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Region-based Active Contour Model based on Markov Random Field to Segment Images with Intensity Non-Uniformity and Noise

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ABSTRACT

This paper represents a new region-based active contour model that can be used to segment images with intensity non-uniformity and high-level noise. The main idea of our proposed method is to use Gaussian distributions with different means and variances with incorporation of intensity non-uniformity model for image segmentation. In order to integrate the spatial information between neighboring pixels in our proposed method, we use Markov Random Field. Our experiments on synthetic images and cerebral magnetic resonance images show the advantages of the proposed method over state-of-art methods, i.e. local Gaussian distribution fitting.

Key words: Segmentation, level set, intensity non-uniformity, markov random field, MRI

INTRODUCTION

Image segmentation is an important step in many image analyses. The goal of image segmentation is to partition an image into a number of regions, each having similar characteristic. In the recent years, different methods have been developed for image segmentation. One of the most popular methods is active contour.

Active contours are based on the theory of surface evolution under a speed function determined by local, global and independent properties. They are able to provide smooth and closed contours to extract the boundaries of objects in image. They can be divided into two main groups: geometric and parametric. Parametric active contours are explicitly represented as parameterized contour/surface in a Lagrangian formulation.[1] One of main drawbacks of parametric active contours is the difficulty of naturally handling topological changes for splitting and merging of contours.

Osher and Sethian[2] proposed a level set frame work for geometric active contour to solve this problem. The main idea of the level set framework is to implicitly represent an evolving curve/surface C in the image plane ($\Omega \in \Re^n$) as zero level of a function φ defined in a higher dimension. According to defined energy functional, they can be broadly categorized into two classes: Edge-based models[3,4] and region-based models.[5-8]

Edge-based active contour models use image gradient as a constraint to stop the evolving curve on the desired object boundary. However, these models are not appropriate for segmenting images with high-level noise and weak edges.[8] Region-based models use global information such as region intensity homogeneity to evolve the curve. Therefore, they provide performance improvement over edge-based methods.

Active contour based on piecewise constant (PC) model originally proposed by Chan and Vese[5] is a popular region-based active contour model. This model assumes that each image region has statistically homogeneous intensity. In this model, Chan and Vese proposed a level set formulation for the approach proposed by Mumford-Shah to segment an input image domain Ω into two separated homogeneous regions $\{\Omega_i\}_{i=1,2}$, defined by the evolving contour C that minimizes the following functional:[9]

$$E(c_1,c_2,C)=\lambda_1 \int_{outside\ C} |I(x)-c_1|^2\,dx + \lambda_2 \int_{inside\ C} |I(x)-c_2|^2\,dx+\nu|C| \quad (1)$$

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where $I(y):\Omega \rightarrow \Re$ is an image defined on Ω and the constants c_1 and c_2 approximate the image intensity inside and outside of the contour C. Obviously, because of intensity non-uniformity in real images, the constants c_1 and c_2 can be far from original image intensities in each region.

In order to overcome difficulty of segmentation of images with intensity non-uniformity, Li *et al.*[6,10] proposed the local binary fitting (LBF) model to use local intensity information for image segmentation. They locally approximate the intensities outside and inside the evolving contour using two fitting functions $f_1(x)$ and $f_2(x)$. The energy functional of the LBF model is defined as follows:

$$E_{LBF}(\phi, f_1, f_2) = \lambda_1 \int\int W(x-y)\,|I(y)-f_1(x)|^2 H(\phi(y))dydx + \lambda_2 \int\int W(x-y)\,|I(y)-f_2(x)|^2\,(1-H(\phi(y))dydx + \nu\int|\nabla H(\phi(x))|\,dx + \mu\int\frac{1}{2}(|\nabla\phi(x)|-1)^2dx \quad (2)$$

Where λ_1, λ_2, ν and $\propto$ are positive weighting constants and $W(u)$ is a kernel function with localization property. Typically, $W(u)$ is chosen as truncated Gaussian kernel, i.e. $W(u)=0,\ u>\sigma$.[6]

In the presence of intensity non-uniformity and noise, image segmentation based on local intensity mean cannot provide accurate results. Thus, Wang *et al.*[7,8] proposed the local Gaussian distribution fitting (LGDF) model in which the local intensity is modeled by Gaussian distribution. The energy functional for LGDF model for each pixel is defined as follows:

$$E_{LGDF}(\phi, u_1, u_2, \sigma_1, \sigma_2) = \int\int -W(x-y)\log P_{i,x}(I(y))H(\phi(y))dydx + \int\int -W(x-y)\log P_{i,x}(I(y))(1-H(\phi(y))dydx + \nu\int|\nabla H(\phi(x))|\,dx + \mu\int\frac{1}{2}(|\nabla\phi(x)|-1)^2dx \quad (3)$$

where $P_{i,x}(I(y))$ is:

$$P_{i,x}(I(y)) = \frac{1}{\sqrt{2\pi}\sigma_i}\exp\left(-\frac{(u_i-I(y))^2}{2\sigma_i^2}\right) \quad (4)$$

In this energy functional, u_i and σ_i^2 are local mean and variance for intensity of the image, respectively.[8,11]

However, the region based-models are based on the assumption that pixels in each region are statistically independent of each other. This assumption ignores the correlations between pixels, which holds for most real images. To address this problem, Markov random fields can be used to model the correlations between neighboring pixels. Recently, Xu *et al.*[12] applied the Markov random field model into the region-based active contour proposed by Chan and Vese.[5] However, in this model, the intensity non-uniformity correction was not addressed in the proposed energy functional. Furthermore, the intensity means and standard deviations were simply calculated globally for each region without using a Gaussian kernel or any localized energy.

In this paper, we propose a novel region-based active contour model in a level set formulation that can be used to segment images with intensity non-uniformity and high-level noise. The main idea of our proposed method is to use Gaussian distributions with different means and variances while incorporating a model of intensity non-uniformity (bias) for simultaneous segmentation and intensity non-uniformity correction. Furthermore, by incorporating Markov random field to integrate the spatial information between neighboring pixels in the active contour model, the proposed generalized region-based model can be used to segment images in the presence of image artifacts.

The rest of the paper is organized as follows. The proposed method is introduced in following Section. Detailed simulation results are provided in Result Section and concluded remarks are given at the end.

PROPOSED METHOD

Let $\Omega \in \Re^2$ be image domain and $I(y):\Omega \rightarrow \Re$ be the observed gray level intensity. Let $h:\Omega \rightarrow \{\Omega_1, \Omega_2\}$ be a function that maps each point y in image domain into one of two regions $\{\Omega_1, \Omega_2\}$ where $\Omega_1 \cap \Omega_2 = \Omega$ and $\omega \in \Omega_i$ implies $h_\omega = \Omega_i$. The goal of image segmentation is to determine the function h that optimally partitions the image domain. In statistical framework, an optimal partitioning $P(H=h)$ can be obtained by maximizing *a posteriori* probability $P(H=h\,|\,I)$. This conditional probability can be expressed using the Bayes rule as follows:[13]

$$\max P(H=h\,|\,I) \propto P(I\,|\,H=h)\,P(H=h) \quad (5)$$

where conditional probability $P(I\,|\,H=h)$ is the *a posteriori* segmentation probability.

The $P(H=h)$ is the prior probability about regions to be segmented and can be estimated using the Markov random field to model the image. A random field is Markov random field if all of its local conditional probability density functions satisfy the Markov property as follows: $P(h_\omega\,|\,h_{-\omega}) = P(h_\omega\,|\,h_{\eta_\omega})$, where $h_{-\omega} = \{h(r):\ r\in\Omega,\ r\neq\omega\}$,

$h_{\eta_\omega} = \{h(r): r \in \eta_\omega, r \neq \omega\}$, and the neighborhood η_ω of ω is any bounded region such that $s \in \eta_\omega \leftrightarrow \omega \in \eta_s$, $\omega \notin \eta_\omega$ and $\omega, s \in \Omega$. Thus, the prior probability $P(H = h)$ can be approximated by the normalized pseudo-likelihood as follows:[14]

$$P(H = h) \approx \frac{1}{Z} \prod_{i=1}^{2} \prod_{\omega \in \Omega_i} P(H_\Omega = \Omega_i \mid h_{\eta_\omega})^{dc} \quad (6)$$

where

$$P(H_\Omega = \Omega_i \mid h_{\eta_\omega}) = \frac{1}{Z_\omega} \exp\{-\beta \int_{\eta_\omega \cap \Omega_i} dc\} = \frac{1}{Z_\omega} \exp\{-\beta A(\eta_\omega, \Omega_i)\} \quad (7)$$

and Z and Z_ω are normalization constants, β is an appropriately selected constant, dc represents the bin volume that guarantees the correct continuum limit,[11] $A(\eta_\omega, \Omega_i)$ is the area of the region defined by $\eta_\omega \cap \Omega_i$ where η_ω is selected to be a rectangular window that defines on initial contour.

To estimate the conditional probability $P(I \mid H = h)$, we assume that the pixels within each region are independent and identically distributed realizations of the same random process. Thus, $P(I \mid h)$ can be written as follows:

$$P(I \mid h) = \prod_{i=1}^{2} \prod_{\omega \in \Omega_i} P(I_\omega \mid H_\Omega = \Omega_i)^{dc} \quad (8)$$

A common choice for conditional probability for a given value I with respect to h is to use Gaussian distributions with mean $\propto_i$ and variance σ_i^2 as follows:

$$P(I_\omega \mid H_\Omega = \Omega_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp(-\frac{(I - \mu_i)^2}{2\sigma_i^2}) \quad (9)$$

One of the main problems in image segmentation, e.g. medical images, is intensity non-uniformity or bias field that often arises from the imperfection of imaging devices. The bias field can be modeled as a smooth and spatially varying field $b(x)$ multiplied by the constant true signal of the same tissue c. Thus, image intensity corresponding to the object domain Ω_i (equation 9) can be approximated by Gaussian distribution with local mean bc_i and variance σ_i^2 as follows:[15,16]

$$P(I_\omega(y) \mid H_\Omega = \Omega_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp(-\frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2}), \quad y \in \Omega_i \quad (10)$$

Maximization of the *a posteriori* probability is equivalent to minimization of its negative logarithm.

$$-\log(P(H = h \mid I)) = -\{\log P(I \mid H = h) + \log(P(H = h))\} \quad (11)$$

After integrating over the entire image domains, the following energy functional is obtained:

$$E(\{\Omega_1, \Omega_2\}) = -\sum_{i=1}^{2} \int_\Omega \int_{\Omega_i} W(x - y) \log P(H = h \mid I) dy dx \quad (12)$$

where $W(x - y)$ is a truncated Gaussian kernel with $\sigma > 0$. With equations (7) and (10), energy functional in (12) can be re-written as follows:

$$E(\{\Omega_1, \Omega_2\}) = \sum_{i=1}^{2} \int_\Omega \int_{\Omega_i} W(x - y) \{\left(\log(\sqrt{2\pi}\sigma_i) + \frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2} \right) + \beta A(\eta_\omega, \Omega_i) + \log(Z)\} dy dx \quad (13)$$

Note that proposed energy functional has two differences from the functionals proposed by Wang *et al.*[7,8] and Xu *et al.*[12] First, in the proposed functional, a Gaussian kernel and a model for intensity non-uniformity are used to localize energy functional and simultaneously perform segmentation and bias correction. Second, integrating Markov random filed in the proposed energy functional improves the image segmentation in the presence of artifices. Thus, the proposed functional is of general form in comparison with other methods.

Level Set Formulation

The goal is that the image domain Ω can be partitioned into two regions $\{\Omega_1, \Omega_2\}$ background and foreground, respectively, by using functional $E(\Omega_1, \Omega_2, C)$. These two regions can be represented as the regions outside and inside of the zero level set φ. Thus, using $M_i(\varphi(y))$ as the characteristic function of region Ω_i, the energy functional[14] can be expressed using level set function $\varphi(y)$ as follows:

$$\begin{aligned} E(\phi, b, c_1, c_2, \sigma_1, \sigma_2) = & \int_\Omega \int W(x - y) \left(\log(\sqrt{2\pi}\sigma_1) + \frac{(I(y) - b(x)c_1)^2}{2\sigma_1^2} \right) M_1(\phi(y)) dy dx \\ & + \int_\Omega \int W(x - y) \left(\log(\sqrt{2\pi}\sigma_2) + \frac{(I(y) - b(x)c_2)^2}{2\sigma_2^2} \right) M_2(\phi(y)) dy dx \\ & + \beta \int_\Omega \int W(x - y) \left[A(\eta_\omega, \Omega_1) M_1(\phi(y)) + A(\eta_\omega, \Omega_2) M_2(\phi(y)) \right] dy dx \\ & + \nu \int \left| \nabla H(\phi(x)) \right| dx + \mu \int \frac{1}{2} (\left| \nabla \phi(x) \right| - 1)^2 dx \end{aligned} \quad (14)$$

where β, ν and μ are positive weighting constants. Using the Heaviside function H, the characteristic function of regions $M_i(\varphi(y))$ are defined as follows:

$$\begin{cases} M_1(\varphi) = H(\varphi) \\ M_2(\varphi) = 1 - H(\varphi) \end{cases} \quad (15)$$

The Heaviside function and the Delta function, the derivation of Heaviside function, can be approximated as follows:

$$H_\varepsilon(\varphi) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{\varphi}{\varepsilon}\right)\right),$$
$$\delta_\varepsilon(\varphi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + \varphi^2} \quad (16)$$

where ε is a constant.

For fix φ, by calculus of variations with gradient descent flow, it can be shown that the parameters c_i, σ_i^2, b that minimize the energy functional in equation (14) can be obtained as follows:

$$c_i = \frac{\int\int W(x-y)I(y)b(x)M_i(\varphi(y))dydx}{\int\int W(x-y)b^2(x)M_i(\varphi(y))dydx} \quad (17)$$

$$\sigma_i^2 = \frac{\int\int W(x-y)M_i(\varphi(y))(I(y)-b(x)c_i)^2 dydx}{\int\int W(x-y)M_i(\varphi(y))dydx} \quad (18)$$

$$b(x) = \frac{\sum_{i=1}^{2}\left(\int W(x-y)I(y)M_i(\phi(y))\right)\frac{c_i}{\sigma_i^2}dy}{\sum_{i=1}^{2}\int (W(x-y)M_i(\phi(y)))\frac{c_i^2}{\sigma_i^2}dy} \quad (19)$$

Minimization of energy functional $E(.)$ with respect to φ can be achieved by solving the gradient decent flow equation as follows:

$$\frac{\partial\varphi}{\partial t} = -[d_1 - d_2]\delta(\varphi) + \beta[W * (A(\eta_w, \Omega_1) - A(\eta_w, \Omega_2))]\delta(\varphi) + \nu\delta(\varphi)div\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right) + \mu\left(\nabla^2(\varphi) - div\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right)\right) \quad (20)$$

where

$$d_i(y) = \int_\Omega W(x-y)\left(\log(\sqrt{2\pi}\sigma_i) + \frac{(I(y)-b(x)c_i)^2}{2\sigma_i^2}\right)dx \quad (21)$$

and $*$ indicates the convolution operation.

The pseudocode for image segmentation is given in Table 1.

RESULTS

To validate the proposed model, an extensive validation was performed based on two imaging data types: (i) synthetic images and (ii) simulated and real medical images. In this section, the following parameters $\sigma = 3, \mu = 1, \varepsilon = 1, \nu = 0.00001 \times 255 \times 255, \beta = 0.1, \Delta t = 0.01$ were set.

Synthetic Images

Figure 1 shows the application of the proposed method for segmentation of synthetic images with noise and intensity non-uniformity. The segmentation results using the proposed method achieves satisfactory result.

Medical Images

The proposed method is applied to simulated and real medical images with intensity non-uniformity and noise. The result of the vessel image segmentation is shown in Figure 2. As can be seen, the image has weak boundaries and is also corrupted by intensity non-uniformity. However, the method can segment the desired tissue appropriately.

In order to study the robustness of the proposed method for brain tissue segmentation from magnetic resonance (MR) images with different noise (n) and intensity non-uniformity (RF), the white matter (WM) is segmented from simulated T1-weighted MR images with different noise and intensity non-uniformity (bias) level. They have a matrix size of 181×272×181 and voxel dimensions of 1 mm×1 mm×1 mm. Figure 3 shows the results of WM segmentation from simulated brain MR images using the Brainweb MR image simulator. The results obtained using the proposed method were compared with those obtained by the LGDF method. The first column in Figure 3 shows the selected axial slices with n=5%, RF=40; n=7%, RF=40 and n=9%, RF=40%, while the second and third columns illustrate the segmented WM using LGFD and the proposed method, respectively. As can be seen, the proposed method can properly extract WM in the presence of high-level intensity non-uniformity and noise in comparison with the LGDF method.

¥Available at http://www.cma.mgh.harvard.edu/ibsr

Table 1: The pseudocode for image segmentation

Initialize the level set functions φ, c_i, σ_i^2 and $b(x)$
While the convergence criteria is not met do
Update c_i, σ_i^2 and $b(x)$ using Eqs. (17), (18) and (19), respectively
Update the level set function φ according to Eq. (20)
End While

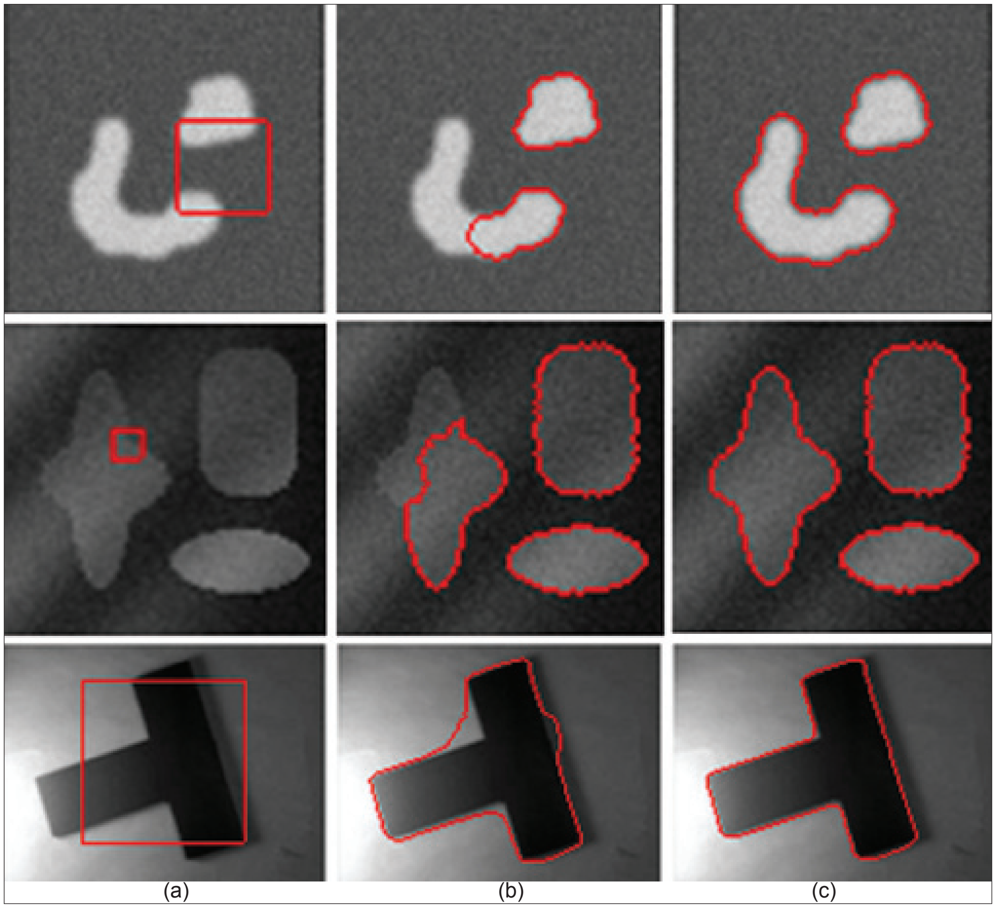


Figure 1: Application of the proposed method for segmentation of synthetic image with noise and intensity non-uniformity. (a) Original image and initial contours; (b) curve evolution after 50 iterations; and (c) final zero-level contour using the proposed method

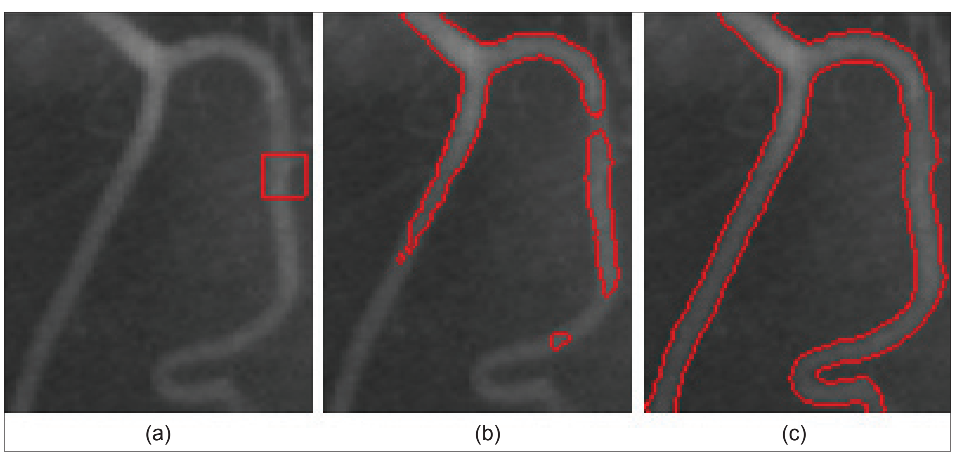
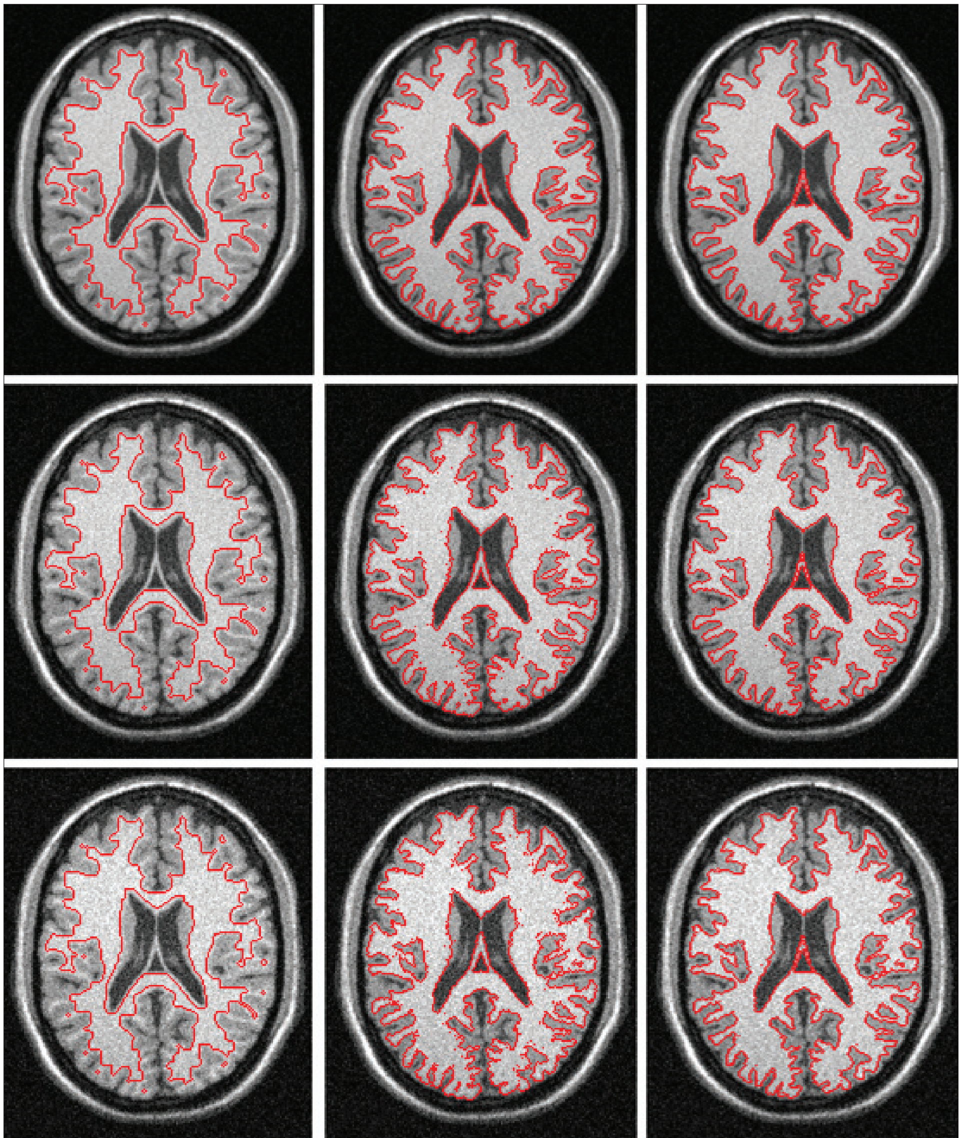


Figure 2: Segmentation of vessel image using the proposed model. (a) Original image with initial contour; (b) curve evolution after 20 iterations; and (c) final zero-level contour

Furthermore, we applied our proposed model to segment WM from T1-weighted brain images of 20 normal subjects provided by the Center for Morphometric Analysis at Massachusetts General Hospital¥ (IBSR). IBSR provides T1-weighted coronal MR images where each slice has 256×256 pixels and the voxel dimensions are 1.17 mm× 1.17 mm×3.1 mm. The real MR brain data and their hand-guided expert segmentation results are available at these datasets. This database consists of clinical datasets that are a result of real MRI scanning. The images involve various problems related to segmentation of real MRI data, such as intensity non-uniformity and noise.

In order to quantitatively evaluate the proposed method, the Dice similarity metric is used,[4,17] which is defined as follows:



(a) (b) (c)

Figure 3: Comparison between the proposed method and local Gaussian distribution fitting (LGDF) method brain magnetic resonance images obtained from Brainweb. From top to down, the images are corrupted with noise = 5%, RF = 40; noise = 7%, RF = 40 and noise = 9%, RF = 40%. (a) Original image with initial contour; (b) final zero-level contour of LGDF method; (c) final zero-level contour of the proposed method

$$DSM = \frac{2n(L_a \cap L_r)}{n(L_a) + n(L_r)} \quad (22)$$

where L_a and L_r represent the obtained segmentation and ground truth, respectively, and n (.) indicates the number of voxels. This metric represents spatial overlap between two binary images and its value range between 0 (no overlap) and 1 (perfect agreement). On the other hand, to assess the success and error rate of the proposed method, the sensitivity (true positive fraction) and specificity (true negative fraction) were calculated. Sensitivity refers to the ability to correctly identify appropriate tissue in the segmented mask and specificity refers to the ability of the proposed segmentation method to correctly remove non-desired voxels. Sensitivity and specificity are the measures computed based on true positive (TP), false negative (FN) and false positive (FP).

$$Sensitivity = \frac{TP}{TP + FN} \quad (23)$$

$$Specificity = \frac{TN}{TN + FP} \quad (24)$$

Figure 4 illustrates the Dice similarity values (DSM) of the proposed method for WM segmentation from simulated MR images using the Brainweb MR image simulator in comparison with the LGDF method. It can be seen that the similarity values of our method are generally higher than those of LGDF, especially in high-level noise and intensity non-uniformity. In addition, the average results for WM segmentation from the eight simulated and 20 real datasets

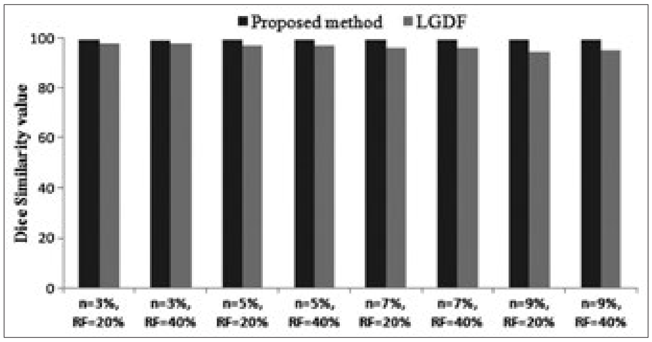


Figure 4: Dice similarity values for the segmented white matter from the simulated magnetic resonance images using the Brainweb simulator using the proposed method and local Gaussian distribution fitting method

Table 2: Quantitative evaluation of the proposed method for WM segmentation from simulated and real dataset IBSR

	DSM	Specificity	Sensitivity
Brainweb datasets			
Proposed method	0.99±0.023	0.99±0.01	0.99±0.01
LGDF	0.96±0.13	0.99±0.01	0.93±0.11
IBSR real datasets			
Proposed method	0.98±0.02	0.99±0.01	0.97±0.02
LGDF	0.94±0.01	0.99±0.01	0.88±0.01

WM – White matter; IBSR – Internet brain segmentation repository; DSM – Dice similarity values; LGDF – Local gaussian distribution fitting

using the proposed method and LGDF are shown in Table 2. As can be seen, the method can segment the WM with mean similarity (Dice) of 99% and 98% in case of simulated and real images, respectively. If a segmentation result can be classed as high quality with an arbitrarily high threshold on the Dice coefficient, such as DSM >90%, then the proposed method demonstrates high performance for segmented WM from simulated and real IBSR datasets.

CONCLUSION

In this paper, we proposed a new method that can be used to segment images with intensity non-uniformity and noise. The segmentation framework is based on region-based active contour that uses Gaussian distributions with different means and variances. It incorporates a model of intensity non-uniformity to segment the image and correct the intensity non-uniformity. Furthermore, we have used the Markov random field to integrate the spatial information between neighboring pixels in our proposed method.

Recently, different region-based active contours have been proposed that use the intensity non-uniformity model and Markov random field separately to overcome bias and noise. However, in this research, we proposed a generalized region-based active contour model that integrates Markov random field and intensity non-uniformity model into energy functional. Furthermore, in the proposed model, we utilized local means and standard deviations by using Gaussian kernel. Thus, while the proposed model allows tissue segmentation and intensity non-uniformity correction to be performed simultaneously, it handles noise efficiently in real images such as cerebral MR images. Moreover, the proposed model is robust against initializations, allowing fully automatic applications.

We applied our method to the synthetic and cerebral MR images. Assessment of synthetic image segmentation was performed qualitatively and the brain tissue segmentation was performed quantitatively. As this method can be used to segment medical images, it is applied to segment brain tissues from simulated and real MR images. Experimental results show desirable performance of our proposed method to segment synthetic images and brain MR images in comparison with state-of-the-art methods such as LGDF even for images with high-level noise and bias.

REFERENCES

1. Kass M, Witkin A, Terzopoulos D. Snakes: Active contour models. Int J Comput Vis 1987;1:321-31.
2. Osher S, Sethian J. Fronts propagation with curvature-dependent speed: Algorithms based on the Hamilton-Jacobi formulation. J Comput Phys 1988;79:12-149.
3. Caselles V, Catte F, Coll T, Dibos F. A geometric model for active contours in image processing. Numer Math 1993;66:1-31.
4. Li C, Xu C, Gui C, Fox MD. Level set evolution without re-initialization: A new variational formulation. In: Proceedings of IEEE conference on computer vision and pattern recognition (CVPR). vol. 1. 2005. p. 430-6.
5. Chan TF, Vese LA. Active contours without edges. IEEE Trans Image Process 2001;10:266-77.
6. Li C, Kao C, Gore JC, Ding Z. Minimization of region-scalable fitting energy for image segmentation. IEEE Trans Image Process 2008;17:1940-9.
7. Wang L, Li C, Sun Q, Xia D, Kao CY. Active contours driven by local and global intensity fitting energy with application to brain MR image segmentation. Comput Med Imaging Graph 2009;33:520-31.
8. Wang L, Chen Y, Pan X, Hong X, Xia D. Level set segmentation of brain magnetic resonance images based on local Gaussian distribution fitting energy. J Neurosci Methods 2010;188:316-25.
9. Mumford D, Shah J. Optimal approximations by piecewise smooth functions and associated variational problems. Commun Pure Appl Math 1989;42:577-685.
10. Li C, Kao C, Gore J, Ding Z. Implicit active contours driven by local binary fitting energy. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Minneapolis, Minnesota, USA, 2007. p. 1-7.\
11. Cremers D, Mikael R, Rachid D. A review of statistical approaches to level set segmentation: Integrating color, texture, motion and shape. IJCV 2009;72:195-215.
12. Xu J, Monaco JP, Madabhushi A. Markov random field driven region-based active contour model (MaRACel): Application to medical image segmentation. Med Image Comput Comput Assist Interv 2010;13:197-204.
13. Paragios N, Deriche R. Geodesic active regions and level set methods for supervised texture segmentation. IJCV 2002;46:223-47.
14. Monaco JP, Tomaszewski JE, Feldman MD, Hagemann I, Moradi M, Mousavi P, *et al.* High-throughput detection of prostate cancer in histological sections using probabilistic pairwise markov models. Med Image Anal 2010;14:617-29.
15. Vovk U, Pernus F, Likar B. A review of methods for correction of

intensity in homogeneity in MRI. IEEE Trans Med Imag 2007;26:405-21.
16. Zhang K, Zhang L, Zhang S. A variational multiphase level set approach to simultaneous segmentation and bias correction. ICIP 2010:4105-8.
17. Dice LR. Measures of the Amount of Ecologic Association between Species. Ecology 1945;26:297-302.

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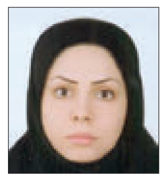

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