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Image Segmentation based on Energy Fitting Models – A Review

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Abstract—As a result of changes in imaging technology, segmenting the area of interest (ROI) from medical images is an extremely important yet challenging task. It is still difficult for the global energy-based active contour model (ACM) to properly extract the ROI from medical images, despite the fact that many techniques based on the local region-based active contour model have been proposed to deal with intensity inhomogeneity. This brief study aims to assess the performance of current techniques that have been published in the recent years and have been used to image segmentation. The methods under consideration include the various energy fitting models that have been created to drive the active contour are highlighted in this review study. Each model was examined against a medical image, an MRI brain image, and an image that was not taken by a medical professional. According to the results of the comparison study, it can be determined which technique is better appropriate for image segmentation even when there is intensity inhomogeneity in the images.

Keywords- Active Contour, Laplacian of Gaussian, Intensity fitting, Local Image fitting.

I. INTRODUCTION

Segmentation is a crucial part of the image recognition system, since it is via segmentation that the interesting aspects of an image are isolated and processed, such as for recognition or identification. In practice, image segmentation is applied for image pixel categorization [3]. Segmentation methods are used to separate the directed item from the image for examination. In this case, image segmentation is used to identify a tumor, cancer, or a blockage in the blood flow, as these issues would be segregated from their backgrounds by image segmentation [2]. For the segmentation of monochromatic images, several methods are available. As each pixel in the color images is vector valued, the segmentation of color images is more difficult [3]. Active contour models are one of the most successful picture segmentation techniques [4, 5]. There are two types of active contour models currently available: edge-based models [6] and region-based models [7]. Both of these models have their advantages and disadvantages, and their use in applications is determined by the image's properties.

This brief review is divided into four parts. After that, Section 2 explains a current active contour driven by energy fitting models, Section 3 analyses the results obtained via each of the models, and Section 4 summarizes the research.

II. ACTIVE CONTOUR – ENERGY FITTING MODELS

A. Active Contour-Local Binary Fitting (LBF) Energy Model

Using image information in local areas, Chunming, et. 2001, proposed a region-based active contour model [8] that takes use of image information in local regions. One of the most significant contributions is the inclusion of a local binary fitting energy combined with a kernel function, which allows for the accurate extraction of local image information. As a result, the LBF model may be used to segment images with inhomogeneous intensities, therefore circumventing a limitation associated with piecewise constant modelling. The LBF demonstrates the advantages of computation efficiency and precision. Additionally, it may be used to reduce the amount of noise in an image. The proposed energy functional is, proposed energy functional is,

$$F(\phi, C_1, C_2) = F^{LBF}(\phi, C_1, C_2) + \mu\, p(\phi) + \nu l(\phi) \quad (1)$$

Where, μ and ν are the scaling factors and are positive constants. ϕ is the e level set function. The functions C, C_2 are given as

$$C_1 = \frac{K_\sigma(\mathbf{x}) * [H_\varepsilon(\phi(\mathbf{x}))I(\mathbf{x})]}{K_\sigma(\mathbf{x}) * H_\varepsilon(\phi(\mathbf{x}))} \quad (2)$$

and

$$C_2 = \frac{K_\sigma(\mathbf{x}) * [(1-H_\varepsilon(\phi(\mathbf{x})))I(\mathbf{x})]}{K_\sigma(\mathbf{x}) * [1-H_\varepsilon(\phi(\mathbf{x}))]} \quad (3)$$

Penalize term $p(\phi) = \int_\Omega \frac{1}{2}(|\nabla\phi(\mathrm{x})| - 1)^2 dx \quad (4)$

and length of the zero-level curve

$$l(\phi) = \int_\Omega \delta(\phi(\mathrm{x}))|\nabla\phi(\mathrm{x})|dx \quad (5)$$

B. Active Contours Driven by Local and Global Intensity Fitting Energy

In a variational level set formulation, Li Wang et al. 2009, presented an enhanced region-based active contour model [9]. Constructed an energy functional with a local intensity fitting term that generates a local force that attracts and stops the contour at object borders, as well as an auxiliary global intensity fitting term that pushes the contour's motion away from the object boundaries. As a result, the combination of these two forces enables the outlines to be initialized in a flexible manner. This energy is then integrated into a level set formulation together with the required level set regularization term for correct calculation in the relevant level set technique. The suggested model is given first as a two-phase level set formulation and subsequently as a multi-phase formulation. The defined energy functional is

$$\mathcal{E}^{\mathrm{LGIF}}(\phi, f_1, f_2, c_1, c_2) = (1-\omega)\mathcal{E}^{\mathrm{LIF}}(\phi, f_1, f_2) + \omega\mathcal{E}^{\mathrm{GIF}}(\phi, c_1, c_2) \quad (6)$$

Where,

$$f_1(\mathrm{x}) = \frac{K_\sigma(\mathrm{x}) * [H_\epsilon(\phi(\mathrm{x}))I(\mathrm{x})]}{K_\sigma(\mathrm{x}) * H_\epsilon(\phi(\mathrm{x}))} \quad (7)$$

$$f_2(\mathrm{x}) = \frac{K_\sigma(\mathrm{x}) * [(1-H_\epsilon(\phi(\mathrm{x})))I(\mathrm{x})]}{K_\sigma(\mathrm{x}) * [1-H_\epsilon(\phi(\mathrm{x}))]} \quad (8)$$

$$c_1 = \frac{\int I(\mathrm{x})H_\epsilon(\phi(\mathrm{x}))dx}{\int H_\epsilon(\phi(\mathrm{x}))dx} \quad (9)$$

$$c_2 = \frac{\int I(\mathrm{x})(1-H_\epsilon(\phi(\mathrm{x})))dx}{\int (1-H_\epsilon(\phi(\mathrm{x})))dx} \quad (10)$$

And the approximated Heaviside function H is

$$H_\epsilon(\mathbf{x}) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{\mathrm{x}}{\epsilon}\right)\right] \quad (11)$$

Minimizing (6),

$$\frac{\partial\phi}{\partial t} = \delta_\epsilon(\phi)(F_1 + F_2) + \nu\delta_\epsilon(\phi)\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\left(\nabla^2\phi - \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \quad (12)$$

The model proposed by [9] can further be extend into a multi-phase level set formulation.

C. Active contours driven by local image fitting energy

In 2010, Kaihua Zhang et al. presented a unique region-based active contour model that combines the image's local information and embeds it in the active contour model [10], which was published in the journal Image Processing. This model is capable of segmenting images with intensity inhomogeneities because it contains the local image fitting (LIF) energy, which is used to retrieve the local image information from the images during the segmentation process. It was also proposed that a novel technique for regularizing the level set function, based on Gaussian filtering for variational level set, be developed. In addition, the level set function is assured to be smooth, and the requirement for re-initialization is removed, resulting in time savings by avoiding the need for time-consuming computational re-initialization, which saves time. The sub-pixel accuracy and border regularization characteristics of the original method are preserved with this technique. The model proposed by [10] is that

$$I^{\mathrm{LFI}} = m_1 H_\varepsilon(\phi) + m_2(1 - H_\varepsilon(\phi)) \quad (13)$$

where m_1 and m_2 are

$$\begin{cases} m_1 = \mathrm{mean}\left(I \in (\{x \in \Omega \mid \phi(x) < 0\} \cap W_k(x))\right) \\ m_2 = \mathrm{mean}\left(I \in (\{x \in \Omega \mid \phi(x) > 0\} \cap W_k(x))\right) \end{cases} \quad (14)$$

By minimizing the LIF energy functional

$$E^{\mathrm{LIF}}(\phi) = \frac{1}{2}\int_\Omega \left|I(x) - I^{\mathrm{LFI}}(x)\right|^2 \mathrm{d}x,\ x \in \Omega \quad (15)$$

The level set formulation is

$$\frac{\partial\phi}{\partial t} = \mu\left(\nabla^2\phi - \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) + \nu\delta_\varepsilon(\phi)\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + (I - I^{\mathrm{LF}})(m_1 - m_2)\delta_\varepsilon(\phi) \quad (16)$$

The suggested Gaussian regularizing level set method (GRLSM) may be readily extended to pure PDE driven level set techniques, according to the authors.

D. Active contours driven by optimised LoG Energy.

The ability to segment images with intensity inhomogeneity, particularly around contours, has long been recognized, but it relies on where those contours start. In order to address the shortcomings of the RSF model, a model based on a customized LoG energy functional coupled with the RSF model [11] is suggested by Keyan Ding et. al, in 2017. In the LoG, the operator designed for edge detection is known across the field as a prominent second-order differential operator. The inclusion of the LoG term results in an indifferent outcome regardless of the locations of the original contour. In order to highlight the

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edges in an image, the first step is to use a Gaussian filter to smooth it. Then, to extract those edges, a Laplacian operator is used. Thus, combined optimized LoG energy with the RSF energy as follows:

$$E^{RSFSL} = E^{RSF}(\phi, f_1, f_2) + E^{OL}(\phi) \tag{17}$$

Minimizing (17), it is possible to get the gradient flow equation shown below.

$$\frac{\partial \phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + \omega\delta_\varepsilon(\phi) \times L + \nu\delta_\varepsilon(\phi)\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\left(\Delta\phi - \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \tag{18}$$

The model made use of an edge detecting operator of second order. Images with edges and objects that are difficult to identify may provide incorrect segmentation results.

E. Fuzzy region-based-global and local fitting energy model.

Fang, Jiangxiong, et al., in 2021, a novel active contour model for image segmentation based on global and local fuzzy image fitting (GLFIF) was proposed [12], in which two fitted images were created: a global fuzzy fitted image (GFFI) and a local fuzzy fitted image (LFFI). After that, the energy function is constructed, which contains both a global and a fitting term. The global term is taken from the fuzzy energy-based active contour (FEAC) model in order to balance the object's importance relative to the backdrop, while the fitting term is generated from GFFI and LFFI in order to account for intensity inhomogeneity in provided images. The energy function is then demonstrated to be convex, ensuring that the segmentation results are independent of initialization. Finally, unlike previous models that compute the change in the energy function pixel by pixel, this model uses a direct method to calculate the difference between the old and new energy functions in the whole image for each iteration in order to update the pseudo level set function. The energy function that includes both local and global energy is given by,

$$E^F(u,g) = \alpha_1\int_\Omega g\|I(x) - I^{LFI}(x)\|dx + \alpha_2\int_\Omega g\|I(x) - I^{GFI}(x)\|dx \tag{19}$$

The rewritten energy function is given by

$$\begin{aligned} E(u,g) = {} & \lambda_1\int_\Omega [u(x)]^m g(I(x) - c_1)^2 dx \\ & +\lambda_2\int_\Omega [1 - u(x)]^m g(I(x) - c_2)^2 dx \\ & +\alpha_1\int_\Omega g\|I(x) - I^{LFFI}(x)\|dx \\ & +\alpha_2\int_\Omega g\|I(x) - I^{GFFI}(x)\|dx \end{aligned} \tag{20}$$

Differentiating the equation (20). The variable $u(x)$ is expressed as:

$$u(x) = \begin{cases} \dfrac{1}{1+\left(\frac{\lambda_1(I(x)-c_1)^2+\alpha_1 f_2+\alpha_2 c_2}{\lambda_2(I(x)-c_2)^2+\alpha_1 f_1+\alpha_2 c_1}\right)^{\frac{1}{m-1}}} & \text{where } I(x) - I^{LFF}(x) > 0 \\ \dfrac{1}{1+\left(\frac{\lambda_1(I(x)-c_1)^2+\alpha_1 f_1+\alpha_2 c_1}{\lambda_2(I(x)-c_2)^2+\alpha_1 f_2+\alpha_2 c_2}\right)^{\frac{1}{m-1}}} & \text{where } I(x) - I^{LFFI}(x) < 0 \end{cases} \tag{21}$$

To segment images with noise, blurring boundaries, and intensity inhomogeneity, the model proposed in [12] used a fuzzy region-based active contour driven by global and local fitting energy. Its objective is to build an energy function that includes a global component derived from the existing model and a local term derived from the design of GFFI and LFFI images. The former is used to balance the object's and background areas' weights.

III. RESULT AND DISCUSSION

A. Common things followed in the result and discussion

For the objective of verifying the effectiveness of each technique, two different images were considered: one that was medical and one that was not. The non-medical image has a significant amount of intensity inhomogeneity. The inhomogeneity of intensity is the current issue being addressed by the majority of segmentation researchers that are now working on it.

The common things followed while comparing the result of each model is that the figure window of MATLB is divided into four, each of the divisions are named as 'a', 'b', 'c' and 'd', mentioned in the square box, positioned in the middle every MATLAB figure window. 'a' represent the input image taken for verifying the strength of the method in terms of segmentation of region of interest, 'b' represents the initial contour size, shape and its position on input image. The initial contour is either red or blue in color of shape may be of rectangle or square. 'c' indicates the movement of contour on the input image after some iterations, iteration number is specified on the top of the figure. 'd' represents the final contour produced by the respective model.

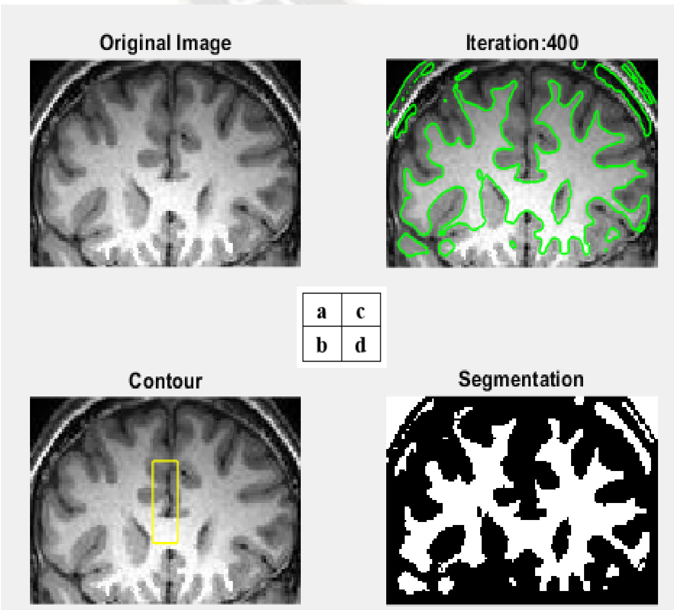
Each model has two sets, a group of four figures. In each case, the top group of four indicates the segmentation performance of the respective model for medical image and the bottom group of four indicates the segmentation performance of non-medical image.

B. Specific discussion of energy fitting models

Figure 1 shows the segmentation result of the LBF model. For medical image, the initial contour is specified by a small yellow rectangle, figure 1(top group, bottom left). The segmentation result shows that the region of interest (ROI) is not completely segmented and for the non-medical input same kind of initial contour was used but the final segmentation result has unwanted traces.

The Local and Global Intensity fitting Energy model was verified for two kind of initial contour. Figure 2 shows the result obtained for the initial contour of maximum size and the figure 3 shows the segmentation result for the initial contour of minimum size. The result clearly exhibit the fact that the model's segmentation performance depends on size of the initial contour.

Local energy fitting model works well for the medical input but gives poor result for non-medical input. From the figure 4, it takes 600 iterations to produce comparable segmentation result. Higher the iterations more the segmentation time. Final segmentation result of non-medical image shows that still it has room to improve to produce better segmentation result. The segmentation result of energy fitting model uses LOG is shown in figure 5. Segments both the medical and non-medical images well even in the presence of high intensity inhomogeneity.
The model [12] uses fuzzy based energy fitting model the segmentation result of it show in figure 6. The segmentation result produces unintended result for both medical and non-medical inputs. Based on the results obtained using different models the LOG based energy fitting model handles intensity inhomogeneity and also produces an acceptable result. Moreover, the performance of each model is verified and compared based on the final segmented result, no statistical data was tabulated to ensure the same. This may be addressed in next review work. Reference [13] provides the code for LBF, LIF and LoG fitting models, Reference [14] has the code for local and global energy fitting model.



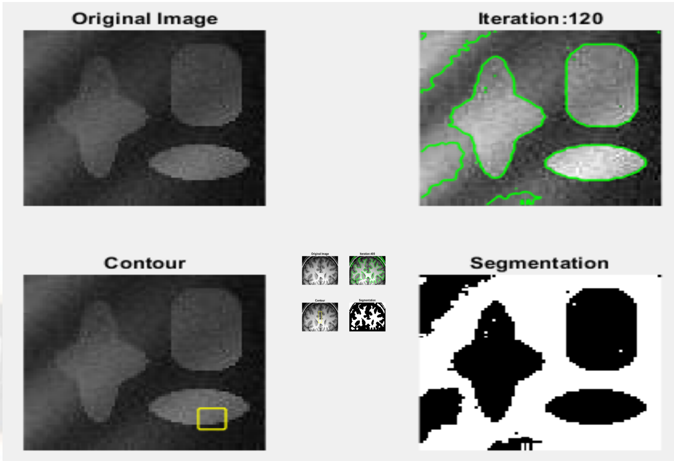


Figure 1. Segmentation result of LBF model for medical (top group) and non-medical images(bottom group).

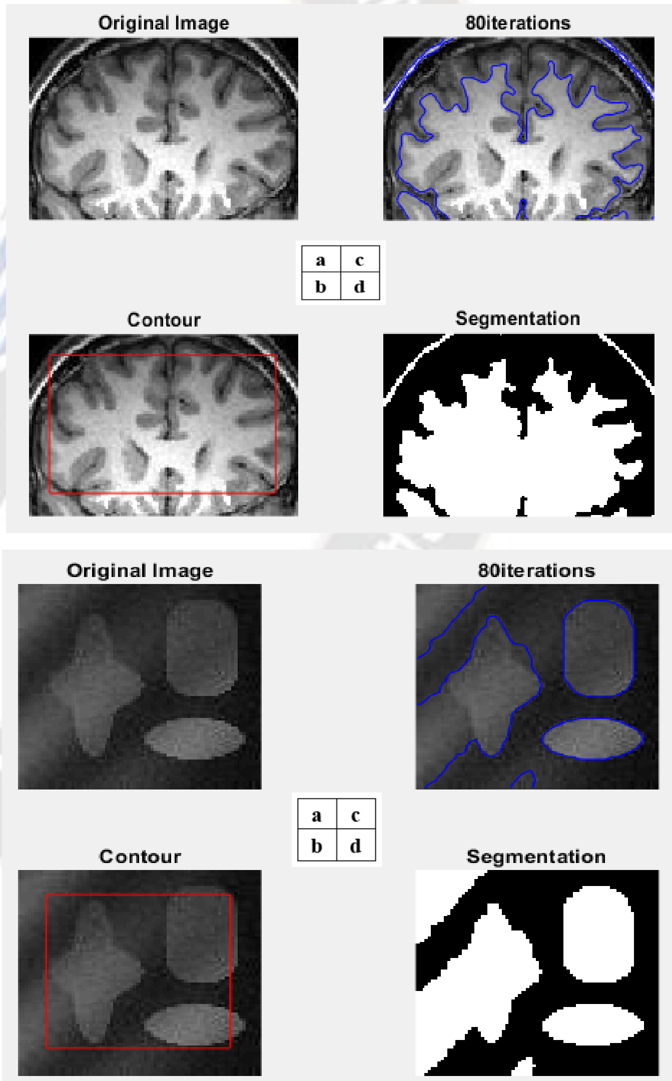


Figure 2. Segmentation result of Local and Global Intensity fitting Energy model, initial contour of maximum size

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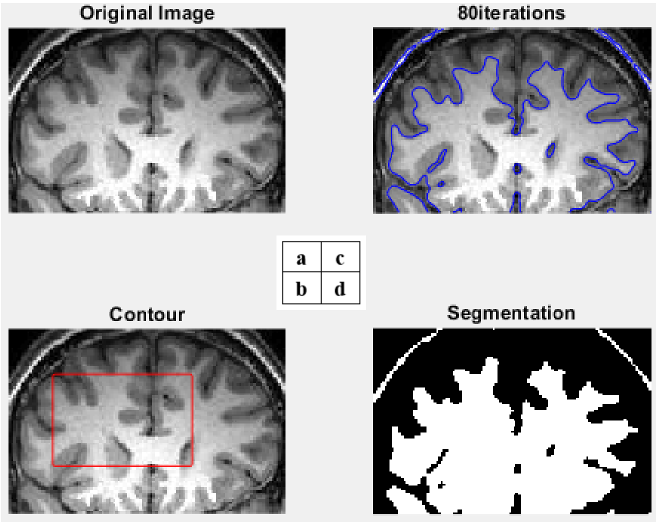


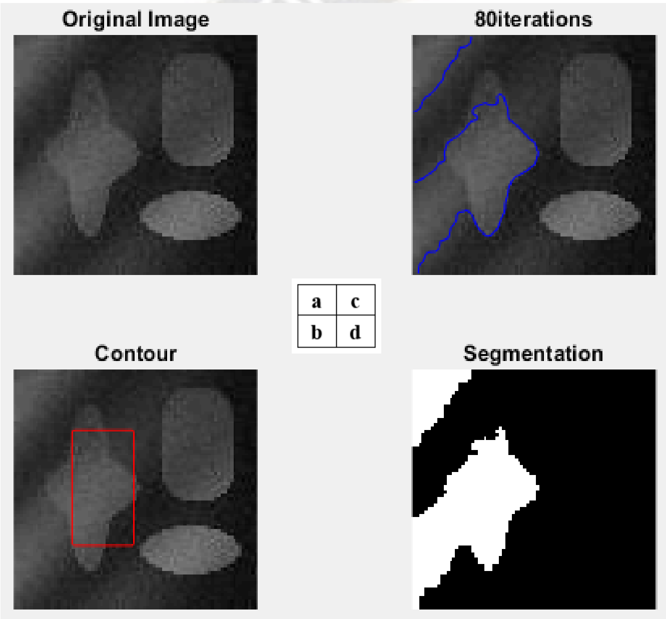
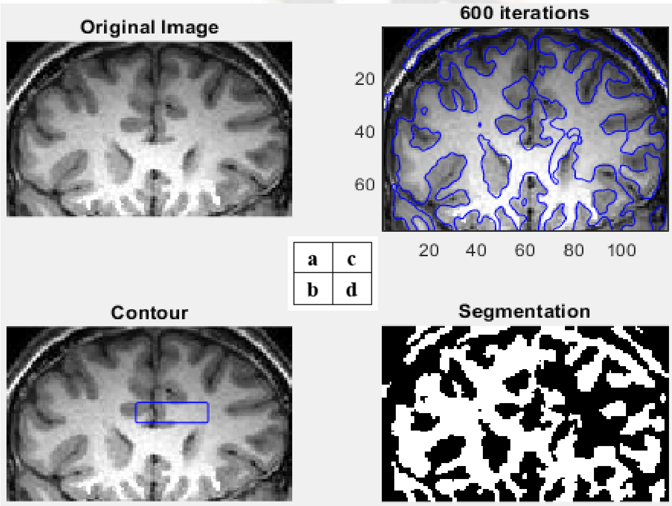


Figure 3. Segmentation result of Local and Global Intensity fitting Energy model, initial contour of minimum size.



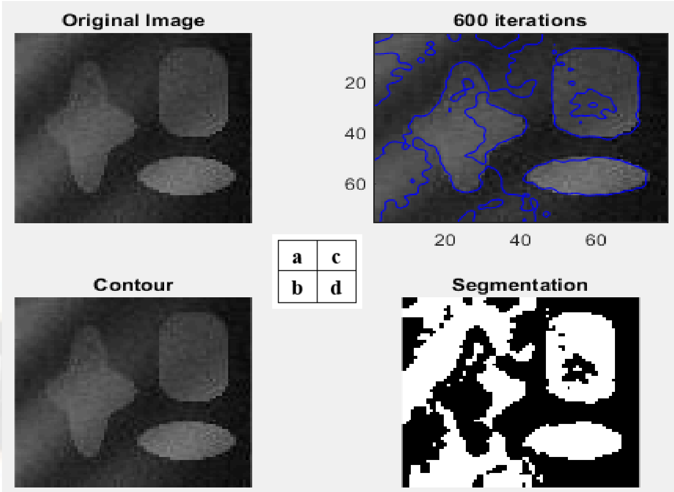
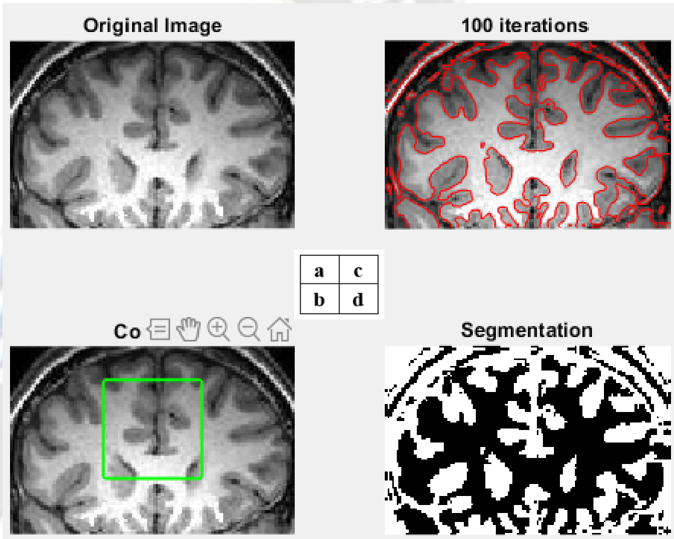


Figure 4. Segmentation result of local Image fitting energy model for medical (top group) and non-medical images(bottom group).



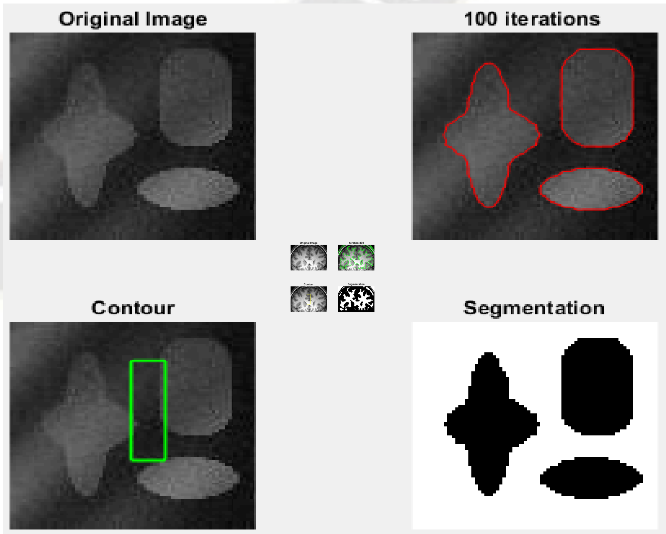


Figure 5.

Figure 6. Segmentation result of Laplacian of Gaussian Energy fitting model for medical (top group) and non-medical images (bottom group).

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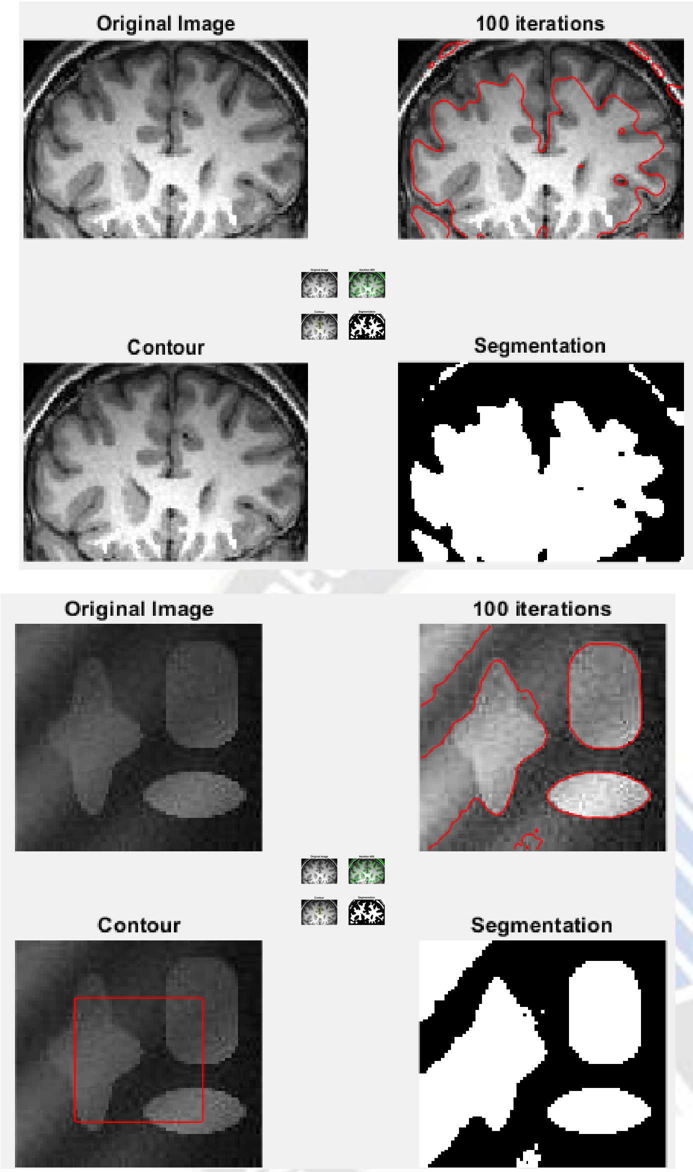

Figure 7. Segmentation result of Fuzzy region-based-global and local fitting energy model for medical (top group) and non-medical images(bottom group).

IV. CONCLUSION

This concise study compares the performance of state-of-the-art energy fitting models to visualize segmentation applications. Each of the five techniques is evaluated using a medical and a non-medical image. The ability to segment images relies not only on the concept presented, but also on the starting values assumed, the position and size of the initial contour. This brief study will undoubtedly aid researchers in their quest for an effective image segmentation method. Today's challenge in image segmentation is dealing with images with inhomogeneous intensities. This brief study concludes that the active contour model driven by the Laplacian of Gaussian demonstrates its resilience in dealing with contemporary problems such as images with inhomogeneous intensity.

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REFERENCES

[1] Cai WL, Chen SC, Zhang DQ. Fast and robust fuzzy C-means clustering algorithms incorporating local information for image segmentation. Pattern Recognition Journal. 2007;40(3):825-838

[2] Gadpayle P, Mahajani PS. Detection and classification of brain tumor in MRI images, International Journal of Emerging Trends in Electrical & Electronics. 2013;5(1):45-49

[3] Aggarwal P, Vig R, Bhadoria S, Dethe CG. Role of segmentation in medical imaging: A comparative study. International Journal of Computer Applications. 2011;29(1):55-64

[4] V. Caselles, R. Kimmel, and G. Sapiro. Geodesic active contours. Int'l J. Comp. Vis., 22:61–79, 199

[5] C. Xu and J. Prince. Snakes, shapes, and gradient vector flow. IEEE Trans. Imag. Proc., 7:359–369, 1998

[6] C. Li, C. Xu, C. Gui, and M. D. Fox. Level set evolution without re-initialization: A new variational formulation. In IEEE Conference on Computer Vision and Pattern Recognotion (CVPR)., volume 1, pages 430–436, 2005

[7] A. Tsai, A. Yezzi, and A. S. Willsky. Curve evolution implementation of the mumford-shah functional for image segmentation, denoising, interpolation, and magnification. IEEE Trans. Imag. Proc., 10:1169–1186, 2001.

[8] Li, Chunming, Chiu-Yen Kao, John C. Gore, and Zhaohua Ding. "Implicit active contours driven by local binary fitting energy." In *2007 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1-7. IEEE, 2007.

[9] Wang, Li, Chunming Li, Quansen Sun, Deshen Xia, and Chiu-Yen Kao. "Active contours driven by local and global intensity fitting energy with application to brain MR image segmentation." *Computerized medical imaging and graphics* 33, no. 7 (2009): 520-531.

[10] Zhang, Kaihua, Huihui Song, and Lei Zhang. "Active contours driven by local image fitting energy." Pattern recognition 43, no. 4 (2010): 1199-1206.

[11] Ding, Keyan, Linfang Xiao, and Guirong Weng. "Active contours driven by region-scalable fitting and optimized Laplacian of Gaussian energy for image segmentation." *Signal Processing* 134 (2017): 224-233.

[12] Fang, Jiangxiong, Huaxiang Liu, Jun Liu, Haiying Zhou, Liting Zhang, and Hesheng Liu. "Fuzzy region-based active contour driven by global and local fitting energy for image segmentation." *Applied Soft Computing* 100 (2021): 106982.

[13] https://github.com/dingkeyan93/Active-Contour-Model-Matlab

[14] https://github.com/fangchj2002/GLFIF