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Comparison of Level Set-based Active Contour Models on Subcortical Image Segmentation

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ABSTRACT

In this paper, we have compared three level set-based active contour (LSAC) methods on inhomogeneous MR image segmentation which is known as an important role of brain diseases to diagnosis and treatment in early. MR image is often occurred a problem with similar intensities and weak boundaries which have been causing many segmentation methods. However, LSAC method could be able to segment the targets such as the level set based on the local image fitting energy, the local binary fitting energy, and local Gaussian distribution fitting energy. Our implemented and tested the subcortical image segmentations were the corpus callosum and hippocampus and finally demonstrated their effectiveness. Consequently, the level set based on local Gaussian distribution fitting energy has obtained the best model to accurate and robust for the subcortical image segmentation.

Key words: Level Set-based Active Contour Method, Image Segmentation, Corpus Callosum, Hippocampus, Inhomogeneous Intensity

1. INTRODUCTION

Segmentation is an important task in medical image analysis for the process of partition a given image into interested regions for a specific purpose. However, the medical image is often corrupted by noise, lack of boundaries, and also inhomogeneity due to technical limitations or artifacts introduced by the object being imaged. In particular, the inhomogeneities in magnetic resonance images arise from the non-uniform magnetic fields which produced by radio-frequency coils as well as from variations in object susceptibility. Especially the intensity of the hippocampus and corpus callosum are difficult to distinguish with other tissues located around them that cause misclassification between interested region and background. Therefore, the segmentation is challenging difficulty in medical images.

In previous research, the level set-based active contour methods have been extensively used in medical image segmentation because of its advantageous properties such as they can achieve sub-pixel accuracy of object boundaries. They also can be easily formulated under principled energy minimization framework, and allow incorporation of various prior knowledge. Moreover, they can provide smooth contours to the object being segmented [1,2]. The level set methods can be categorized into two types: firstly the edge-based model which is used image gradient to stop the contours on the boundaries of interested regions and attract the contours to the desired boundaries, even the controlling contours to expend or shrink [3-5].

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Secondly, the region-based model is used the image statistical information to construct constraints but more powerful than the edge-based model for image segmentation on the interested object with lack of boundaries or even without boundaries [6-8]. Zhang et al. proposed a novel active contour model that embeds the image information which can be used to segment images with inhomogeneous intensity, by utilizing the local image information to construct a local image fitting (LIF) energy functional [9]. The similar previous studies are also found in literatures for the differences between the fitting image and the original image [10]. Moreover, a novel method is used to regularize the level set function by using Gaussian kernel filtering for the smoothness of the level set function which is avoided the reinitialization step that causes computationally expensive. Recently, local intensity information has been incorporated into the active contour models [11,12] for more accurate segmentation, especially in the presence of inhomogeneous intensity. For example, Li et al. [13] proposed a local binary fitting (LBF) energy in a region-based model for more accurate and efficient segmentation. The LBF model draws upon local intensity means, which enables it to cope with reinitialization. In order to make possibility of the image reinitialization segmentation Wang et al. [14] also proposed an active contour driven by local Gaussian distribution fitting (LGDF), starting from a point of the local image data then the local energy integrated over the entire image domain by using Gaussian distributions with different means and variances to described the local image intensities. The LGDF energy then incorporated into a variation level set formulation with a level set regularization term. There are two variables of the energy functional such as local intensity means and variances which are derived from a variational principle [14,15]. Izmantoko. et al [16] presented an active shape model (ASM) which uses a prior knowledge from sample images with the object in different shape and size to make a model for segmenting another image. The evaluation of active contour and active shape model for medical image segmentation is also presented in [17].

In our study, we have evaluated three level set-based active contour models for subcortical MR brain images to the local image fitting model [9], local binary fitting model [13], and local Gaussian distribution fitting model [14], by applying them to the corpus callosum and hippocamus. These models are based on a level set evolution and variation framework. In the rest part of this paper is organized as follows. In section II, we briefly describe a few level set-base active contour method that uses in this study. Section III shows implementation results to demonstrate the effectiveness of the chosen level set-based active contour methods. Finally the conclusion of this paper is served in section IV.

2. METHODOLOGY

In this section, we provide the brief introduction of the models which used in our study. The three level set-based active contour models were used such as the local image fitting (LIF), the local binary fitting (LBF), and the local Gaussian distribution fitting (LGDF) models to segment MR brain images. In order to evaluate these models are able to the suitable model for the MR brain image segmentation.

2.1 The LIF model

The local image fitting (LIF) model was recently proposed by Zhang et. al [9] for segmenting images with the intensity inhomogeneity. It provides less computational complexity than the classical active contour. The major contribution of this model is to introduce a local image fitting energy into a variation framework. The LIF energy function was also used the Gaussian filtering. However, the reinitialization is still necessary for this method. The

LIF energy functional defines as follows:

$$E^{LIF}(\phi) = \frac{1}{2}\int_{\Omega}\left|I(x) - I^{LFI}(x)\right|^2 dx, x \in \Omega \quad (1)$$

where ϕ is a level set function, $I(x)$ is the original image, and I^{LFI} is the local fitted image defined as follows:

$$I^{LFI} = m_1 H_{\varepsilon}(\phi) + m_2(1 - H_{\varepsilon}(\phi)) \quad (2)$$

Heaviside function $H_{\varepsilon}(\phi)$ is usually approximated by a smoothing function defined as

$$H_{\varepsilon}(x) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{x}{\varepsilon}\right)\right] \quad (3)$$

the weighting parameters (m_1, m_2)are defined as

$$\begin{cases} m_1 = mean\left(I \in \left(\{x \in \Omega \mid \phi(x) < 0\} \cap W_k(x)\right)\right) \\ m_2 = mean\left(I \in \left(\{x \in \Omega \mid \phi(x) > 0\} \cap W_k(x)\right)\right) \end{cases} \quad (4)$$

where $W_k(x)$ is a rectangular window function, in this study a truncated Gaussian window with size ($4k$+1) by ($4k$+1) is used which is smaller than the standard deviation.

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

$$\frac{\partial \phi}{\partial t} = \left(I - I^{LFI}\right)\left(m_1 - m_2\right)\delta_{\varepsilon}(\phi) \quad (5)$$

where $\delta_{\varepsilon}(\phi)$ is regularized Dirac function, the derivative of H_{ε} is the following smooth function defined as

$$\delta_{\varepsilon}(x) = H_{\varepsilon}^{'} = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + x^2} \quad (6)$$

2.2 The LBF model

The local binary fitting (LBF) model has been recently proposed by Li et al [13] for segmenting images. By utilizing image information in local regions and incorporating a local binary fitting energy with a kernel function $K(x)$ as a Gaussian kernel into a level set formulation, the model is able to extract interested region with inhomogeneous intensity and using two fitting functions $f_1(x)$ and $f_2(x)$ to localize the inside and outside intensity of the contour. The LBF energy function can be written as:

$$\begin{aligned} E^{LBF}\left(\phi, f_1(x), f_2(x)\right) = \lambda_1 \int_{\text{int}(C)} K(x-y)\left|I(y) - f_1(x)\right|^2 dx \\ + \lambda_2 \int_{out(C)} K(x-y)\left|I(y) - f_2(x)\right|^2 dx \end{aligned} \quad (7)$$

The kernel function $K(x)$ chooses as a Gaussian kerne $K_{\sigma}(x)$ with a localization property such that $K_{\sigma}(x-y)$ decreases and approaches zero as y goes far away from x.The LBF energy function with Heaviside function $H_{\varepsilon}(\phi)$ is defined in Eq. (3) which approximates by a smoothing function e.g., rewritten as:

$$E^{LBF}(\phi, f_1, f_2) = \int_{\Omega} E^{LBF}\left(\phi, f_1(x), f_2(x)\right)dx$$

$$= \lambda_1 \int\left[\int_{ins(C)} K_{\sigma}(x-y)\left|I(y) - f_1(x)\right|^2 H\left(\phi(y)\right)dy\right]dx \quad (8)$$

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

where λ_1 and λ_2 are the weighting positive constants. The distance regularizing term is added to ensure the level set evolution which is stable

$$p(\phi) = \int \frac{1}{2}\left(\left|\nabla\phi(x)\right| - 1\right)^2 dx \quad (9)$$

the level set regularization term used to penalize the deviation of the level set function ϕ from a signed distance function. To regularize the zero level contour of ϕ, which is given by

$$l(\phi) = \int \delta(\phi)\left|\nabla\phi(x)\right|dx \quad (10)$$

the term in (10) is the length of the zero level set contour of ϕ. $\delta(\phi)$ is regularized Dirac function as defined in Eq. (6). The entire energy functional can be defined as

$$E(\phi, f_1, f_2) = E^{LBF}(\phi, f_1, f_2) + \mu p(\phi) + v l(\phi) \quad (11)$$

Minimizing the energy function in Eq. (11) with respect to ϕ, we have the gradient descent flow as follows:

$$\begin{aligned} \frac{\partial \phi}{\partial t} = -\delta_{\varepsilon}(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + v\delta_{\varepsilon}(\phi)div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) \\ + \mu\left(\nabla^2\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \end{aligned} \quad (12)$$

where

$$\begin{cases} e_1 = \int_\Omega K_\sigma(y-x)\left|I(x)-f_1(y)\right|^2 dy \\ e_2 = \int_\Omega K_\sigma(y-x)\left|I(x)-f_2(y)\right|^2 dy \end{cases} \tag{13}$$

with

$$\begin{cases} f_1(x) = \dfrac{K_\sigma * \left[H_\varepsilon(\phi)I(x)\right]}{K_\sigma * H_\varepsilon(\phi)} \\ f_2(x) = \dfrac{K_\sigma * \left[(1-H_\varepsilon(\phi))I(x)\right]}{K_\sigma * (1-H_\varepsilon(\phi))} \end{cases} \tag{14}$$

2.3 The LGDF model

The local Gaussian distribution fitting (LGDF) model has been recently proposed by Li Wang et. al [14] for segmenting images with inhomogeneous intensity. The image domain can be partitioned into two regions corresponding to the foreground object and background. These two regions can be represented as the regions outside and inside the zero level set of function ϕ. The energy as in terms of ϕ, u_i and σ_i^2 can be expressed

$$\begin{aligned} E_x^{LGDF}&(\phi,u_1(x),u_2(x),\sigma_1(x)^2,\sigma_2(x)^2) \\ &= -\int \omega(x-y)\log p_{1,x}(I(y))M_1(\phi(y))dy \\ &\quad -\int \omega(x-y)\log p_{2,x}(I(y))M_2(\phi(y))dy \end{aligned} \tag{15}$$

where $M_1(\phi(x))=H(\phi(x))$ and $M_2(\phi(x))=1-H(\phi(x))$. Thus the energy E^{LGDF} can be rewritten as

$$\begin{aligned} E^{LGDF}&(\phi,u_1,u_2,\sigma_1^{\,2},\sigma_2^{\,2}) \\ &= -\int E_x^{LGDF}(\phi,u_1(x),u_2(x),\sigma_1(x)^2,\sigma_2(x)^2)dy \end{aligned} \tag{16}$$

where $H(\phi(x))$ is Heaviside function as defined in Eq. (3).

For more accurate computation involving the level set function and its evolution, we need to regularize the level set function by penalizing its deviation from a signed distance function [18], the energy function which is defined in Eq. (9). The level set method needs to regularize the zero level set by penalizing its length to drive a smooth contour during evolution as defined in Eq. (10). Therefore, the entire energy function as follows

$$\begin{aligned} E(\phi,u_1,u_2,\sigma_1^{\,2},\sigma_2^{\,2}) &= E^{LGDF}(\phi,u_1,u_2,\sigma_1^{\,2},\sigma_2^{\,2}) \\ &\quad + vp(\phi) + \mu l(\phi) \end{aligned} \tag{17}$$

where v and μ are positive weighting constants. The minimization of the energy function is in Eq. (17) with respect to ϕ

$$\begin{aligned} \frac{\partial\phi}{\partial t} &= -\delta(\phi)(e_1-e_2) + v\delta(\phi)div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) \\ &\quad + \mu\left(\nabla^2\phi + div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \end{aligned} \tag{18}$$

where $\delta(\phi)$ is Dirac function as defined in Eq. (6). The new image-based terms (e_1, e_2) are independent of the scale of local intensity caused by inhomogeneous intensity.

$$\begin{aligned} e_1(x) &= \int_\Omega \omega(y-x)\left[\log(\sigma_1(y)) + \frac{(u_1(y)-I(x))^2}{2\sigma_1^2(y)}\right]dy \\ e_2(x) &= \int_\Omega \omega(y-x)\left[\log(\sigma_2(y)) + \frac{(u_2(y)-I(x))^2}{2\sigma_2^2(y)}\right]dy \end{aligned} \tag{19}$$

Therefore, the new local intensity means $\mu_i(x)$ and variances $\sigma_i(x)^2$ can define as

$$u_i(x) = \frac{\int \omega(x-y)I(y)M_{i,\varepsilon}(\phi(y))dy}{\int \omega(x-y)M_{i,\varepsilon}(\phi(y))dy} \tag{20}$$

$$\sigma_i(x)^2 = \frac{\int \omega(x-y)(u_i(x)-I(y))^2 M_{i,\varepsilon}(\phi(y))dy}{\int \omega(x-y)M_{i,\varepsilon}(\phi(y))dy} \tag{21}$$

3. EXPERIMENTAL RESULTS

We have taken the MR images which contained the corpus callosum and normal hippocampus from Haeundae Paik Hospital, Korea with the scanner type of 3.0T and subject age is 29 years old man. However, to illustrate the segmenting process in the real implementation, we performed our experiments in this study following the three LSBAC models such as; the LIF, the LBF, and the LGDF model dealing with MR brain images. To compare the efficient performance of these models, we firstly show the segmentation the target with satisfied results. The based on the results, we could choose the suitable model for medical image segmentation.

Fig. 1 shows the segmentation results obtained

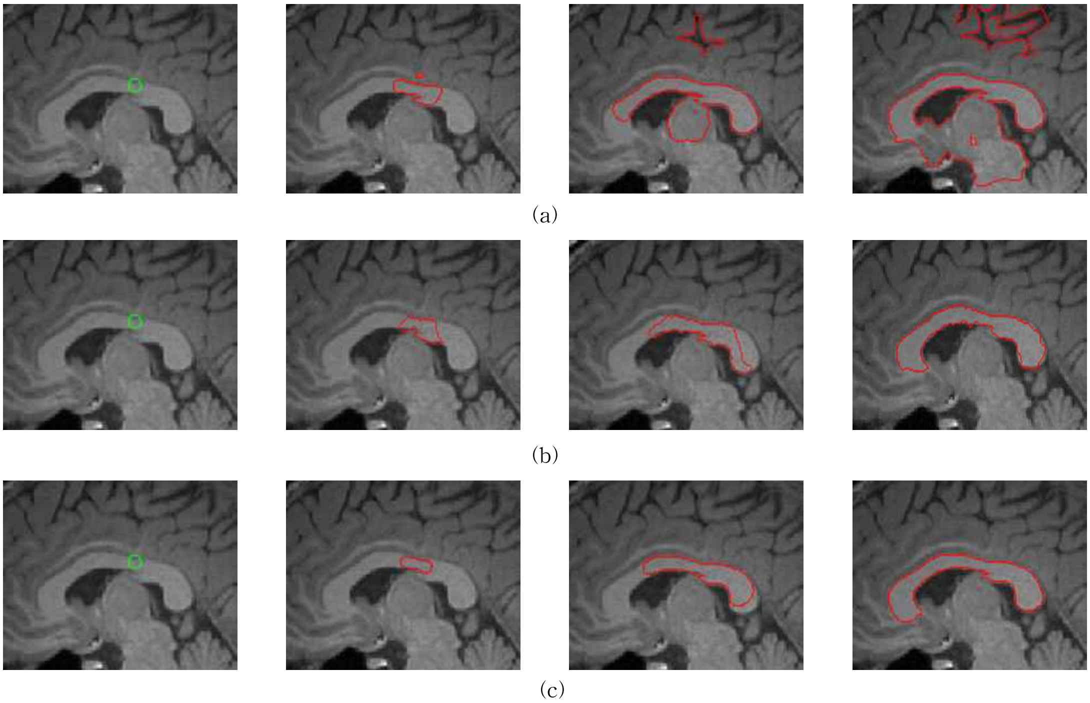

Fig. 1. The segmented results of Corpus Callosum on MR brain images by (a) LIF, (b) LBF, and (c) LGDF method. An initial curve, two curve evolutions and the final result were shown from the left to right column respectively.

by using the LIF, LBF, and LGDF methods respectively. In this case, the initial contours are located at the same position in the image. The test image is a corpus callosum in an MR brain image. As we can see Fig. 1 LIF model which is failed to segment the corpus callosum as shown in Fig. 1 (a). The LBF model can segment the Corpus Callosum but the contour is not smooth as shown in Fig. 1 (b). With the LGDF model, the segmented result is satisfied since it exactly segment the corpus callosum.

Fig. 2 is comparison of the LIF, the LBF, and the LGDF models in segmenting the real hippocampus MR images. The hippocampus in this case is an intensity inhomogeneous image. One can see from this figure, the LIF fails to segment the image with some parts invisible as shown in Fig. 2 (a). With the LBF model, even though the segmentation result as in Fig. (b) is better than that by the LIF model, it also detect an unexpected region. In Fig. 2 (c) shows the accurate result when using the LGDF model.

4. CONCLUSION

This paper has presented the level set based on the LIF, the LBF, and LGDF model for general classification of imagery whose regions of interest cannot be distinguished according to their respective pixel intensity distributions. While a number of active contour models were proposed to solve the image segmentation problem but only a few models have been proposed to solve the MR brain image segmentation problem due to the efficiency of methods and also the difficulty on MR brain image itself which cause many algorithms failed to segment hippocampus or corpus callosum. Therefore, this study has presented the performance validation of some recent level set-based active contour methods when dealing with intensity inhomogeneous images. The LGDF model has given the best result visualization for the subcortical

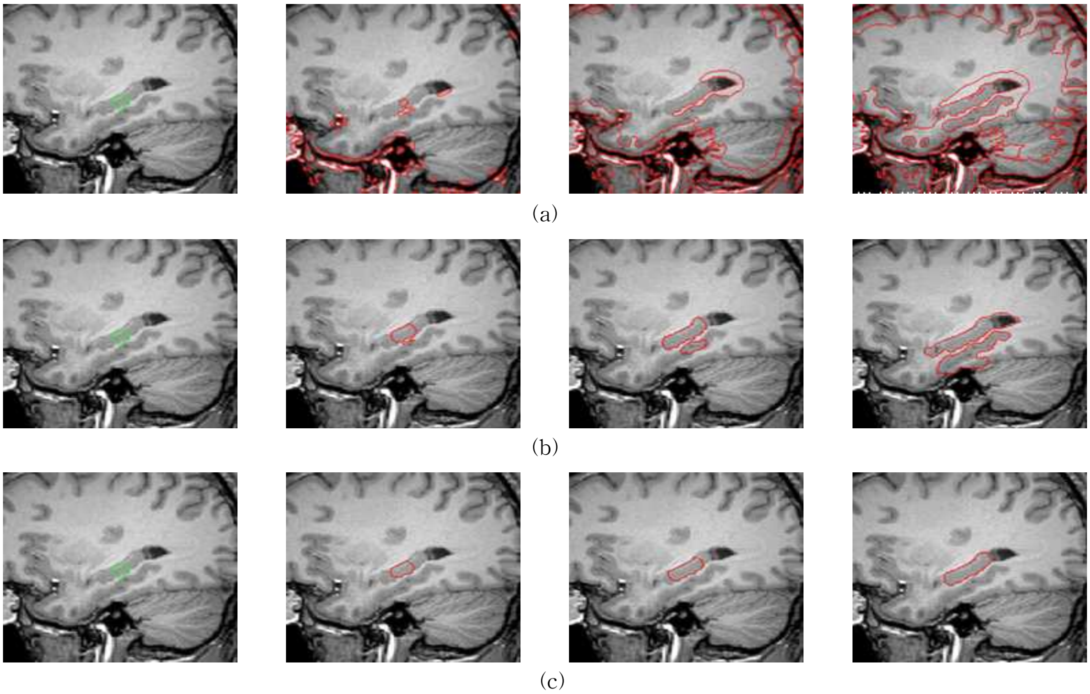

Fig. 2. The segmented results on the hippocampus MR images by (a) LIF, (b) LBF, and (c) LGDF method. An initial curve, two curve evolutions and the final result have shown from the left to right column respectively.

image segmentation.

REFERENCES

[1] V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic Active Contours," *International Journal of Computer Vision*, Vol. 22, No. 1, pp. 61-79, 1997.

[2] Y. Chen, H. Tagare, S. Thiruvenkadam, F. Huang, D. Wilson, K. Gopinath, et al., "Using Prior Shapes in Geometric Active Contours in a Variational Framework," *International Journal of Computer Vision*, Vol. 50, No. 3, pp. 315-328, 2002.

[3] M. Leventon, W. Grimson, and O. Faugeras, "Statistical Shape Influence in Geodesic Active Contours," *Proceeding of IEEE Conference on Computer Vision and Pattern Recognition*, Vol. 1, pp. 316-323, 2000.

[4] C. Xu and J.L. Prince, "Snakes, Shapes, and Gradient Vector Flow," *IEEE Transactions on Image Processing*, Vol. 7, No. 3, pp. 359-369, 1998.

[5] R. Malladi, J.A. Sethian, and B.C. Vemuri, "Shape Modeling with Front Propagation: A Level Set Approach," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 17, No. 2, pp. 158-175, 1995.

[6] C. Samson, L. Blanc-Feraud, G. Aubert, and J. Zerubia, "A Variational Model for Image Classification and Restoration," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 22, No. 5, pp. 460-472, 2000.

[7] T.F. Chan and L.A. Vese, "Active Contour without Edges," *IEEE Transactions on Image Processing*, Vol. 10, No. 2, pp. 266-277, 2001.

[8] B. Rosenhahn, T. Brox, and J. Weickert, "Three-dimensional Shape Knowledge for Joint Image Segmentation and Pose Tracking," *International Journal on Computer Vision*, Vol. 73, No. 3, pp. 242-262, 2007.

[9] K. Zhang, H. Song, and L. Zhang, "Active Contour Driven by Local Image Fitting Energy," *Pattern Recognition*, Vol. 43, No. 4, pp. 1199-1206, 2010.

[10] Y. Shi and W.C. Karl, "Real-time Tracking using Level Sets," *Proceeding of IEEE Conference on Computer Vision and Pattern Recognition*, Vol. 2, pp. 34-41, 2005.

[11] J. Piovano, M. Rousson, and T. Papadopoulo, "Efficient Segmentation of Piecewise Smooth Images," *Proceeding of Scale Space and Variational Methods in Computer Vision,* pp. 709-720, 2007.

[12] C. Li, "Active Contours with Local Binary Fitting Energy," *Proceeding of IMA Workshop on New Mathematics and Algorithms for 3-D Image Analysis*, pp. 1-7, 2006.

[13] C. Li, C. Kao, J. Gore, and Z. Ding, "Minimization of Region-scalable Fitting Energy for Image Segmentation," *IEEE Transaction on Image Processing*, Vol. 17, No. 10, pp. 1940-1949, 2008.

[14] L. Wang, L. He, A. Mishra, and C. Li, "Active Contours Driven by Local Gaussian Distribution Fitting Energy," *Signal Processing*, Vol. 89, No. 12, pp. 2435-2447, 2009.

[15] T. Brox and D. Cremers, "On the Statistical Interpretation of the Piecewise Smooth Mumford - Shah Functional," *Proceeding of Scale Space and Variational Methods in Computer Vision*, pp. 203-213, 2007.

[16] Y.S Izmantoko, H. S. Yoon, A. Enkhbolor, C. W. Mun, Y. Huh, and H.K. Choi, "Implementation of 2D Active Shape Model-based Segmentation on Hippocampus," *Journal of Korea Multimedia Society,* Vol. 17, No. 1, pp. 1-7, 2014.

[17] A. Enkhbolor, Y.S Izmantoko, and H.K. Choi, "Comparison of Active Contour and Active Shape Approaches for Corpus Callosum Segmentation," *Journal of Korea Multimedia Society,* Vol. 16, No. 9, pp. 1018-1030, 2013.

[18] C. Li, C. Xu, C. Gui, and M.D. Fox, "Level Set Evolution without Re-initialization: a New Variational Formulation," *Proceeding of IEEE Conference on Computer Vision and Pattern Recognition*, Vol. 1, pp. 430-436, 2005.

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