the proposed method over other representative algorithms.

1. Introduction

Medical image segmentation [1,2] is the basis of medical image analysis and understanding. It plays an important role in pathology analysis, pathology treatment and clinical diagnosis. In the imaging process [3,4], the formations of the medical image are susceptible to some factors such as noise and the effect of bias field. Those factors lead to the presence of intensity inhomogeneity of the image. In some cases, due to the characteristics of local body and tissue itself, some complex compositions exist in medical image. All these increase the difficulty in segmentation.

The active contour models based on curve evolution have been increasingly used in image segmentation [5–15,19]. Normally, active contour models can be categorized into two classes: edge-based modules [16–18] and region-based modules [8–10,20–31]. The region-based methods possess many advantages over the edge-based methods, including robustness against noise and the initial location of the curve. The well-known Mumford-Shah model [13] was proposed by Mumford and Shah. Minimizing of energy function is the core of the method of region-based variation level set. Since the energy function is non-convex, several local minimums may exist in this module. The CV model was proposed by Chan and Vese [14] which simplified Mumford-Shah model by setting two piecewise constants. Due to the medical images are of intensity inhomogeneity, the region-based methods [13,14] using global intensity distributions are not applicable in this case. To overcome the limitations of CV model in dealing with the images with intensity inhomogeneity, Chan and Vese proposed piecewise smooth (PS) module [15] with a more complex calculation processing. This limits its practical application. Recently, some methods of local region-based [27–31] modules have been proposed to deal with images with intensity inhomogeneity, such as local binary fitting (LBF) module [28], local region-based (LRB) module [27], local intensity clustering (LIC) module [29], local region model (LRM) [30] and local Chan–Vese (LCV) module [31]. Both of LBF and LRB modules utilize local intensity means instead of global intensity means. This has great progress compared to CV module in dealing with the medical image of intensity inhomogeneity. However, without considering region variance may lead to inaccurate segmentation. LIC module uses local gray clustering criterion in the local neighborhood of the image. But the locally weighted K-means clustering method is based on the

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clustering means only, without considering the clustering variance. In LRM module not only the local region means and variances are considered, but also the local region statistics are applied. However, the local region means and variances are only defined empirically. LCV module mixes the local gray information into the global model, and thereby it is effective to segment the image with intensity inhomogeneity. The preconditions of this module are that the local regions should be approximately with intensity homogeneity and different intensity statistical characteristics between the background and target should exist. With this module, precise segmentation results cannot be obtained.

The main contributions consist of the following aspects:

(1) This paper provides a novel module for medical image segmentation by combining local region statistics with multi-parameter intensity fitting. It can not only accurately segment the image with intensity inhomogeneity, but also be useful for the image with complex composition.
(2) It is difficult to segment medical image with intensity inhomogeneity by only adapting the local region statistics. Our method combines local region statistics with bias field correction. In iteration, the local region statistics after bias field correction are used to replace the original local region statistics. This can eliminate the effect of intensity inhomogeneity. Then we devise a maximum likelihood energy functional based on the distribution of each local region. Image segmentation and bias field estimation can be jointly obtained by minimizing the proposed energy function.
(3) Unlike the LBF, LRB, LIC and LCV which only use a single average intensity to characterize the feature of local region, the proposed method yields two parameters to fit the average brightness inside and outside of the counter, respectively. In addition, the variance of the local region is also considered in the proposed module. In this way, the features of each local region can be characterized effectively. This can well handle the medical image with complex composition, such as texture.

The remainder of this paper is arranged as follows. In Section 2, we review the classical region-based modules and discuss the advantages and disadvantages of them. The proposed algorithm will be introduced in Section 3. In Section 4, the comparisons with several representative methods on synthetic and medical images are made, which demonstrates the superior performance of our method in terms of accuracy, efficiency, and robustness. The quantitative results are also provided. Finally, we conclude this paper in Section 5.

2. Background

2.1. Local binary fitting model

To improve the segmentation performance of region-based method for image with intensity inhomogeneity, Li et al. proposed the local binary fitting model [28]. The energy function can be expressed as:

$$E = \lambda_1 \int_{\Omega}\int_{inC} K_\sigma\big(I(y) - f_1(x)\big)dydx + \lambda_2 \int_{\Omega}\int_{outC} K_\sigma\big(I(y) - f_2(x)\big)dydx + \mu\bullet l + \nu p(\varphi) \tag{1}$$

where λ_1, λ_2, μ and ν are the fixed values of function (1), and K_σ is the Gaussian kernel with standard deviation σ. $f_1(x)$ and $f_2(x)$ are the weighted intensity averages in a Gaussian window inside and outside C, respectively. Using $f_1(x)$ and $f_2(x)$ to substitute the constant parameters in CV model, in some extent, eliminates the influence of the intensity inhomogeneity. Since this module does not consider region variance and bias field, the segmentation may be inaccurate. There exists the same problem in LRB [27] module.

2.2. Local intensity clustering model

By using local gray clustering criterion in the local neighborhood of the image, local intensity clustering [29] module was proposed. The energy function can be expressed as:

$$E = \lambda_1 \int_{\Omega}\int_{inC} K_\sigma\big(I(y) - b(x)c_1\big)dydx + \lambda_2 \int_{\Omega}\int_{outC} K_\sigma\big(I(y) - b(x)c_2\big)dydx + \mu\bullet l + \nu p(\varphi) \tag{2}$$

where λ_1, λ_2, μ and ν are the fixed values of function (2), and K_σ is the Gaussian kernel with standard deviation σ. $b(x)$ approximates to the intensity inhomogeneity and c_i are constants. Local gray cluster centers can be expressed as $b(x)c_i$. By introducing K_σ, this module can be regarded as local intensity clustering model. Without considering the clustering variance, this module can not well handle the severe intensity inhomogeneity as LBF module.

2.3. Local Chan–Vese model

Wang [31] combined the global statistical model with the local region-based method, and proposed LCV module. The energy function can be expressed as:

$$\begin{aligned} E &= E^L + E^G \\ &= \beta\left[\lambda_1 \int_{\Omega}\int_{inC} |K_w \otimes I(y) - I(y) - d_1|^2 dydx + \lambda_2 \int_{\Omega}\int_{outC} |K_w \otimes I(y) - I(y) - d_2|^2 dydx\right] \\ &\quad + \alpha\left[\lambda_1 \int_{\Omega}\int_{inC} (I(y) - c_1)dydx + \lambda_2 \int_{\Omega}\int_{outC} (I(y) - c_2)dydx\right] \\ &\quad + \mu\bullet l + \nu p(\varphi) \end{aligned} \tag{3}$$

In function (3), E^L and E^G are the energy functions of local region-based method and the global statistical model, respectively. λ_1, λ_2, μ and ν are the fixed values, and K_σ is convolution operator with $w \times w$ size window. d_1 and d_2 are the average intensity of $K_w \otimes I(y) - I(y)$ inside and outside of the curve, respectively. β and α are the weighting factor of E^L and E^G, respectively. However, the values of those two parameters lack self-adaptive. In addition, after Gaussian filtering, the weak edge which always exists in the medical images is further weakened. This will induce an inaccurate segmentation result.

3. Proposed method

Normally, the medical image is always mixed with intensity inhomogeneity and complex composition. Besides, the gray values may have a larger difference even in the same region, such as texture. Due to intensity feature of medical image with non-linear distribution, the medical image can be substituted by approximation of piecewise constant image. In order to segment medical image with above properties, the medical image can be represented by the following model [29]:

$$I(x) = B(x) \times J(x) + N \tag{4}$$

where I represents the original image and J is the ideal image which is assumed to be piecewise constant. B is an unknown bias field and N represents the noise in the image.