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Research Article

SEGMENTING OF IMAGES FOR SUPERIOR FEATURE EXTRACTION THROUGH LEVEL SET METHOD

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ABSTRACT

Level set methods have been widely used to implement active contours for image segmentation application due to their good boundary detection accuracy. However, there are several disadvantages in the weighted level set evolution, since the edge stopping function depends on the image gradient, only objects with edges defined by gradient can be segmented. Another disadvantage is that in practice, the edge-stopping function is never exactly zero at the edges, and so the curve may eventually pass through object boundaries. This proposed method based on weighted $p(x)$ Dirichlet integral, an external energy, and a level set regularization term. Due to the good properties of the weighted $p(x)$-Dirichlet integral term, it extracts the weak boundaries in noisy and intensity in homogeneity images. An added benefit of the proposed method is that the level set function can be initialized to a constant function. This implies that the model is free of manual initialization. The proposed methods leads to more accurate boundary detection results than the state-of-the –art based method.

INTRODUCTION

The segmentation of an image is one of the most important techniques for analysis the image, understanding and interpretation. Segmentation is an important tool in many applications for image analysis [1]. In medical image, the segmentation helps us to extracting the local information from the image data that techniques are usually formulated as an optimization problem and where the segmentation criteria and the contour characteristics are specified by an objective functional.

The level set method, originally introduced by Osher *et al*. [5] and Sethian. Which the implicitly represents the curve as the zero level of the level set, ϕ, of a high dimensional function. This Level set methods have been successfully used in many application to implement the active contours for segmentation in an image. The aim of a level set method is to represent the contours as in the level set function. This function should be, to evolve the level set function according to a partial differential equation (PDE) [7],[9],[11]. This approach allows us to automatically handle the topological changes to detect the boundary [13]. From the defined on the level set function, the evolution PDE of the level set function can be directly derived from the problem of minimizing a certain energy functional. This various type of variational methods, which are known as variational level set methods, these are highly amenable to incorporating the more additional information in the level set evolution (LSE), such as an region based information [7],[15] , shape-prior information [17] and phase-based information , which is usually gives us rise to very accurate boundary detection results.

Recently, there are several authors have been proposed the image segmentation approaches, that employed the variation level set methods that incorporate the different image features into the energy functional. These methods, which have also been used to develop the medical image segmentation approaches, aims at solving the common issues that hinder the image segmentation accuracy, such as leakage around the weak edges and high sensitivity to intensity in homogeneities images[19], [21]–[22], [22]–[23]. For example, Kimmel proposed a contour method to evolve a boundary detection, that employs a level set method in an image with an energy functional, this method combines an alignment term and that leads the curve to the desired boundary of the region. Specifically, in this method that alignment term can attempts to align all the normal vector of the zero level set with the

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gradient of images. Although this method alignment term leads to be more accurate segmentation results compare to other method, sometimes this method may fail to accurately drive the zero level set to the boundary of the desired region around the weak edges, due to the fact that the gradient of image around weak edges is relatively small [24]. Belaid *et al*. [25] proposed a phase-based level set (PBLS) Method, in the medical image segmentation it implements an active contour method with high levels of noise and weak edges in an image. In this PBLS method, the authors construct an speed term with based up on two phase features: local phase, it is derived from the monogenic signal and local orientation, it measures the alignment between the local image orientations and the active contours normal direction of the movement. This method perform very well in the presence of weak edges, it requiring a careful tuning of the parameters in an image associated with the edge map used by this method [26]. Estellers *et al*. [27] proposed a segmentation method in a medical image based on the geometric representation of 2D manifolds embedded in a higher dimensional space. This method, termed the harmonic active contours (HAC), aligns the gradient in images with the gradient of the level set function for all the level sets method. This results obtained from the image in an objective functional that is able to exploit the alignment of the neighboring level set function to pull the contour in an image to the right position. Although this HAC has been shown to provide a excellent image segmentation results on medical images, it may perform poorly with several intensity in homogeneities in an images.

Zhou*et al*. [28] proposed to combined an both edge-based contour model and the region-based contour model for segmentation of image in the left ventricle in cardiac CT images. Based on the image gradient this method slightly adjusts the effect of two models. Although this method showed the good performance around the weak Edges and the results are dependent highly on the place of initial contour. Ji *et al*. [29] proposed a local region-based contour model for segmenting the images, that uses a spatially varying both the mean and variance of local intensities and to construct a local likelihood image fitting (LLIF) with an energy functional. This LLIF method performed very well in images with low in both contrast and intensity in homogeneities images. However, the other region-based contour model it assumes the existence of two well-differentiated in regions, which may not always be true in medical images.

Motivated by our previous method, we proposing a segmentation method that employs an active contour implemented using a variational level set method that weights the level set evolution based on adaptive regularized level set method. In this paper, we focus on the issue of zero level curve regularization with variational level set method. Length regularization [2, 4, 6, 8] is a popular choice of the geometric constraint on zero level curve, in the spirit of the Mumford-Shah functional [10]. But it is a less robustness to noise. In [12], two smoother regularizations were introduced. However, the smoother regularizations may cause the active contours to pass through the weak objects boundaries. Recently, there were many different choices of regularization for example: *p*-Dirichlet integral regularization [14] and weighted *p*-Dirichlet integral regularization[16]. Different value should be substitute on $p \geq 1$ results in a constrain which is somewhere between the length-based and smoother regularizations. However, that the constant exponent p cannot reflect the image local property and thus the *p*-regularization does not adapt the exponent to fit in the image data automatically. This problem has limited in their application.

This paper proposes an adaptive variational level set formulation, based upon three terms a weighted $P[x]$-Dirichlet integral, an external energy, and a level set regularization term. The weighted $P[x]$-Dirichlet integral term means integrating the gradient information is designed to the geometric regularization. On the zero level curve, which is used to diminish the influence of image noise on the level set evolution while the active contours not to pass through the weak object boundaries. The effectiveness of the weighted $p[x]$-Dirichlet integral term, we apply it to an edge-based GAC model for image segmentation and an external energy based up on Laplacian of Gaussian [LoG] filter is defined, and then it drives the level set function to deform in the opposite direction [up or down]on either side of the edge. The level set regularization term makes the level set function, it behave approximately like a signed distance function, which ensures the stable level set evolution. The resulting evolution in the level set function is that the gradient flow minimizes the overall energy functional. Due to the imaging data fitting in the weighted $p[x]$-Dirichlet integral , the intensity information in local regions is extracted to guide the regularization of active contours. so our model can extract the weak boundaries in noisy images and/or intensity in homogeneity images. An added benefit of this proposed model is, that the level set function can be initialized to be a constant function. That the constant function is more easier to use in practice, than the widely used signed distance function or binary step function.

Adaptive Regularized Level Set Method

Image segmentation in medical applications is based up on the active contours implemented using a variational level set method, various type of image information, such as intensity, region, edge or texture, can be used to define in an objective functional. Here, we employ an region information as the main image features that drives the active contour to the desired boundary in the image. In this level set method, a moving curve $C[t]$ is represented by the zero level set and the Lipschitz function $\varphi[x, y, t]$ is defined on the image domain. The curve evolution $C[t]$ along its normal direction with the speed F is denoted by the following evolution PDE,

$$\frac{\partial \phi}{\partial t}+F\left|\nabla\phi\right| = 0 \qquad (1)$$

The initial condition sets to be $\varphi[x, y, 0]$ and $\varphi[0,x, y]$. For the image segmentation, that the speed function F is depend on both the image data and level set function φ. The φ function may develop a shocks during the contour evolution. In the result, some of the regularities must to be imposed on φ and in order to prevent the φ to be too steep or too fat near the zero level curve in an image. To initialize and periodically reinitialized the level set function in a signed distance function so as to keep the steady level set method in contour evolution and ensure the usable results. This reinitialization equation is denoted as,

$$\frac{\partial \phi}{\partial t} = \mathrm{sign}\left(\hat{\phi}\right)(1 - |\nabla \phi|), \tag{2}$$

Where φ function to be re-initialized in an image, and sign $[\cdot]$ is the sign function. Although the reinitialization in an function as a numerical remedy is able to maintained the regularity of the level set function [18, 20].In order to control the smoothness in contour evolution of the zero level curve and it further avoided the occurrence of small, the isolated regions in the final segmentation, the zero level curve should be regularized very important in level set methods. The length regularization [2, 4, 6, 8] in an evolution is to minimize the following energy functional:

$$L(\phi) = \int_\Omega |\nabla H(\phi)| dx\, dy = \int_\Omega \delta(\phi) |\nabla \phi| dx\, dy, \tag{3}$$

where $H[\cdot]$ is Heaviside function and $\delta[\cdot]$ is Dirac delta function. The energy functional $L[\varphi]$ computes the length regularization of the zero level curve of φ in the conformal metric $ds|C\ '(p)|dp$. The length regularization imposed a penalty on the image in length of the curve that smoothes the desired zero level curve and diminishes some of the false contours. But smoothing is only along with the tangent direction in the each level line, so this regularization should produce a less robustness to noise. In [16], Zhou and Mu proposed a weighted p-Dirichlet integral regularized level set method. The geometric regularization denoted in the following form

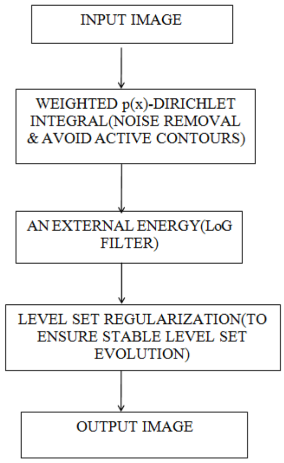
$$L_p(\phi) = \int_\Omega \delta(\phi) |\nabla \phi|^p dx\, dy. \tag{4}$$

Different value of $p \geq 1$ results obtained in a tradeoff between the length and smoother regularization. However, if the image intensities should be representing an objects are non uniform or if an image is highly degraded in the contour, this regularization may be become sensitive to exponent p.

Weighted $p(x)$-Dirichlet Integral Regularized Level Set Evolution in an image segmentation.we evaluate a new variational level set formulation for segmentation process,in an image weighted $p(x)$-Dirichlet integral term is used to regularize the zero level curve.

Let $\Omega \subset R2$ be an image domain. In an image $I : \Omega \rightarrow R$ and a level set function $\Phi(x, y)$

$: \Omega \rightarrow R$, energy functional $E(\varphi)$ should be defined by



$$E(\phi) = L_{p(\cdot)}(\phi) + \nu E_{\mathrm{ext}}(\phi) + \mu P(\phi) \tag{5}$$

where v and $\mu > 0$ are constants, $Lp\cdot(\varphi)$is the zero level curve in the regularization term, $E\mathrm{ext}(\varphi)$is an external energy term it would drived the motion of a zero level curve of φ and $P(\varphi)$ where it is the level set function regularization term in the curve. In the level set function it controls the smoothness during the level set evolution. The zero level method regularization in the curve term $Lp(\cdot)(\varphi)$ is defined,

$$L_{p(\cdot)}(\phi) = \int_\Omega \frac{1}{p(|\nabla G_\sigma * I|)} \delta(\phi) |\nabla \phi|^{p(|\nabla G_\sigma * I|)} dx\, dy \tag{6}$$

where the∇ is gradient operator and $G\sigma*\ I$ is the convolution of the image I with the Gaussian function G with standard deviation σ. The value of exponent $p(s) : [0, \infty] \rightarrow [1, 1.5]$ is monotonically increasing functions within the limit$s\rightarrow 0 p(s)=1$ and limit$s\rightarrow +\infty p(s)=1.5$. The functional weighted p-Dirichlet integral with the variable exponent $P(|\nabla G\sigma * I|)$ is called the weighted $p(x)$-Dirichlet integral.

In an segmentation of level set function, an external energy term is depending on an information of image it must be defined to move the zero level curve in an image toward the boundaries. The weighted $p(x)$-Dirichlet integral term can be used in an various different applications with the different definitions of the external energy. We define and evaluate the term an external energy E ext(φ) based on the Laplacian of a Gaussian (LoG) filter , it drives the level set function to deform in the opposite direction on either the side of edge

$$E\ \mathrm{ext}(\varphi)=\int(\Delta\ G\ \sigma * I)\ \cdot \mathrm{H}(-\varphi\ )dx\ dy \tag{7}$$

where $\Delta G\ \sigma$ is the LoG filter, where the LoG filter calculates the second derivative of an segmentation image, which it is often used for zero crossing detectors. It is known very well that at the point of inflection the second derivative fully vanishes and changes the sign. The LoG filter response is zero in particular areas where this image has a constant intensity. When the change in intensity, the response of LOG is positive on the darker side and negative on the lighter side. By incorporating this edge-based information on the LoG filter into the external energy term, this level set function can be move into either up or down on the sides of edges and cause the sign of φ to flip around the edges. The objects boundaries should be extracted at the locations of images.

RESULTS

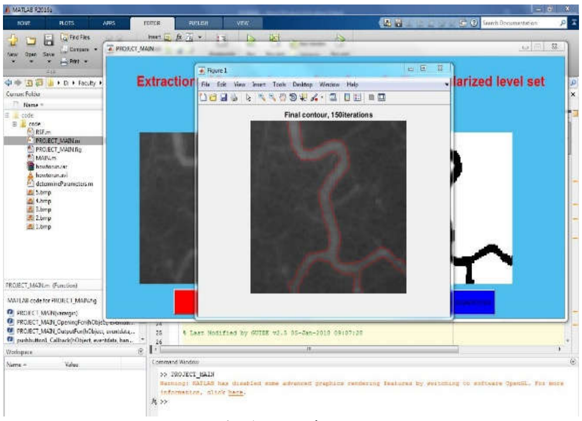


Fig 1 Input image

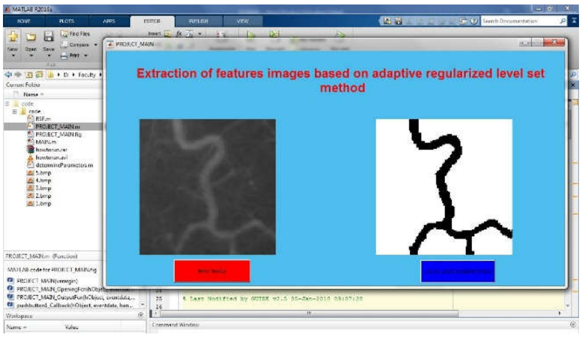


Fig 2 Output image by using adaptive regularized level set method

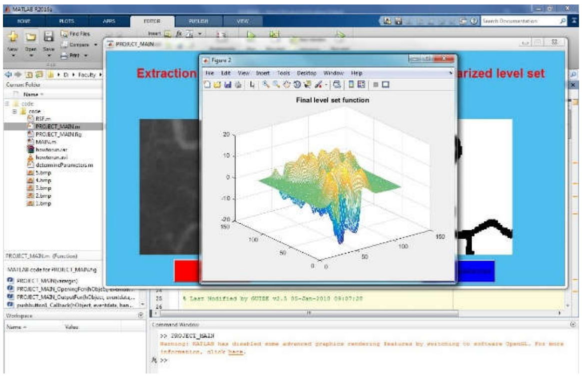


Fig 3 Final level set function

The accuracy of detection evaluated the methods is measured by the method Dice similarity coefficient (DSC), this method using a manually annotated ground truth. This DSC represents the ratio between the intersectional area of A and B and their summation area, i.e.,

$$DSC = \frac{2\,|A \Pi B|}{|A| + |B|}$$

where A and B represent the segmented region and the ground truth and $|.|$ denotes the cardinal of a set. The value of the DSC is within the range [0; 1], where 1 indicates the perfect overlap and 0 indicates no overlap between A and B.

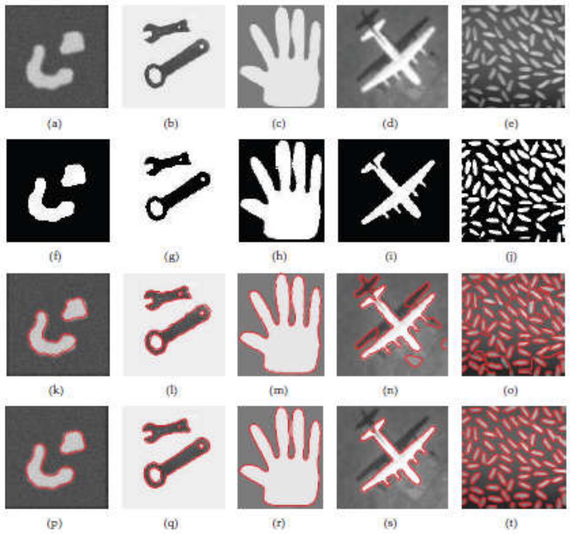


Fig 4 Segmentation results on bimodal images. Row 1: original images. Row 2: results of thresholding method (left to right: the threshold values are 140, 150, 180, 110, and 110, resp..) Row 3: results of the WLSE model. Row 4: results of our model (ν 0.4).

The DSC values of the WLSE model and our model for the images:

IMAGE	(a)	(b)	(c)	(d)	(e)
WLSE MODEL	0.9759	0.9801	0.9881	0.5020	0.5164
OUR MODEL	0.9903	0.9951	0.9905	0.9571	0.9164

This figure shows the comparison of the proposed model with the WLSE model on bimodal images. The goal of the method is to show the accuracy of our proposed model. Five test images, which are in Row 1, are a synthetic image (84 × 84), wrench image (100 × 100), hand image (108 × 130),plane image (135 × 125), and rice image (128×128), respectively. The true objects should be extracted from the original images by using a thresholding algorithm (Row 2). The segmentation results obtained by the WLSE model and our model are shown in Rows 3 and 4. It can be observed that the WLSE model and our model have achieved similar final results for the first three images by the comparison. This table shows the DSC values of the LIF model and our model. It can be clear that our model achieves more accurate results.

CONCLUSION

This paper proposed a novel variational level set formulation for image segmentation based on weighted $p(x)$-Dirichlet integral and LoG filter. By incorporating the local intensity information into the weighted $p(x)$-Dirichlet integral and this regularization term it preserves the properties of both the length regularization and p-Dirichlet integral regularization. The external energy E ext(φ) is based up on the LoG filter, this filter drives the respected level set function up or down on either the side of edges. For the good properties of the weighted $p(x)$-Dirichlet integral term, the proposed model extracts the weak edge in noise and intensity in homogeneity images. This method always allows the use of more general initialization of the level set function, ie., constant function. It implies that proposed model is free of manual initialization. Based on the efficiency and accuracy, obtained from the results, the proposed method is useful for real-time applications.

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. T. F. Chan and L. A. Vese, "Active contours without edges," *IEEE Transactions on Image Processing*, vol. 10, no. 2, pp. 266–277, 2001.
3. X. Zhao, Y. Wang, and G. Jozsef, "Robust shape-constrained active contour for whole heart segmentation in 3D CT images for radiotherapy planning," in IEEE International Conference on Image Processing. IEEE, 2014, pp. 1–5.
4. C. Li, C. Kao, J. C. Gore, and Z. Ding, "Minimization of region-scalable fitting energy for image segmentation," *IEEE Transactions on Image Processing*, vol. 17, no. 10, pp. 1940–1949, 2008.
5. S. Osher and J. A. Sethian, "Fronts propagating with curvaturedependent speed: algorithms based on hamilton-jacobi formulations," *Journal of Computational Physics,* vol. 79, no. 1, pp. 12–49, 1988.
6. L. Wang, C. Li, Q. Sun, D. Xia, and C. Y. Kao, "Active contours driven by local and global intensity fitting energy with application to brain MR image segmentation," *Computerized Medical Imaging and Graphics*, vol. 33, pp. 520–531, 2009.
7. C. Li, C. Xu, C. Gui, and M. D. Fox, "Level set evolution without reinitialization: a new variational formulation," in Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 1. IEEE, 2005, pp. 430–436.
8. K. Zhang, H. Song, and L. Zhang, "Active contours driven by local image fitting energy," *Pattern Recognition*, vol. 43, no. 4, pp. 1199–1206, 2010.
9. D. Peng, B. Merriman, S. Osher, H. Zhao, and M. Kang, "A PDE-based fast local level set method," *Journal of Computational Physics,* vol. 155, no. 2, pp. 410–438, 1999
10. D. Mumford and J. Shah, "Optimal approximations by piecewise smooth functions and associated variational problems," *Communications on Pure and Applied Mathematics*, vol. 42, no. 5, pp. 577–685,1989.
11. J. Weickert and G. K¨uhne, Fast methods for implicit active contour models. Springer, 2003.
12. G. Chung and L. A. Vese, "Image segmentation using a multilayer level-set approach," *Computing and Visualization in Science*, vol. 12, no. 6, pp. 267–285, 2009.
13. 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.
14. M. Droske and W. Ring, "A Mumford-shah level-set approach for geometric image registration," *SIAM Journal on Applied Mathematics*, vol. 66, no. 6, pp. 2127–2148, 2006.
15. T. F. Chan and L. A. Vese, "Active contours without edges," IEEE Transactions on Image Processing, vol. 10, no. 2, pp. 266–277, 2001.
16. B. Zhou and C. Mu, "Level set evolution for boundary extraction based on a p-Laplace equation," *Applied Mathematical Modelling*, vol. 34, no. 12, pp. 3910–3916, 2010.
17. B. Vemuri and Y. Chen, "Joint image registration and segmentation," in Geometric level set methods in imaging, vision, and graphics. Springer, 2003, pp. 251–269.
18. S. Osher and R. Fedkiw, *Level Set Methods and Dynamic Implicit Surfaces*, Springer, New York, NY, USA, 2002
19. A. Belaid, D. Boukerroui, Y. Maingourd, and J.-F. Lerallut, "Phasebased level set segmentation of ultrasound images," IEEE Transactions on Information Technology in Biomedicine, vol. 15, no. 1, pp. 138–147, 2011.
20. J. Gomes and O. Faugeras, "Reconciling distance functions and level sets," *Journal of Visual Communication and Image Representation*, vol. 11, no. 2, pp. 209–223, 2000.
21. R. Kimmel and A. Bruckstein, "On edge detection, edge integration and geometric active contours," in Proceedings of ISMM, vol. 3, 2002, pp. 37–45.
22. P. H. Lim, U. Bagci, and L. Bai, "Introducing willmore flow into level set segmentation of spinal vertebrae," IEEE Transactions on Biomedical Engineering, vol. 60, no. 1, pp. 115–122, 2013.
23. S. Ghadimi, H. A. Moghaddam, R. Grebe, and F. Wallois, "Skull segmentation and reconstruction from newborn ct images using coupled level sets," IEEE *journal of biomedical and health informatics*, vol. 20, no. 2, pp. 563–573, 2016.
24. V. Estellers, D. Zosso, X. Bresson, and J.-P. Thiran, "Harmonic active contours," IEEE Transactions on Image Processing, vol. 23, no. 1, pp. 69–82, 2014.
25. A. Belaid, D. Boukerroui, Y. Maingourd, and J.-F. Lerallut, "Phasebased level set segmentation of ultrasound images," IEEE Transactions on Information Technology in Biomedicine, vol. 15, no. 1, pp. 138–147, 2011
26. W. Wang, L. Zhu, J. Qin, Y.-P. Chui, B. N. Li, and P.-A. Heng, "Multiscale geodesic active contours for ultrasound image segmentation using speckle reducing anisotropic diffusion," Optics and Lasers in Engineering, vol. 54, pp. 105–116, 2014.
27. V. Estellers, D. Zosso, X. Bresson, and J.-P. Thiran, "Harmonic active contours," IEEE Transactions on Image Processing, vol. 23, no. 1, pp. 69–82, 2014.
28. Y. Zhou, W.-R. Shi, W. Chen, Y.-l. Chen, Y. Li, L.-W. Tan, and D.- Q. Chen, "Active contours driven by localizing region and edge-based intensity fitting energy with application to segmentation of the left ventricle in cardiac ct images," *Neurocomputing*, vol. 156, pp. 199–210, 2015.
29. Z. Ji, Y. Xia, Q. Sun, G. Cao, and Q. Chen, "Active contours driven by local likelihood image fitting energy for image segmentation," *Information Sciences*, vol. 301, pp. 285–304, 2015.

30. I. Rianto and P. Pranowo, "Distance regularized level set evolution for medical image segmentation," in The 1st Conference on Information Technology, Computer, and Electrical Engineering (CITACEE), vol. 1. Department of Computer Engineering, 2013, pp. 49–51.
31. L. Jin-qing and L. Wei-wei, "Adaptive medical image segmentation algorithm combined with drlse model," Procedia Engineering, vol. 15, pp. 2634–2638, 2011.
32. M. Roh, T. Kim, J. Park, and S. Lee, "Accurate object contour tracking based on boundary edge selection," *Pattern Recognition*, vol. 40, no. 3, pp. 931–943, 2007.
33. C. Li, C. Xu, C. Gui, and M. D. Fox, "Distance regularized level set evolution and its application to image segmentation," *IEEE Transactions on Image Processing*, vol. 19, no. 12, Article ID 5557813, pp. 3243–3254, 2010.
34. M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int. J. Comput. Vis.*, vol. 1, no. 4, pp. 321–331, January 1988
35. C. Xu and J. L. Prince, "Snakes, shapes, and gradient vector flow," *IEEE Trans. Image Process.*, vol. 7, no. 3, pp. 359–369, Mar. 1998
36. R. Ronfard, "Region-based strategies for active contour models," *Int. J. Comput. Vis.*, vol. 13, no. 2, pp. 229–251, 1994.
37. T. Pappas, "An adaptive clustering algorithm for image segmentation," *IEEE Trans. Signal Process.*, vol. 40, no. 4, pp. 901–914, Apr. 1992
38. X.Yu, T.D Bui, . & *et al*. (1994) "Robust Estimation for Range Image Segmentation and Reconstruction", *IEEE trans. Pattern Analysis and Machine Intelligence*, 16 (5), 530-538.
39. B.Sowmya & B. Sheelarani. (2009) "Colour Image Segmentation Using Soft Computing Techniques", *International Journal of Soft Computing Applications*, Issue 4**,** 69-80.
40. N. Senthilkumaran & Rajesh R (2009) "Edge Detection Techniques for Image Segmentation – A Survey of Soft Computing Approaches", *International Journal of* Recent *Trends in Engineering*, Vol. 1, No. 2, 250-254.

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