MR Image Segmentation Using Active Contour Model Incorporated with Sobel Edge Detection

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Abstract. This paper proposes a segmentation method which combines Active contour model with Sobel edge detection. The introduction of distance regularized formulation eliminates the need for reinitialization when we minimize the energy function by using the level set method. We test our method on MR image and compare it with several methods in the literature. The results achieved are better than the ones of existing techniques, showing the effectiveness of the proposed method.

Keywords: Image segmentation · Active contour model · Edge detection operator · Level set method

1 Introduction

Image segmentation has been widely used in medical analysis such as identifying tumors or soft tissue injuries from medical illustration [1], [2]. Active contour model is an excellent method and has been applied to image segmentation [3], [4], [11]. The general idea is to first initialize a curve around the object and then makes the curve move toward the object's interior morphology under the control of an energy function and finally stop at the boundary of the target area. Compare with classical image segmentation methods, active contour model has two advantages. Firstly, active contour model can be easily derived by energy minimization framework [5], [6]. Secondly, active contour model is able to achieve the sub-pixel accuracy of object boundaries [7]. It can be divided into two types: parametric active contour model and geometric active contour model. Parametric active contour was introduced by Kass et. al [8]. The energy function is minimized to attract the contour toward the edges, in which first derivative and second derivative were used to control the smoothness of the active contour, and therefore their method belongs to parametric active contour. However, the main disadvantage of the parametric active contour models is that the relation between the parametrization of the contour and geometry of the objects is not obvious.

To overcome the drawback of the parametric active contour model, geometric active contour model was proposed, which can be further categorized into edge-based models and region-based models. Edge-based models use edge information to attract

H. Zha et al. (Eds.): CCCV 2015, Part I, CCIS 546, pp. 429–437, 2015.
DOI: 10.1007/978-3-662-48558-3_43

the active contour move toward the object boundaries. But it still remains a challenge to find a proper trade-off between noise smoothing and edge information preservation, especially in the real condition. While, most MR image is noisy, if the isotropic smoothing such as Gaussian is strong, the edge would be smooth too. Region-based models used a certain region descriptor to guide the motion of the active contour, and therefore it could detect contours without edges. However, the region-based models are limited by intensity homogeneity. In fact, intensity inhomogeneity often occurs in MR images. Tsai et al. [9] proposed region-based model which regards image segmentation as a problem of finding a best approximation of the original image by a piecewise smooth function. The model has certain ability to solve intensity inhomogeneity. Michailovich et al. [10] proposed an active contour model using the Bhattacharyya difference between the intensity distributions inside and ouside a con-tour, and to some extent, solved the limitation of intensity homogeneity.

In this paper, the region-based active contour model and Sobel edge detection are combined. The proposed method is evaluated on some MR images, and the experimental results show that it is effective for such an issue.

The remainder of the paper is organized as follows. Section 2 introduces the Sobel operator based edge detection, and Section 3 presents how the region based active contour model is combined with the Sobel operator. We describe the solution of the energy function using the distance regularized level set method in Section 4. Experimental results are shown and analyzed in Section 5. Section 6 concludes the paper.

2 An Edge Detection Model Based on Sobel Operator

In digital images, the edge is a collection of pixels whose gray values have great changes. Therefore, it is the most basic feature of the image. Edge extraction is one of the most important and fundamental techniques in image processing and many related domains.

Sobel edge detection is a gradient based edge detection method. It has two advantages. Firstly, it is based on convolving the image with a small filter, and thus relatively inexpensive in terms of computation. Secondly, it actually uses an average factor to smooth the random noise of the image.

The operator contains two 3-dimensional matrices: one for horizontal changes, and anotherfor vertical ones. The two 3*3 kernels convolved with the original image are used to calculate the approximation of the horizontal and vertical differences. If we define *I* as the original image, Gx and Gy are two images which contain the longitudinal and transverse edge detection result. Then Gx and Gy are obtained as follows:

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * I \; and \; G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * I \tag{1}$$

where '*' is the convolution operator. At each point of the image, the gradient of *I*(x, y) is defined as f, and denotes the change of f. The resulting gradient approximations are combined to give the gradient magnitude:

$$mag(\nabla f\,) = \sqrt{{G_x}^2 + {G_y}^2} \tag{2}$$

For faster computation, (2) is approximated as:

$$mag(\nabla f) \approx |G_x| + |G_y| \tag{3}$$

This expression still preserves the relative changes in intensity. According to the value of $mag(\nabla f)$, we can determine whether there is an edge passing through the point (x, y).

3 Region-Based Active Contour Model Combines with Sobel Operater

Let $\Omega \in R^2$ be the image domain, and $I : \Omega \rightarrow R$ be a given gray level image. Mumford and Shah [12] solved the image segmentation problem by minimizing a function. By this way, they found a contour C which segments the image. The energy function is defined as follows:

$$F^{MS}(u, C) = \int_{\Omega} (u - I)^2 dx + \mu \int_{\Omega \backslash C} |\nabla u|^2 dx + v|C| \tag{4}$$

Where $v|C|$ is the Euclidean length, or more generally, the length of the contour *C*. The role of the first two terms is smooth image and ensures an image u that approximates the original image *I*. The minimized problem is called the minimal partition problem. In practice, the function is difficult to minimize mathematically.

Chan and Vense proposed an active contour model which is a particular case of the minimal partition problem [13]. It is a simplified version of Mumford–Shah model. The C-V model introduced the energy function by:

$$F(C, c_1, c_2) = \mu \cdot length(C) + v \cdot area(insideC)$$

$$+\alpha_1 \int_{inside(C)} |I - c_1|^2 dxdy + \alpha_2 \int_{outside(C)} |I - c_2|^2 dxdy \tag{5}$$

where c_1 and c_2 are two constants that approximate the image intensity in inside(C) and outside(C). The inside(C) and outside(C) represent the areas inside and outside the contour C. They also added some regularizing terms, e.g. the length of *C* and the area inside *C*, and μ, v, α_1, α_2 are fixed parameters.

In the (5), the two regularizing terms are not only difficult to calculate accurately, but have no relation with image of the geometric structure of the image as well. Therefore, we embed Sobel operater into the energy function to highlight gradient cues.

Z_1	Z_2	Z_3
Z_4	Z_5	Z_6
Z_7	Z_8	Z_9

(a)

-1	-2	-1
0	0.5	0
1	2	1

(b)

-1	0	1
-2	0.5	2
-1	0	1

(c)

Fig. 1. (a) 3x3 region of an image. (b) 0° Sobel kernel. (c) 90° Sobel kernel

We replace the center of one kernel from 0 to m, and the one of another kernel is thus 1-m. To simplify this case, we set m at 0.5 in our study. The two 3×3 templates are shown as Fig. 1 (b) and (c). Every point in the image uses these two kernels for convolution. Then, (1) becomes:

$$G_{x_{plus}} = (Z_7 + 2 \times Z_8 + Z_9) - (Z_1 + 2 \times Z_2 + Z_3) + 0.5 \times Z_5$$

$$G_{y_{plus}} = (Z_3 + 2 \times Z_6 + Z_9) - (Z_1 + 2 \times Z_4 + Z_7) + 0.5 \times Z_5 \tag{6}$$

We define I_{plus} as:

$$I_{plus} = G_{x_{plus}} + G_{y_{plus}} \tag{7}$$

By this way, we embed the Sobel operater to the center pixel. Then, we replaced I with I_{plus}, and the energy function (5) can be written as:

$$F_{plus}(C, c_1, c_2) = \alpha_1 \int_{inside(C)} \left|I_{plus} - c_1\right|^2 dxdy + \alpha_2 \int_{outside(C)} \left|I_{plus} - c_2\right|^2 dxdy \tag{8}$$

The minimal function problem can be formulated and solved using the level set method. In this paper, we introduce the distance regularization energy [14], which is presented in the next section.

4 The Distance Regularized Level Set Formulation of the Function

In level set methods [15], an evolving curve C is represented by the zero level set of a Lipschitz function Φ. So, $C = \{(x, y) \in \Omega : \Phi(x, y) = 0\}$, which is called a level set function, and we choose φ to be positive inside C and negative outside C. Let H be the Heaviside function, therefore, the new energy still denoted by $F_{plus}(\Phi, c_1, c_2)$, becomes:

$$F_{plus}(\Phi, c_1, c_2) = \alpha_1 \int_{\Phi \geq 0} \left|I_{plus} - c_1\right|^2 dxdy + \alpha_2 \int_{\Phi < 0} \left|I_{plus} - c_2\right|^2 dxdy \tag{9}$$

The Heavised function H is approximated by a smooth function H_ϵ which is defined by

$$H_\epsilon(x) = \frac{1}{2}\left[1 + \frac{2}{\pi} arctan\,(\frac{x}{\epsilon})\right] \tag{10}$$

The derivative of H_ϵ is

$$\sigma_\epsilon(x) = \frac{d}{dx}H_\epsilon(x) = \frac{1}{\pi}\frac{\epsilon}{\epsilon^2+x^2} \tag{11}$$

The two terms of F_{plus} can be rewritten in the following way:

$$\int_{\Phi\geq 0}\left|I_{plus} - c_1\right|^2 dxdy = \int_{\Omega}\left|I_{plus} - c_1\right|^2 H(\Phi)dxdy$$

$$\int_{\Phi<0}\left|I_{plus} - c_2\right|^2 dxdy = \int_{\Omega}\left|I_{plus} - c_2\right|^2 (1 - H(\Phi))dxdy \tag{12}$$

Then (10) can be written as:

$$F_{plus}(\Phi, c_1, c_2) = \alpha_1 \int_{\Omega}\left|I_{plus} - c_1\right|^2 H(\Phi)dxdy$$

$$+\alpha_2 \int_{\Omega}\left|I_{plus} - c_2\right|^2 (1 - H(\Phi))dxdy \tag{13}$$

In order to keep the regularity of the level set function, we should preserve the stability of level set evolution. Therefore, we introduce a distance regularization term in the level set formulation. As proposed in [16], we define the level set regularization term as:

$$P(\Phi) = \int \frac{1}{2}(\nabla\varphi(x) - 1)^2 dx \tag{14}$$

Then, we minimize the energy function:

$$F(\Phi, c_1, c_2) = \quad F_{plus}(\Phi, c_1, c_2) + \mu P(\Phi) \tag{15}$$

The function (16) can be minimized by the Euler-Lagrange equation: (paramterizing the descent direction by an artificial time):

$$\frac{\partial\Phi}{\partial t} = \mu div\left[\nabla\Phi\left(1 - \frac{1}{\nabla\Phi}\right)\right] + \sigma_\epsilon(\Phi)\left[\alpha_2\left(I_{plus} - c_2\right)^2 - \alpha_1\left(I_{plus} - c_1\right)^2\right] \tag{16}$$

where $\mu, \alpha_1,\ \alpha_2$ are fixed parameters. In the end, we introduce τ, and then we reach the result:

$$\Phi_{k+1} = \Phi_k + \tau\,\frac{\partial\Phi_k}{\partial t} \tag{17}$$

5 Experimental Result

The proposed method is validated on MR images. Both the traditional region-based model and the active contour model incorporated with Sobel edge detection are used to segment MR images for comparison. We also compare our method with the

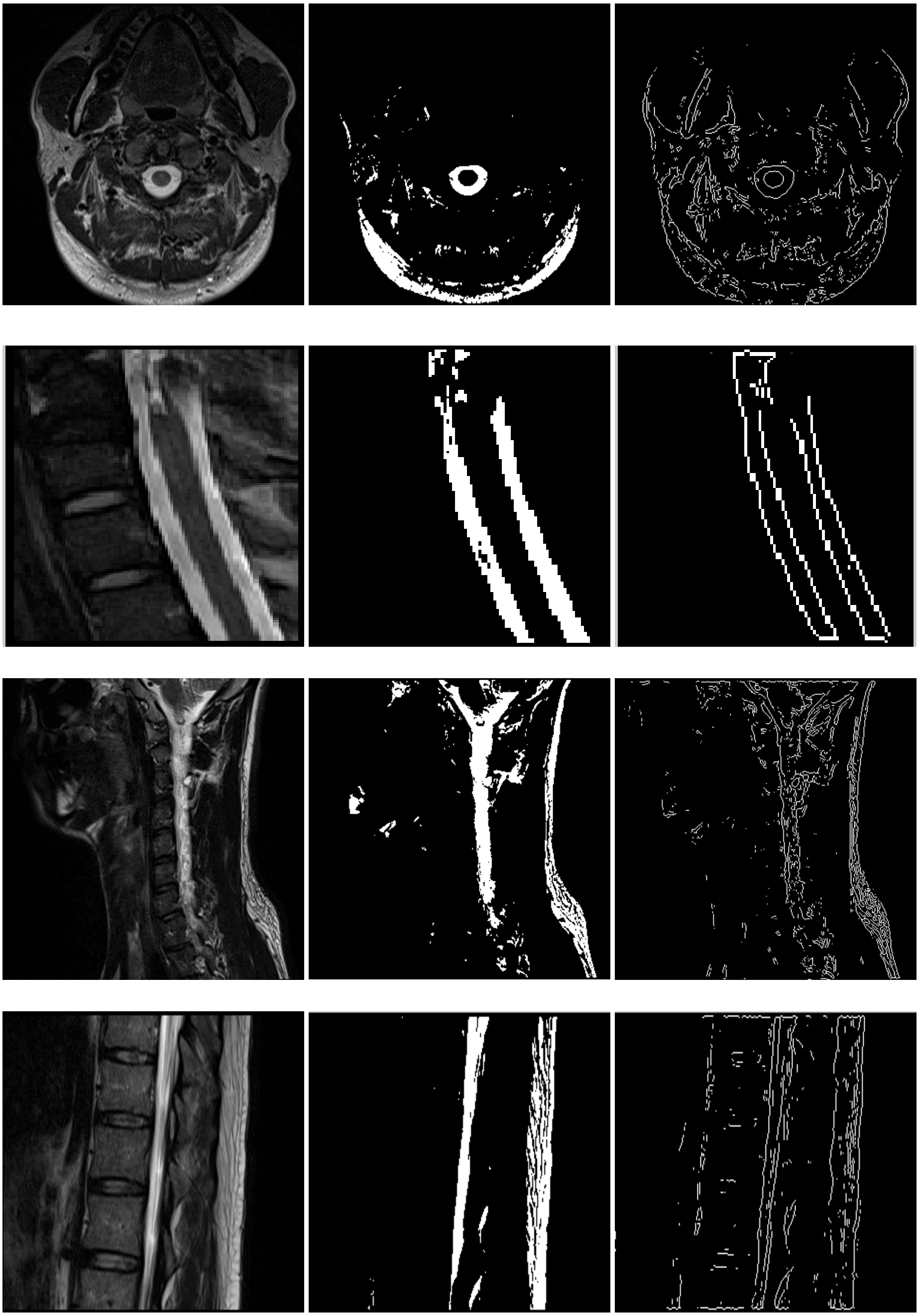

Fig. 2. Error of thresholding and Sobel edge detection for MR image. Column 1: Original images. Column 2: Thresholding results. Column 3: Result of Sobel edge detection.

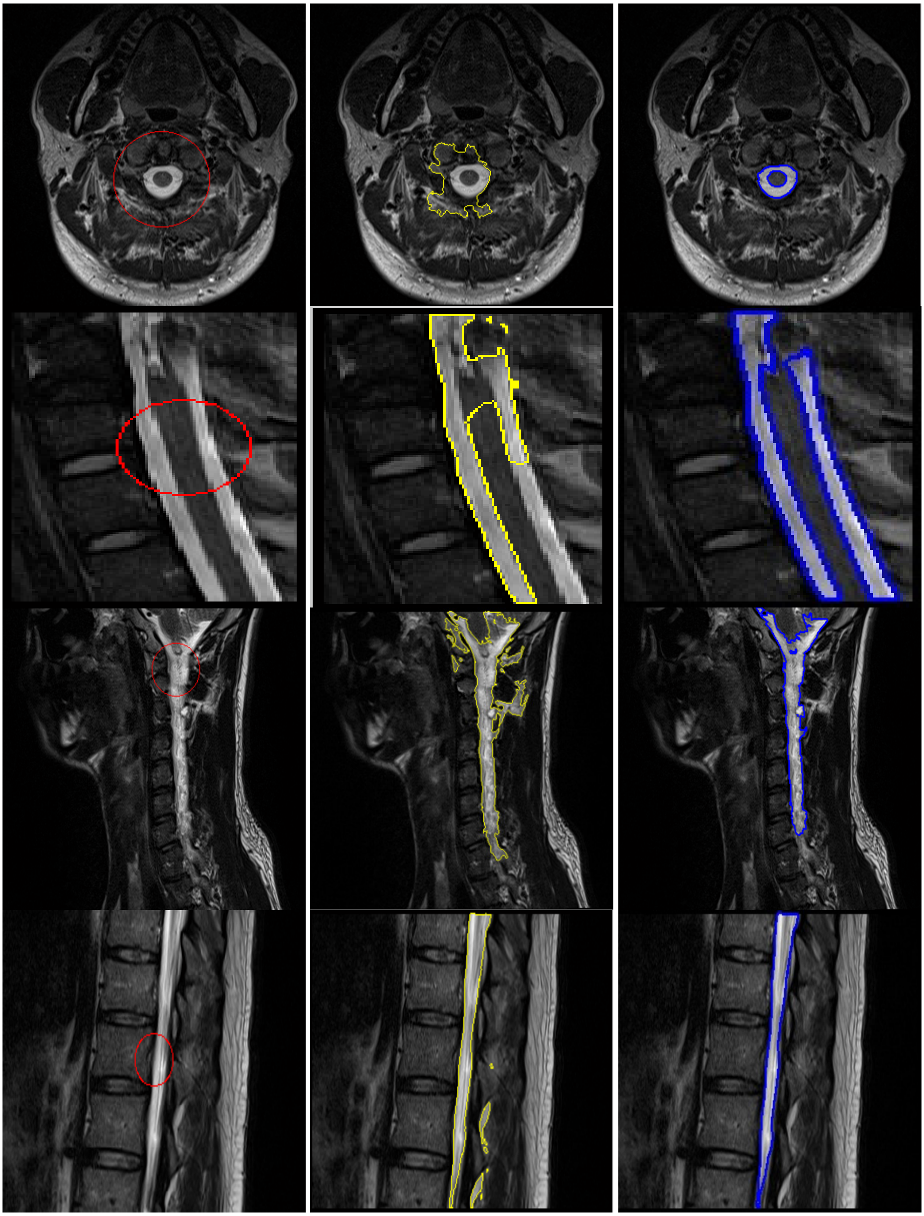

Fig. 3. Results of traditional active contour model and our method. Column 1: Initial contour and original image. Column 2: traditional active contour model method. Column 3: the proposed method.

thresh-old method and the edge detection method. It turns out that the proposed active con-tour model that is combined with Sobel edge detection achieves better results than the other two methods. The results are shown in Fig.2 to Fig.4. The MR image in

Fig. 2 is segmented with simple thresholding and Sobel edge detection, and the result are not enough. The second and third columns in Fig. 3 show the results with the same initial contours. The Fig. 4 shows the contour evolution process from the initial contour to the final contour using our method.

Fig. 4. Results of our method for MR images. The contour evolution process from the initial contour to the final contour is displayed.

The region-based active contour model combined with Sobel edge detection is able to segment the target from the image, but traditional active contour model fails. Because of the simple thresholding, edge detection and traditional active contour model could only use single information of the image while the active contour model with Sobel operater combines the region-base model with edge information other than single information. At the same time, it also inherits the advantage of Sobel operator which could smooth the random noise of image.

6 Conclusion

In this paper, we present a region-based active contour model combined with the Sobel edge detection operator. The proposed method is able to provide better quality of MR image segmentation. With distance regularized level set formulation, the pro-cess of segmentation can maintain the stability of level set evolution. As the experi-mental results demonstrate, our method works better than some well-known methods of MR image segmentation.

Refeerences

1. Prakash, R.M., Kumari, R.S.S.: Nonsubsampled contourlet transform based expectation maximization method with adaptive mean shift for automatic segmentation of MR brain images. In: 2014 International Conference on Electronics and Communication Systems (ICECS), pp. 1–5, February 13–14, 2014
2. Rodtook, A., Makhanov, S.S.: Multi-feature gradient vector flow snakes for adaptive segmentation of the ultrasound images of breast cancer. Journal of Visual Communication and Image Representation **24**(6), 1414–1430 (2013)
3. Malladi, R., Sethian, J.A., Vemuri, B.C.: Shape modeling with front propagation: a level set approach. IEEE Trans. Pattern Anal. Mach. Intell. **17**(2), 158–175 (1995)

4. Li, C., Xu, C., Gui, C., Fox, M.D.: Level set evolution without re-initialization: a new variational formulation. In: Proc. IEEE Conf. Computer Vision and Pattern Recognition, vol. 1, pp. 430–436 (2005)
5. Chen, Y., Tagare, H., Thiruvenkadam, S., Huang, F., Wilson, D., Gopinath, K., Briggs, R., Geiser, E.: Using prior shapes in geometric active contours in a variational framework. Int. J. Comput. Vis. **50**, 315–328 (2002)
6. Leventon, M., Grimson, W., Faugeras, O.: Statistical shape influence in geodesic active contours. In: Proc. IEEE Conf. Computer Vision and Pattern Recognition, vol. I, pp. 316–323 (2000)
7. Caselles, V., Kimmel, R., Sapiro, G.: Geodesic active contours. Int. J. Comput. Vis. **22**, 61–79 (1997)
8. Kass, M., Witkin, A., Terzopoulos, D.: Snakes: active contour models. Int. J. Comput. Vis. **1**, 321–331 (1987)
9. Tsai, A., Yezzi, A., Willsky, A.S.: Curve evolution implementation of the Mumford-Shah functional for image segmentation, denoising, interpolation, and magnification. IEEE Trans. Image Process. **10**(8), 1169–1186 (2001)
10. Michailovich, O., Rathi, Y., Tannenbaum, A.: Image segmentation using active contours driven by the bhattacharyya gradient flow. IEEE Trans. Image Process. **16**(11), 2787–2801 (2007)
11. He, N., Zhang, P., Lu, K.: A geometric active contours model for multiple objects segmentation. In: Huang, D.-S., Wunsch II, D.C., Levine, D.S., Jo, K.-H. (eds.) ICIC 2008. LNCS, vol. 5226, pp. 1141–1148. Springer, Heidelberg (2008)
12. Mumford, D., Shah, J.: Optimal approximations by piecewise smooth functions and associated variational problems. Commun. Pure Appl. Math. **42**, 577–685 (1989)
13. Chan, T., Vese, L.: Active contours without edges. IEEE Trans. Image Process. **10**(2), 266–277 (2001)
14. Li, C., Kao, C.-Y., Gore, J.C., Ding, Z.: Minimization of Region-Scalable Fitting Energy for Image Segmentation. IEEE Transactions on Image Processing **17**(10), 1940–1949 (2008)
15. Zhao, H.-K., Osher, S., Merriman, B., Kang, M.: Implicit and nonparametric shape reconstruction from unorganized data using a variational level set method. Computer Vision and Image Understanding **80**(3), 295–314 (2000)
16. Li, C., Xu, C., Gui, C., Fox, M.D.: Level set evolution without re-initialization: a new variational formulation. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 1, pp. 430–436, June 20-25, 2005