A Novel Local Regional Model Based on Three-Layer Structure

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Abstract. In this paper, considering the local variance of intensity inhomogeneity, we propose a novel local regional level set model based on a so-called Three-Layer structure to segment images with intensity inhomogeneity. The local region intensity mean idea is used to construct region descriptor. Especially, three descriptors separately based on 'large', 'median' and 'small' scales of local regions are utilized to derive the Three-Layer structure. Compared to the traditional methods based on fixed scale for all local regions, the Three-Layer structure is more reliable for capturing local intensity information. Then, the Three-Layer structure is incorporated into the level set energy functional construction. As a result, more effective local intensity information is incorporated into the level set evolution. Finally, the experimental results demonstrate that the proposed method yields results comparative to and even better than the existing popular models for segmenting images with intensity inhomogeneity.

Keywords: local information, level set, intensity inhomogeneity, three-Layer structure.

1 Introduction

The level set methods for capturing dynamic interface and shape [1] are the state-of-the-art techniques for image segmentation [2]. The fundamental idea of the level set function is to represent a contour as the zero level set of a higher dimensional function and formulate the motion of the contour as the evolution of the level set function.

Recently, many region-based models are proposed to segment images with intensity inhomogeneity by utilizing local intensity information, such as the local region based model (LRB) model [3], the local binary fitting (LBF) model [4], the local intensity clustering (LIC) model [5], the local Chan-Vese model [6], the local

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image fitting (LIF) model [7], etc. However, some drawbacks are existed in these local region-based models. The Dirac functional used there is restricted to a neighborhood around the zero level set, which makes level set evolution act locally. Therefore, the local minima often occur in LRB model. For LBF model, the local region descriptor function is utilized to describe each local region in the whole image. However, the intensity inhomogeneity of local regions is different to some extent. The local region descriptor with fixed scale cannot accurately describe all local regions of image. Besides, the LIC model can also be seemed as the locally weighted K-means clustering. Unfortunately, the cluster variance is not considered in LIC model. Therefore, it is unavailable for images with sever intensity inhomogeneity.

However, it is difficult to determine the desired local region scale for each model. Meanwhile, it is also a difficult problem to utilize local region descriptor with single certain scale to describe all local regions. Thus, some desirable hybrid structures [8-10] and neural networks [11-14] are proposed and proved to be more effective than traditional methods. Motivated by these methods, a novel local regional level set model based on Three-Layer structure is proposed to segment images with intensity inhomogeneity. By analyzing the role of local region information, we propose using local region descriptor based on Three-Layer structure to describe the local regions. The local region descriptor based on Three-Layer structure is composed by three descriptors separately based on 'large', 'median' and 'small' scales. It works with three local regions each of which is created based on a specific kind of local region, and fuses the descriptors in the level set energy functional. Firstly, the three kernel functions with different variance scales are given. Then, the local region mean idea is used to represent the each local region descriptor. Finally, the local operation based on Three-Layer structure is incorporated into level set method and the overall energy functional is constructed.

The rest of the paper is organized as follows. The proposed method and variational formulation are described in Section 2. In Section 3, we verify the effectiveness of our method by some experiments. The conclusion is presented in Section 4.

2 Model Description

(a) Three-Layer Structure

As described above, the local information is used to describe images with intensity inhomogeneity. However, the local region with predefined single scale generally cannot capture enough desirable intensity distribution information. Fig.1 shows three local regions with different scales s_1, s_2, s_3 and the same center point (red point) are exhibited in the input image I. While the local region scale is s_1, the local region does not include the intensity inhomogeneity or boundary information. Then, the descriptor derived from the local region cannot capture the intensity inhomogeneity feature. If the value s_3 is selected as the local region scale, many of intensity information is included in the local region with scale of s_3. However, the descriptor based on intensity mean cannot accurately describe the local region feature with included information. It can be seen that s_2 may be a desired scale of local region. It includes some intensity inhomogeneity information and the local region descriptor based on intensity mean can represent the intensity feature of local region. Thus, for the center point, the desired local region scale s can be determined in the interval $[s_1, s_3]$. Similarly, for all the other points of image, the desired local region scales can also be determined as s_q (q denote the different points of image) which separately locate in some other intervals. Due to the local variance of intensity inhomogeneity, all these intervals may be not identical.

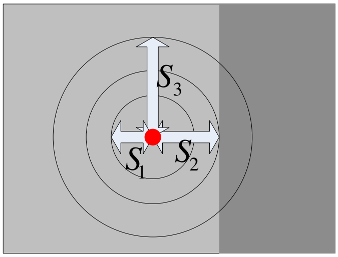

Fig. 1. The illustration of local region scales of image with intensity inhomogeneity

Therefore, considering the uncertainty of optimal scale, we propose a so-called Three-Layer structure to solve the intensity inhomogeneity problem. Since the desirable local region scale located in different intervals, the 'large' (L), 'median' (M) and 'small' (S) local region scales are used to construct the local region descriptors. The aim is to make the intersections between three scales and each desirable scale interval be non-zero.

Firstly, we need to determine the three local regions with L, M, S scales for each point of image. Here, as formula (1) shows, the Gaussian kernel function is used to determine the local regions by setting different variances.

$$k_{\sigma_j}(x-y) = \frac{1}{2\pi^{1/2}\sigma_j^2} e^{-|x-y|^2 / 2\sigma_j^2} \quad (j = L, M, S), (\sigma_j = 4 \cdot j + 1). \tag{1}$$

The three predefined scales (L, M, S) represent the values located in different intervals. Thus, our method based on Three-Layer structure can include enough local region information. Meanwhile, it is noticed that the three descriptors are derived. The local information is extracted by three descriptors based on intensity mean. Then, we fuse the three descriptors by summing the description differences. The illustration of Three-Layer structure is shown in Fig.2. The Gaussian kernel functions k_{σ_L} , k_{σ_M} and k_{σ_S} are used to process the image I . Based on the Three-layer structure idea, the data term of our level set energy functional can be written as the following:

$$E_D = \int_{\Omega} \int_{inside(C)} \varepsilon_1 dydx + \int_{\Omega} \int_{outside(C)} \varepsilon_2 dydx \tag{2}$$

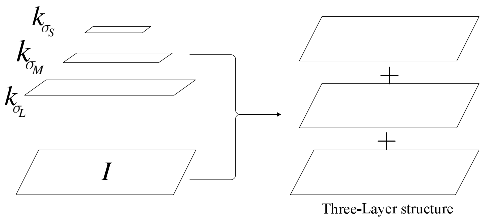

Fig. 2. The illustration of Three-Layer structure

where ε_1 and ε_2 are computed as follows:

$$\varepsilon_1 = k_{\sigma_L}(x-y)(I(y)-m_1(x))^2 + k_{\sigma_M}(x-y)(I(y)-m_2(x))^2 + k_{\sigma_S}(x-y)(I(y)-m_3(x))^2, \quad (3)$$

$$\varepsilon_2 = k_{\sigma_L}(x-y)(I(y)-m_4(x))^2 + k_{\sigma_M}(x-y)(I(y)-m_5(x))^2 + k_{\sigma_S}(x-y)(I(y)-m_6(x))^2, \quad (4)$$

where C denotes the evolving contour, k_{σ_L}, k_{σ_M} and k_{σ_S} denote the three Gaussian kernel functions with L, M and S scales as formula (1) shows. m_i ($i=1,2,3,4,5,6$) denote the local region intensity mean of inside or outside of C.

(b) Numerical Computation

In this paper, we utilize level set method to solve the energy functional in (2). In level set method, the contour C is represented by zero level set of a Lipschitz function ϕ, which is called a level set function. We use $H(x)$ to denote the Heaviside function. Then, the data term in (2) can be formulated as follows:

$$E_D = \iint \varepsilon_1 \cdot H(\phi)dydx + \iint \varepsilon_2 \cdot (1-H(\phi))dydx \quad (5)$$

Here, $H(x)$ and its derivative, i.e. Dirac delta $\delta(x)$, are approximated by the following formula:

$$H(x) = \frac{1}{2}[1+\frac{2}{\pi}.\arctan(\frac{x}{\varepsilon})], \quad \delta(x) = H'(x) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+x^2}. \quad (6)$$

Besides, the regularization terms proposed in [4] are also introduced to regulate the level set function. Finally, the overall energy functional is written as:

$$E = \iint \varepsilon_1 \cdot H(\phi)dydx + \iint \varepsilon_2 \cdot (1-H(\phi))dydx + \mu\int_\Omega (\nabla H(\phi(x)))dx + v\int_\Omega (\nabla\phi(x)-1)^2 dx \quad (7)$$

Then, we use the standard gradient descent method to solve the numerical computation problem. m_i ($i=1,2,3,4,5,6$) are derived by minimizing the energy functional in (7). Fixing ϕ, the optimal m_i ($i=1,2,3,4,5,6$) can be obtained as follows:

$$m_1(x)=\frac{\int_\Omega k_L*(I(x)\cdot H(\phi))dx}{\int_\Omega k_L*H(\phi)dx},\ m_2(x)=\frac{\int_\Omega k_M*(I(x)\cdot H(\phi))dx}{\int_\Omega k_M*H(\phi)dx}, \tag{8}$$

$$m_3(x)=\frac{\int_\Omega k_S*(I(x)\cdot H(\phi))dx}{\int_\Omega k_S*H(\phi)dx},\ m_4(x)=\frac{\int_\Omega k_L*(I(x)\cdot(1-H(\phi)))dx}{\int_\Omega k_L*(1-H(\phi))dx}, \tag{9}$$

$$m_5(x)=\frac{\int_\Omega k_M*(I(x)\cdot(1-H(\phi)))dx}{\int_\Omega k_M*(1-H(\phi))dx},\ m_6(x)=\frac{\int_\Omega k_S*(I(x)\cdot(1-H(\phi)))dx}{\int_\Omega k_S*(1-H(\phi))dx}. \tag{10}$$

The function m_i ($i=1,2,3,4,5,6$) given in (8-10) are weighted averages of intensities in a neighborhood. It is noticed that the scales of local neighborhoods are proportional to the scale parameters L , M and S . In practical implementation, L , M and S are predefined by us according to experience.

Keeping m_i ($i=1,2,3,4,5,6$) fixed, we minimize the energy functional. It can be achieved by using standard gradient descent method:

$$\frac{\partial\phi}{\partial t}=\underbrace{\delta(\phi)(\varepsilon_1-\varepsilon_2)}_{data\quad term}+\underbrace{\mu\delta(\phi).div(\frac{\nabla\phi}{|\nabla\phi|})+v(\nabla^2\phi-div(\frac{\nabla\phi}{|\nabla\phi|})}_{regularization\quad term}. \tag{11}$$

where ∇ is gradient operator and $div(.)$ is the divergence operator.

(c) Algorithm Summary

1. Place the initial contour and initialize the level set function ϕ: if x is located inside initial contour, $\phi(x)=1$ or else $\phi(x)=-1$.
2. Set parameters v, μ, L, M, S, $\sigma_j=4j+1$ ($j=L,M,S$).
3. Evolve ϕ according to the gradient flow equation described in (11).
4. Extract the zero level set from the final level set function.

3 Experimental Results

In this section, the experiment results of our model shall be shown on some synthetic and real medical images. Besides, we also compared our method with the popular LBF and LIF model, respectively. The LBF model extracts the intensity information of local region at a controllable scale. It demonstrates that the problem of intensity inhomogeneity can be solved. The LIF model introduces a local image fitting energy to extract the local image information where the Gaussian kernel with predefined scale is utilized to process original image. Here, we make experiments by Matlab 7.0 on a PC with Intel double core, 2.2GHZ CPU. We shall use the same parameters, i.e. $v=1$, $\mu=0.001\times 255^2$, $L=19$, $M=11$, $S=3$, for all experiments in this section.

In Fig.3, we made the comparison between the LBF model and our method on segmenting two medical images. The initial contours are shown in the first column. The segmentation result of LBF model and our method are shown in the second and third columns, respectively. Obviously, our method achieved better segmentation performance than LBF model. This is because the LBF model based on certain scale parameter could not describe the local variance of intensity inhomogeneity. On the contrary, the local regions with scale parameters L, M and S in our method can efficiently extract more desired local intensity information.

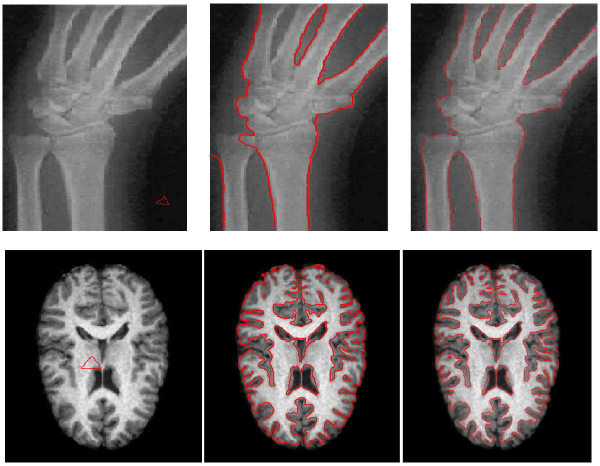

Fig. 3. The comparison between LBF model and our method on segmenting two medical images. Column1: Initial contours. Column2: The segmentation results of LBF model. Column3: Final segmentation results of our method.

The comparison between the LIF model and our method on segmenting two medical images is shown in Fig.4. The initial contours and original images are shown in the first column. The segmentation results of the LIF model and our method are separately shown in the second and third columns. It can be seen that our method is more robust to intensity inhomogeneity than LIF model. Although the local image information is considered in LIF model, the fixed local region is not reliable for describing image. In our method, more desirable local image information can be extracted based on proposed Three-Layer structure. Hence, the better segmentation results were obtained by our method.

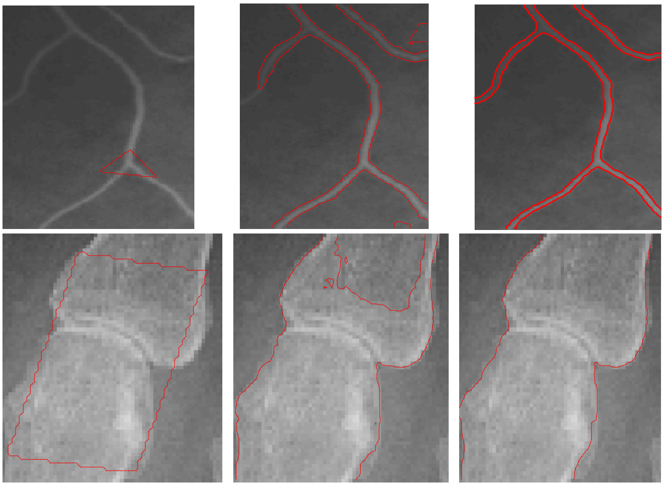

Fig. 4. The comparison between LIF model and our method on segmenting two medical images. Column1: Initial contours. Column2: The segmentation results of LIF model. Column3: Final segmentation results of our method.

4 Conclusion

This paper proposed a new local regional level set model for segmenting images with intensity inhomogeneity. Based on the local variance of intensity inhomogeneity, the local intensity mean idea is utilized to extract more local intensity information. By fusing the proposed Three-Layer structure into the level set method, we successfully derived a novel local regional level set energy functional. Experimental results have demonstrated the superior performance of our method in terms of accuracy for segmenting images with intensity inhomogeneity. In future, the Three-Layer structure shall be further studied and extended to solve the existing complex image segmentation problem.

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