Evaluation of Active Contour on Medical Inhomogeneous Image Segmentation

Yun-Jen Chiu, Van-Tuong Pham, Thi-Thao Tran, and Kuo-Kai Shyu (Member, IEEE)
Department of Electrical Engineering
National Central University
Chung-Li 320, Taiwan
e-mail: kkshyu@ee.ncu.edu.tw

Abstract—Segmentation is an important step in medical image analysis. This process is crucial but challenging due to inhomogeneity in intensity of images. In addition, the images are often corrupted by noise and with contrast edges. There are some approaches aiming to cope with this kind of images such as: region growing, region competition, watershed segmentation, global thresholding, and active contour methods. Among them, active contour methods, especially level set-based active contour is widely used for image segmentation by their advantageous properties such as topology adaptability, and robustness to initialization. In this paper, we present and demonstrate the effectiveness of some recently active contour models for segmenting medical images with inhomogeneity in intensity. Among these techniques, the local binary fitting based model is validated as a promising method for medical image segmentation.

Keywords—Medical Image Segmentation; Active Contour; Level Set Method; Intensity Inhomogeneity Image Segmentation.

I. INTRODUCTION

Medical image analysis is one of the most important procedures in image guide surgery. Current research on image analysis can be classified into four categories according to their purposes: quality enhancement, registration, visualization, and segmentation [1]. The first step, quality enhancement aims to improve the contrast and reduce noise in image in order to get readable image. Image registration integrates information acquired from different modalities such as tissue from magnetic resonance imaging (MRI) and could be added to compute tomography (CT) image to help doctors have exact diagnostics. Image visualization is used to provide effective viewing of complex structures. The final step, image segmentation is the process in which a given image is partitioned into interested regions with least human manipulation.

With medical images which are often inhomogeneous in intensity, corrupted by noise, and with blur boundaries, segmentation is challenging. Some techniques such as region growing, region competition, watershed segmentation, global thresholding, atlas-based, artificial intelligence, and various hybrid methods were proposed for segmenting medical images. Recently, active contours (AC) or deformable models have been widely used in medical image segmentation with promising results. In general, in active contour or deformable models, the curves in 2D or surfaces in 3D are defined in an image domain. They evolve under some constrains from itself and the image data. Constraint from itself keeps the contour or surface smooth during deformation process, whereas constraint from image data deforms the curve or surface toward the desired object’s boundary. The existing active contour models can be classified into two main categories: edge-based [2], [3], [4] and region-based [5], [6], [7], [9]. Edge-based active contour models use the local edge information to evolve the contour toward the object’s boundaries, and region-based active contour models use the statistically information of region to build the region descriptor. This descriptor guides the active contour evolve toward the object boundaries.

More recently, segmentation methods aiming to deal with intensity inhomogeneous image have been studied in image processing, especially in medical image segmentation. In this study, we evaluate three recently developed active contour models for inhomogeneous image segmentation: Chan-Vese multiphase active contour without edges (CVMAC) [8], local binary fitting (LBF) model [10], and local image fitting (LIF) model [11].

This paper is organized as follows. In Section II, we review some AC models evaluated in this study. Section III gives some experimental results when using evaluated models with medical images. The conclusion is given in Section IV.

II. METHODOLOGY

In this section, models used in this study are briefly introduced. These models are based on the theory of curve evolution and level set method framework. Thus, they are adaptive to topology changes.

A. Chan-Vese multiphase AC contour without edge

Chan and Vese in [8] proposed an AC model based on the Mumford-Shah model [12]. Let \( \Omega \) be an image domain and \( I : \Omega \rightarrow R \) be the input image and \( C \) be a closed curve. The energy function is defined as follows:

\[
E^\gamma(c_1, c_2, C) = \mu \cdot \text{length}(C) + \nu \cdot \text{area} \big( \text{inside}(C) \big) + \lambda_1 \int c_1 - I(x)^2 \, dx + \lambda_2 \int c_2 - I(x)^2 \, dx \tag{1}
\]

where \( \mu \geq 0 \), \( \nu \geq 0 \), \( \lambda_1, \lambda_2 > 0 \) are adjustment constants, \( c_1 \) and \( c_2 \) are two constants that approximate the image intensities inside and outside the curve \( C \), respectively.

Using the steepest descent method to minimize the energy function (1) and represent the curve \( C \) as the zero...
level set of Lipschitz function \( \phi: \Omega \rightarrow \), i.e. 
\( \Omega = \{ x \in \Omega | \phi(x) = 0 \} \), we can get the variational formulation as follows:

\[
\frac{\partial \delta_c (\phi)}{\partial t} = \delta_c (\phi) \left[ \mu \text{div} \left( \frac{\nabla f_c}{|\nabla f_c|} \right) - \nu \lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 \right] - \left[ (I - c_{10})^2 + (I - c_{00})^2 \right] \left( 1 - H(\phi) \right)
\]

\[
\frac{\partial \delta_c (\phi)}{\partial t} = \delta_c (\phi) \left[ \mu \text{div} \left( \frac{\nabla f_c}{|\nabla f_c|} \right) - \left[ (I - c_{10})^2 + (I - c_{00})^2 \right] \left( 1 - H(\phi) \right) \right]
\]

where \( \delta_c (\cdot) \) is a slightly regularized version of one-dimensional Dirac measure \( \delta_0 \), defined by:

\[
\delta_0(z) = \frac{d}{dz} H(z); \quad H(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{if } z < 0 \end{cases}
\]

For the multiphase cases, i.e. four phases case, we need to use two level set functions \( \phi_1 \) and \( \phi_2 \), and the variational formulations become

\[
\frac{\partial \phi_1}{\partial t} = \delta_c (\phi_1) \left[ \mu \text{div} \left( \frac{\nabla f_{1c}}{|\nabla f_{1c}|} \right) - \left[ (I - c_{11})^2 + (I - c_{01})^2 \right] H(\phi_1) \right]
\]

\[
\frac{\partial \phi_2}{\partial t} = \delta_c (\phi_2) \left[ \mu \text{div} \left( \frac{\nabla f_{2c}}{|\nabla f_{2c}|} \right) - \left[ (I - c_{10})^2 + (I - c_{00})^2 \right] H(\phi_2) \right]
\]

where

\[
c_{11}(\phi) = \text{mean}(\mu_0) \text{ in } \{ (x, y) : f_c(x, y) > 0, \phi_c(x, y) > 0 \}
\]

\[
c_{10}(\phi) = \text{mean}(\mu_0) \text{ in } \{ (x, y) : f_c(x, y) > 0, \phi_c(x, y) < 0 \}
\]

\[
c_{01}(\phi) = \text{mean}(\mu_0) \text{ in } \{ (x, y) : f_c(x, y) < 0, \phi_c(x, y) > 0 \}
\]

\[
c_{00}(\phi) = \text{mean}(\mu_0) \text{ in } \{ (x, y) : f_c(x, y) < 0, \phi_c(x, y) < 0 \}
\]

In multiphase cases, the C-V model can work with intensity inhomogeneous images. However, the computational cost is expensive.

**B. The LBF model**

The local binary fitting (LBF) model has been recently proposed by Li et al [10] for segmenting images with intensity inhomogeneity characteristic. By choosing the kernel function \( K(x) \) as a Gaussian kernel and using two fitting functions \( f_1(x) \) and \( f_2(x) \), this model can localize the approximation of the intensities inside and outside the contour.

The LBF energy function can be written as:

\[
E^{LBF} (\phi, f_1, f_2) = \nu \int |\nabla H(\phi(x))| dx + \mu \int_{} \left( \frac{1}{2} |\nabla \phi(x) - 1| \right)^2 dx
\]

\[
+ \lambda_1 \int_{} \left( \int_{\text{inside}(C)} K_\sigma (x-y) \left| I(y) - f_1(x) \right|^2 H(\phi(y)) dy \right) dx
\]

\[
+ \lambda_2 \int_{} \left( \int_{\text{inside}(C)} K_\sigma (x-y) \left| I(y) - f_2(x) \right|^2 (1 - H(\phi(y))) dy \right) dx
\]

where \( \nu, \mu, \lambda_1, \lambda_2 \) are weighting positive constants, \( \sigma > 0 \) is a scale parameter used to control the scale of the local region, and \( K_\sigma \) is a kernel function [10] with a localization property such that \( K_\sigma (x-y) \) decreases and approaches zero as \( y \) goes far away from \( x \).

It is noted that the term \( \int |\nabla H(\phi(x))| dx = \text{Length}(C) \) is the length of the zero level set contour of \( \phi \),

\[
P(\phi) = \int_{} \left( \frac{1}{2} |\nabla \phi(x) - 1| \right)^2 dx
\]

is the level set regularization term used to penalize the deviation of the level set function \( \phi \) from a signed distance function [10]. The last two terms in Eq. (5) are the LBF energies.

Minimizing the energy function (5) \( E^{LBF} \) with respect to \( \phi \), we have the gradient descent flow as follows:

\[
\frac{\partial \phi}{\partial t} = \mu \nabla^2 \phi - \text{div} \left( \nabla \phi \right) + \nu \delta_c (\phi) \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right)
\]

\[
- \delta_c (\phi) (\lambda_1 e_1 - \lambda_2 e_2)
\]

where

\[
e_1 = \int_{\text{inside}(C)} K_\sigma (y-x) \left| I(x) - f_1(y) \right| dy
\]

\[
e_2 = \int_{\text{inside}(C)} K_\sigma (y-x) \left| I(x) - f_2(y) \right| dy
\]

with

\[
f_1(x) = \frac{K_\sigma \ast \left[ H_\sigma (\phi) I(x) \right]}{K_\sigma \ast H_\sigma (\phi)}
\]

\[
f_2(x) = \frac{K_\sigma \ast \left[ (1 - H_\sigma (\phi)) I(x) \right]}{K_\sigma \ast (1 - H_\sigma (\phi))}
\]

**C. The LIF model**

The local image fitting (LIF) model was recently proposed by Zhang et al [11] for segmenting images with intensity inhomogeneity. The basic idea of this method is to
introduce a local fitting image formulation $I^{LFI}$ to define a LIF energy functional as follows:

$$E^{LIF}(\phi) = \frac{1}{2} \int_{\Omega} \left[ I(x) - I^{LFI}(x) \right]^2 dx, x \in \Omega$$  \hspace{1cm} (9)$$

where $\phi(\cdot)$ is the level set function, $C$ is the curve as pointed out in section II.A, and $I^{LFI}$ is the local fitting image, defined as follows:

$$I^{LFI} = m_1 H_\varepsilon(\phi) + m_2 (1 - H_\varepsilon(\phi))$$  \hspace{1cm} (10)$$

where $H(\phi)$ is Heaviside function defined in (3), $m_1$ and $m_2$ are the weighting parameters defined as:

$$
\begin{align*}
    m_1 &= \text{mean}\left\{ I \in \{ x \in \Omega \,| \, \phi(x) < 0 \} \cap W_\varepsilon(x) \right\} \\
    m_2 &= \text{mean}\left\{ I \in \{ x \in \Omega \,| \, \phi(x) > 0 \} \cap W_\varepsilon(x) \right\}
\end{align*}
$$  \hspace{1cm} (11)$$

where $W_\varepsilon(x)$ is a rectangular window function, e.g. a truncated Gaussian window [11].

Minimizing the energy function $E^{LIF}(\phi)$ in (9) with respect to $\phi$, one can get the level set formulation of the LIF model:

$$\frac{\partial \phi}{\partial t} = \left( I - I^{LFI} \right) (m_1 - m_2) \delta_\varepsilon(\phi)$$  \hspace{1cm} (12)$$

where $\delta_\varepsilon(\phi)$ is regularized Dirac function defined in (3).

III. EXPERIMENT RESULTS

In this section, the performances of the three AC models dealing with medical heterogeneous images are demonstrated. Once the AC correctly picks out the interested objects boundaries, the segmented result is satisfied. Based on the results, we could pick the suitable model for medical image segmentation.

Fig. 1 shows the segmentation results obtained by using the CVMAC, the LIF and LBF method respectively. In this case, with CVMAC model, we use two level set functions; meanwhile, with the LIF and LBF model, the initial contours are located at the same position in the image. The tested image is a tumor in an MRI brain image. As we can see from Fig. 1, CVMAC model can detect the tumor; however it also detects other regions at the bottom of the image as well as those of the whole image. With the LIF model, though it also detects other regions at the bottom of the image as well as those of the whole image, it is not smooth. In addition, an uninterested region is also detected.

Fig. 2 is comparison of CVMAC, the LIF and the LBF model in segmenting a real blood vessel X-ray image. The vessel in this case is an intensity inhomogeneous image. One can see from this figure, the CVMAC fails to segment the image with some parts are not detected as shown in Fig. 2(a). With the LIF model, though the segmentation result as in Fig. 2(b) is better than that by the CVMAC, it is not smooth. In addition, an uninterested region is also detected.

Fig. 3 demonstrates the effectiveness of LBF model over MACWE and LIF model by applying them to an MR image of corpus callosum. The intensity in this image is highly inhomogeneous. The initial curves are in the first column. As
we can see from Fig. 3 (a) and (b), CVMAC and LIF model give inexact result whereas the desired result is provided by the LBF model.

Fig. 4 is another example to validate the ability of three models with a noisy MR image of the left ventricle of a human heart. It can be seen from Fig. 4 (a) and (b) that the result of CVMAC is unsatisfied. In contrast, the desired object is correctly detected with the LBF model as in Fig. 4(c).

IV. CONCLUSION

This paper has presented and validated the performance of some recent active contour methods when dealing with intensity inhomogeneous images. The segmentation results show that the LBF model is the promising one for medical image segmentation.

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