Segmentation of Images Using Level Set Method Based on Additive Bias Correction (LS-ABC)

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Abstract. Image segmentation is a critical stage in analyzing an input image among the different image processing techniques. Its purpose is to reduce complexity and transform an image's representation into something more relevant and easier to examine. It has numerous applications in a variety of fields. There are many ways for segmenting an image, yet the intensity inhomogeneity has always been a difficult problem to solve. To overcome this problem, this paper proposes a level set method based on additive bias correction (LS-ABC). In this model, local area and clustering criterion are stated first. Then, using a function of level set and transforming this clustering criterion, an energy function is evaluated. Lastly, while segmenting the image, the predicted bias field structure and reflection edge are determined by minimizing this energy function. For images with intensity inhomogeneity, this model can provide optimal segmentation result. To overcome the issue of energy unification and increase robustness, an optimal adaptive data-driven term is developed in this model. Experimental results validate that the proposed (LS-ABC) model segments the images having intensity inhomogeneity accurately. When compared to existing models, this model is found to be accurate, fast and robust.

Keywords: Image segmentation · intensity inhomogeneity · level set method

1 Introduction

In different image processing techniques, image segmentation is a technique for categorizing an input image based on its pixel values. By this, we can process only the key portions of the image instead of processing the whole thing. But there exist several issues in image segmentation. In order to effectively solve those issues, several techniques and approaches for image segmentation have evolved. In that, the most developed and used models are active contour models. These models are divided into: edge-based models [1, 2] and region-based models [3, 4]. Segmentation process of edge-based models is guided by edge indicators. But these models are ineffective for images having noise and weak edges. Likewise, region-based models don't employ any image gradient, which makes them suited for images having weak boundaries.

Popular region-based models include Chan-Vese (CV) model [3]. This method considers only the global information. Thus cannot segment the images having intensity

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inhomogeneity. In 2008, Li et al. presented RSF model [4]. This method uses a kernel function for acquiring local image data. By using the details from local image intensities, this method efficiently segment the images having intensity inhomogeneity. But this model's speed of segmentation is low and it has sensitivity to the initial contour. In 2009, Zhang et al. presented LIF model [5]. This model's segmentation speed is faster compared to RSF model and this model efficiently segments the images having intensity inhomogeneity. However, the problem with the initial contours remained same. Considering how difficult it is for a predetermined distribution to accurately describe the object and its background in most of the images, Liu et al. proposed LHF model [6]. This approach can segment the regions which are having a difficulty to predefine their distribution. But due to the necessity to calculate each grey value's histogram distribution, this model has very high computing costs. Moreover, this model has sensitivity to the initial contour. K. Ding et al. presented LPF model [7]. Likewise, this model efficiently segments the images with intensity inhomogeneity. Yet, rate of segmentation and sensitivity to the initial contour are remain unchanged.

In 2011, Li et al. introduced a bias correction model (BC) by combining active contour model and bias field estimate [8]. The image's initial contour is more robustly handled by this model, but an excessive amount of convolution calculation during iteration leads to slow segmentation. Zhang et al. presented LSACM model [9]. This model efficiently segments the images having intensity inhomogeneity. But, it does not address the issues of initial contour sensitivity and slower segmentation rate (Table 1).

To address the above issues, this paper presents a level set method based on additive bias correction (LS-ABC). The proposed model provides better initial contour robustness, a perfect and fast segmentation result for images having intensity inhomogeneity. In this model, the local area and clustering criterion are stated first. Then, using a function of level set and transforming this clustering criterion, an energy function is evaluated. Lastly, while segmenting the image, the predicted bias field structure and reflection edge are determined, by minimizing this energy function. The proposed addition model increases the calculation speed by converting the multiplication of an image's matrix to an addition operation. This model has the potential to be more widely used in the segmentation of images, especially to the images of medical.

2 Background

Let range of the image be $\Omega \in \Re^2$ and given grayscale image is $I : \Omega \in \Re$. The image domain is splitted to two by the contour C. It is done inside the image area Ω. Those are Ω_1 (inside of C) and Ω_2 (outside of C).

Multiplicative image model was presented in 1974 by Horn et al. [10]. This model examined and resolved the problem of illumination. To address the issue of intensity inhomogeneity, real image is viewed as a technique of image models synthesizing. This model is rewritten and the image observed is:

$$I(x) = b(x)J(x) + n(x) \tag{1}$$

Here, J represents real image. n represents additional noise and b is bias field.

Table 1. Merits and Demerits of existing methods

	RSF	LIF	LHF	LPF	BC	LSACM
Merits	1. Segments the images having intensity inhomogeneity effectively.	1. Segments the images having intensity inhomogeneity effectively. 2. Speed of segmentation is improved compared to RSF model.	1. Segments the images having intensity inhomogeneity effectively.	1. Segments the images having intensity inhomogeneity effectively.	1. Robust to the initial contour.	1. Segments the images having intensity inhomogeneity effectively.
Demerits	1. Low segmentation speed. 2. Sensitive to the initial contour.	1. Sensitive to the initial contour.	1. Low segmentation speed. 2. Sensitive to the initial contour.	1. Low segmentation speed. 2. Sensitive to the initial contour.	1. Low segmentation speed.	1. Low segmentation speed. 2. Sensitive to the initial contour.

The bias correction assumptions and bias field model theory are extensively used. Presently, majority of the active contour models use the multiplicative model and bias correction assumptions described below.

BC model [8] is introduced by Li et al. In this, the local clustering criterion is used to obtain an energy function:

$$\varepsilon(\varphi, c, b) = \int \left(\sum_{i=1}^{2} \int K(y-x)|I(x) - b(y)c_i|^2 dy \right) M_i(\varphi) \mathrm{dx} \tag{2}$$

Here, $c_1, \ldots. c_N$ are constants. $K(u)$ (kernel function) is taken as truncated Gaussian function and $M_1(\varphi) = H(\varphi)$, $M_2(\varphi) = 1 - H(\varphi)$. $H(\varphi)$ is a Heaviside function.

In the proposed level set formula, Eq. (2) is used. Finally, by applying a conventional gradient descent method, a level set formula is acquired. It is defined as:

$$\frac{\partial \varphi}{\partial t} = -\delta(\varphi)(e_1 - e_2) + \nu\delta(\varphi) div\left(\frac{\nabla\varphi}{|\nabla\varphi|} \right) + \mu div(d_p(|\nabla\varphi|)\nabla\varphi) \tag{3}$$

where $H(\varphi) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{\varphi}{\varepsilon}\right)\right)$ is a Heaviside function. Its derivative is $\delta(\varphi) = \frac{1}{\pi}\left(\frac{\varepsilon}{\varepsilon^2 + \varphi^2}\right)$

3 Proposed Method

3.1 Model of Image and Problem Formation

Horn et al. in 1974 considered the bottom reflection ratio problem and proposed a retinex mathematical model. According to it:

$$i(y, x) = b(y, x) + r(y, x) \tag{4}$$

where, $i = log(I)$, b is illumination and r is reflection ratio.

Here in this paper bottom reflection ratio is introduced as a treatment of inconsistent intensities. Then some assumptions were made. Those are:

1. The intensity inhomogeneity b in the local region must be changed smoothly. Therefore the intensity inhomogeneity components in the image's dislocated areas $\Omega_1, \ldots. \Omega_N$ take N distinct fitting functions $b_1(y), \ldots, b_N(y)$. According to Eq. (4), $\{\Omega_i\}_{i=1}^{N}$ forms the divisions $\Omega = \bigcup_{i=1}^{N} \Omega_i$ and $\Omega_i \cap \Omega_j$ (i $\neq$ j) in the image's field.
2. In the reflection ratio r, the edge structure makes up a majority of spatial derivative of the intensity. Therefore, the level set model can be integrated by this newly defined retinex model. The image was designed as:

$$i(y) = b(y) + r(y) + n(y) \tag{5}$$

Here b represents bias field image. r represents reflected image and n represent zero mean Gaussian noise.

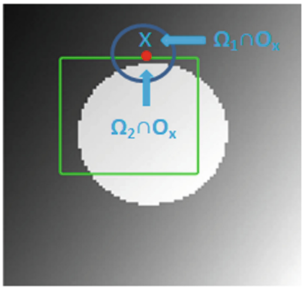

Fig. 1. Description of *Ox, Ω1*and *Ω2.*

3.2 Criterion Functions

According to Fig. 1 and assumptions made above, Eq. (5) can be modified.

For this, consider circular or a rectangular neighborhood having a radius of ρ and centered on every $x \epsilon \Omega$, which is described by $O_x = \{y : |y - x \leq \rho\}$. Then $\{\Omega_j\}_{j=1}^N$ induces the partition of O_x, that is, $\{O_x \cap \Omega_j\}_{j=1}^N$.

The intensity of $O_x \cap \Omega_j$ is taken by $b(y)$ where $y \in O_x \cap \Omega_j$. The curve C represents the dividing line, if Ω is divided into subregions i.e., Ω_1 and Ω_2. But during computing, due to the properties of δ, only small area data of curve C's narrow band is computed. In order to avoid this, *G(x-y)* is defined. It is a truncated Gaussian function. It is given as:

$$G_\sigma(x-y) = \begin{cases} \frac{1}{\beta} e^{-|x-y|^2/2\sigma^2, for |x-y| \leq \rho} \\ 0, \, otherwise \end{cases} \tag{6}$$

Here β is normalized constant and σ is standard deviation. Due to this *G(x-y)*, value outside the O_x will be zero. So O_x can be combined into Ω_1 and Ω_2, as shown in Fig. 1. Hence, $y \in O_x \cap \Omega_j$ can written as $y \in \Omega_j$ and each partition's bias field b can be represented as $b_j(y)$, where $y \in \Omega_j$. Therefore, Eq. (5) can be given as:

$$i(y) \approx b_j(y) + r(y) + n(y) for y \in \Omega_j \tag{7}$$

3.3 Energy Functions

Firstly, by using minimum clustering criterion algorithm, an energy function is defined.

$$E^{ABC}(\varphi, r, b) = \int \sum_{j=1}^{2} \left(\int G_\sigma(x-y)|i(y) - r(x) - b_j(x)|^2 dx \right) M_j(\varphi(y)) dy \tag{8}$$

Calculation of minimization of energy is below performed. The optimal b that minimizes $E^{ABC}(\varphi, r, b)$ for a fixed φ and r is:

$$\hat{b}_j(y) = \frac{G_\sigma * ((i-r)M_j(\varphi))}{G_\sigma * M_j(\varphi)}, j = 1, 2 \tag{9}$$

Equation (9) is optimized and shown in Eq. (10). G_σ *1 is only calculated once before to iteration and three convolutions are computed throughout iteration. These are shown as:

$$\begin{cases} \hat{b}_1(y) = \dfrac{G_\sigma * ((i-r)H(\varphi))}{G_\sigma * H(\varphi)} \\ \hat{b}_2(y) = \dfrac{G_\sigma * (i-r) - G_\sigma((i-r)) * H(\varphi)}{G_\sigma * 1 - G_\sigma * H(\varphi)} \end{cases} \tag{10}$$

Here $G_\sigma * H(\varphi)$, $G_\sigma * (i-r)$, $G_\sigma * (i-r)H(\varphi))$ computed during the iteration. The optimal r that minimizes $E^{ABC}(\varphi,r,b)$ for a fixed φ and b is:

$$\hat{r}(y) = \frac{G_\sigma * [(i-b_1)H(\varphi) + (i-b_2)(1-H(\varphi)]}{G_\sigma * 1} \tag{11}$$

Data terms extracted from Eq. (8) by analyzing the local area problem are:

$$e_j(y) = \int G_\sigma(x-y)|i(y) - r(x) - b_j(x)|^2 dx \tag{12}$$

$$E^{ABC}(\varphi, r, b) = \int \sum_{j=1}^{2} e_j M_j(\varphi(y))dy \tag{13}$$

Then by minimization of energy function $E^{ABC}(\varphi)$ in relation to φ with the usage of a standard gradient decent method, a let set formula is obtained:

$$\frac{\partial\varphi}{\partial t} = -\frac{\partial E^{ABC}}{\partial\varphi} = -\delta(\varphi)(e_1 - e_2) \tag{14}$$

Equation (14) is a CV model optimization. The data driven term e_1-e_2 present in Eq. (14) differs greatly in practical which may leads to the reduction of robustness of the system. To avoid this, an activation function is introduced. This is an odd function whose range is (-1, 1). Near the zero point, the activation function's data is sensitive. For this, in data-driven terms, we smooth the data having the greater dissimilarities and raise the sensitivity of data having the smaller dissimilarities. Therefore, it will be helpful to correctly locate the boundary. Then Eq. (14) is rewritten as:

$$\frac{\partial\varphi}{\partial t} = -\alpha\delta(\varphi)\tanh((e_1 - e_2)/\beta) \tag{15}$$

Here, β is image's standard deviation. In this, α is included to increase the robustness. It has adaptive adjustment ability. Therefore, adjustment of parameters repeatedly is not needed.

3.4 Regularization Method and Function of Length Term

Equation (15) contains a single energy term without having length term $L(\varphi)$ and regularization $R(\varphi)$. Regularization helps preventing an excessively flat or steeper level set function. A de-parameterized regularization function is defined for this:

$$\varphi_R = \tanh(\eta\varphi^{n+1}) \tag{16}$$

Here, η is a fixed constant i.e., 7. The aim of this equation is to suppress the two high point's slope and make the level set function's slope better.

In E^{ABC} minimization process, the zero level set curve C involves edge structure's boundary line gradually. But still there exists some unwanted curves in some areas or in the areas having strong noise. Due to this, the zero level set curve C becomes uneven. So, for smoothening and sharpening the curve, it is important to add a function that performs similar to the length constraint term function $L(\varphi)$. So, using neighborhood average filtering approach is the simpler option. [11–13].

Main steps of algorithm are:

1. Initialization:
1. Stretch the input image I into [0, 1] and take log.
2. Take iterations N and parameters σ, k and α.
3. Repeat:

Initial the level set function φ as:

$$\varphi(y, t = 0) = \begin{cases} -c_0 y \in \Omega_0 - \partial\Omega_0 \\ 0 y \in \partial\Omega_0 \\ c_0 y \in \Omega - \Omega_0 \end{cases} \tag{17}$$

Here, $c_0 = 1$. Ω_0 is the image domain's subset. $\partial\Omega_0$ is the boundary of Ω_0.

2. Calculate β, $G_\sigma * 1$and set an empty $\hat{r}$.
3. Take i from 1 to N.
4. Calculate $\hat{b}_1$ and $\hat{b}_2$ using Eq. (10) and Calculate with Eq. (11).
5. Calculate the gradient decent function using Eq. (15).
6. Calculate evolution of level set function $\varphi^{i+1} = \varphi^i + \Delta t \frac{\partial\varphi}{\partial t}$.
7. Till $\varphi^{i+1} == \varphi^i$, break the iteration.
8. Regularize φ^{i+1} using Eq. (16).
9. Calculate φ_R using neighborhood average filtering approach.

Output: level set function obtained from step 9 and results of segmentation.

4 Results and Discussion

4.1 Robustness to Initial Contour Experiment

Figure 2 shows the proposed LS-ABC model's segmentation results. These images include typical characteristics like weak edges, intensity inhomogeneity, low contrast. Three distinct initial contours each with a different position are set up for every image.

As can be observed in Fig. 2, accurate segmentation outcomes are achieved when the initial contour's position is changing. This demonstrates the proposed model's high level of initial contour robustness.

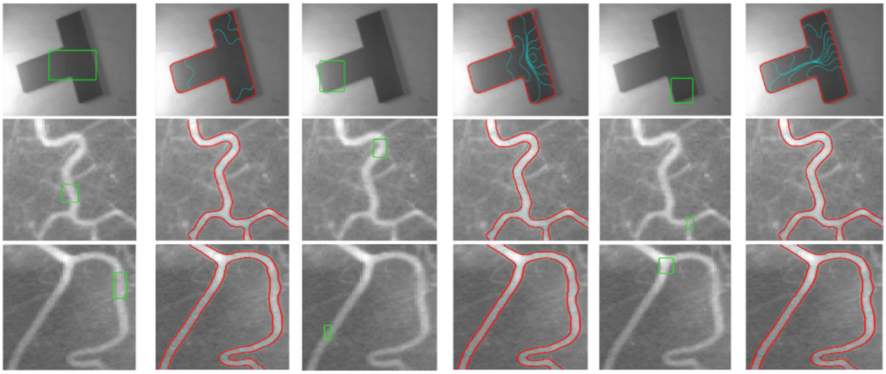

Fig. 2. Robustness to initial contour experiment. Initial contour is indicated by the green line. Final segmentation is indicated by the red line.

4.2 Comparison with the Existing Models

The proposed LS-ABC model is compared to the existing models such as RSF [4] model, LIF [5] model, BC [8] model, LPF [7] model. These models' parameter values and algorithmic operation are based on their literature. The segmentation of each model is done with a fixed initial contour. We choose time and number of iterations to indicate the segmentation speed.

Each model's segmentation result is shown in Fig. 3. The time and no. of iterations of each model are given in Table 2.

From Fig. 3, most of the existing models fall into the incorrect target segmentation whereas the proposed model's segmentation results are accurate. When compared to other models, LPF model have good accuracy in segmentation, but the time taken is long. It is given in Table 2. Therefore, the findings shown in Fig. 3 and Table 2 demonstrate that the proposed LS-ABC model segments the images quickly and accurately than the other four models.

4.3 The Impact of the Additive Bias Correction Experiment

Illumination interference can be successfully corrected with additive bias correction. In this part, an experiment is conducted on images having irregular illumination interference. Figure 4 depicts the results of the experiments. The bias field correction diagram demonstrates how significantly additive bias correction reduces the image's illumination inequality. This can be observed in Fig. 4 fourth column.

5 Conclusion and Future Scope

In this paper, a level set method based on additive bias correction (LS-ABC) is presented. The proposed model provides better initial contour robustness, a perfect and fast segmentation result for images having intensity inhomogeneity. To convert the local clustering criterion to the energy function, a function of level set is introduced. To increase

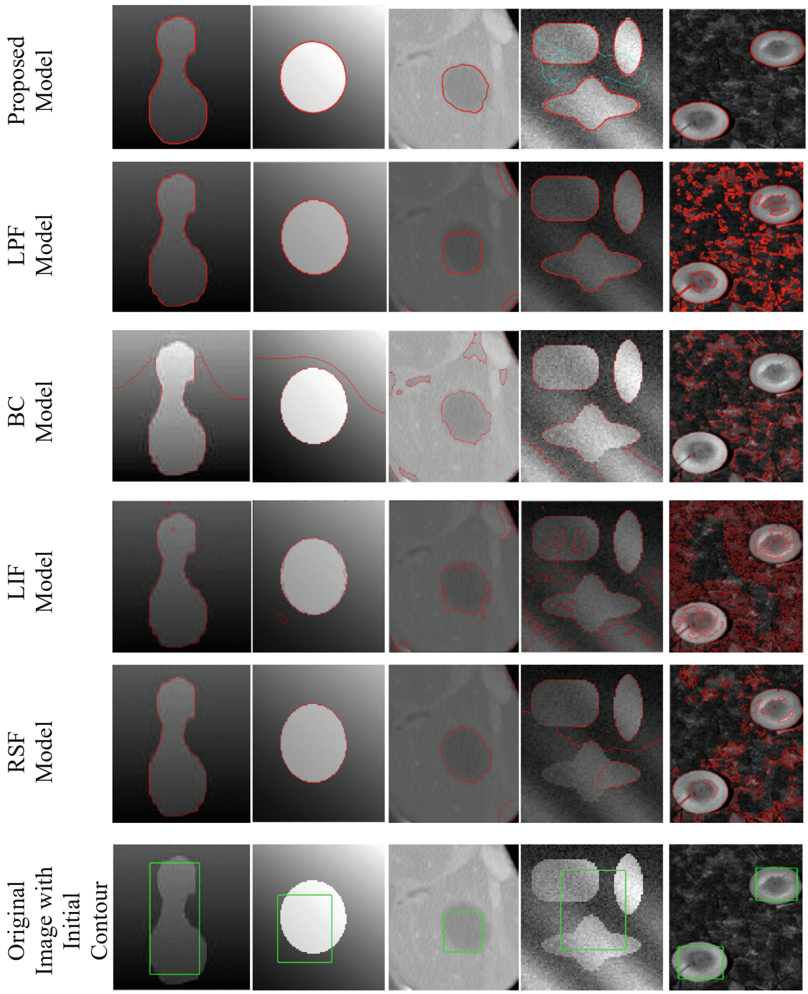

Fig. 3. Comparision with existing models.

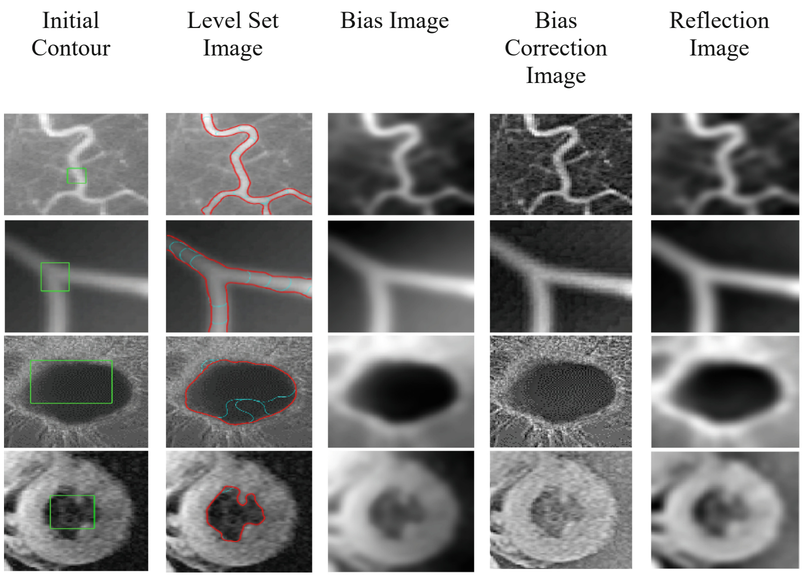

Fig. 4. Bias field correction results.

Table 2. Time and number of iterations taken by each model (no. of iterations/Time(s))

Image	RSF	LIF	BC	LPF	LS-ABC
1	15/ 0.2692	10/ 0.2918	40/ 2.6135	10/ 0.2703	7/ 0.0820
2	1300/ 12.8119	30/ 0.8267	20/ 3.0566	30/ 0.6116	30/ 0.3885
3	15/ 0.1782	10/ 0.3063	30/ 2.0741	10/ 0.2561	8/ 0.0328
4	150/ 2.7241	15/ 0.3440	20/ 2.6005	30/ 0.6805	15/ 0.2746
5	10/ 0.3563	10/ 0.5081	10/ 2.0011	20/ 0.8570	10/ 0.2741

robustness and address the issue of energy unification, an optimal adaptive data-driven term is developed. For images with varying attributes and sizes, continually altering the parameters is not required in this model. Experimental results validate that the proposed (LS-ABC) model segments the images having intensity inhomogeneity accurately. When compared to existing models, this model is found to be accurate, fast, and robust.

From Fig. 3 it is clear that the segmentation of proposed model is accurate compared to existing models. In future scope, we will introduce machine learning and deep learning methods, for further improvement of segmentation accuracy.

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