

International Journal of AdvancedResearch in Science, Engineering and Technology

Vol. 7, Issue 7, July 2020

Image Segmentation 2D and 3D Ultrasound Algorithms: A Survey

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ABSTRACT: The main objective of the survey is to represent a new technology in the field of 3D ultrasound images segmentation. Generally segmentation plays a vital role in medical field in order to gain quality measurements (area, location of objects, dynamic performance of anatomical structure in time etc...,). A new, constant and faster hybrid method for image segmentation must be introduced and implemented for vast extension of ultrasound segmentation usage in medical field. In this survey the existing used techniques are discussed and a best technique outcome is concluded. A variation multi-grid methodology for multi-dimension viewing and various phase field models (Allen-Cahn, Rayleigh equation) are used. Also a deep neural network considering its intensity, gradient, and adaptive normalized intensity score and prediction of retinal image pixel and segmentation regression problems are been discussed.

KEYWORD: image segmentation, ultrasound 3D, multi-grid algorithm, phase field models.

I.INTRODUCTION

In the field of disease diagnosis like cancer, heart problems, illness, one region body issues the exact diagnosing method and best treatment should be formulated. Ultrasound segmentation is the leading image processing technique implemented for detecting the soft tissues. The ultrasound image interpretation is always been a challenging process overcoming the artifacts, noise and shadows in the images designing image acquisition.

Though the ultrasound image suffers from many issues the two main defects making the processing complex are the presence of additive contrast and multiplicative noise. There are processing techniques that indulges several algorithms to improve ultrasound image segmentation. The main advantage of ultrasound are that they intrude at depth of 3mm or even more while other modalities have only limited measures in scanning process[1,2]. The level set segmentation is also a major drawback in calculating the size (tumor, cancer cells etc...,) that lacks accuracy at lesions origin. The previous method proposed an alternative model and named as Cahn-Hilliard phase field model in order to overcome the drawback. The model delivers phase transition in many chemical or physical applications and entities [3][4]. In reference with [5,6 and 7] taken as example of entities to the image processing.

A multi-well potential combined with a constant Mumford Shah functional focussing the basic 2-Dimensional images [8]. Whereas the algorithm used in [9] is considered harder. In process of 2D images a phase field segmentation [10] produced by a parametric statistical estimation is produced which is not apt for high frequency Ultrasound images [4]. The Allen-Cahn Reaction-Diffusion equation [11] states that "the gradient descent of the Cahn-Hilliard energy which shown as a procedural term of a variation formulation" this is widely accepted and adapted in ultrasound images[12].

The main contributions of this work involves the below stated representations

- 1) At first a skin tumor segmentation is taken in which a new variational model in 3D ultrasound images is ensured [13];
- 2) Secondly, a form of multi-grid representation that uses analytic solution and eliminate space discretization and numerical forms are presented.
- 3) Then a segmentation algorithm in multi-dimension for reproducible simulations and for minimal cost optimizing the computational time is been implemented in this theory [14].

In general Ultrasound helps in a proper imaging modality to diagnose hydronephrosis (kidney abnormality). This diagnoising process is done by automatic collecting system segmentation technique by means of 3D U-net deep neural



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learning in neural network. The initial process involves locating anatomical of renal fat spots surrounding the collecting system. The the severity assessment of measuring hydronephrosis Index is followed up where the location is traced and diagnoised [15,16].

Generally the prostate diseases are very common in adult men, and prostate origin detection from ultra-sonographic images plays a vital role in prostate disease diagnosis and curing the disease.



Figure 1. Transverse ultrasound images of the prostate

An example from gong et al [17] proposed the transverse ultrasound images of the prostate. The whole contour are manual implementation that initialize the ground truth and the dotted contour are boundaries by the computer.

The Recent research has focused on computing previous information of shape and speckle

models. Where, Knoll [18] stated that formulating a parameterization of a snake based on a

1-D and 2D dyadic wavelet transform as a multi-scale boundary curve analysis tool.

Sum et al. [19] shorten the total of a world-wide region-based energy and a basic energy based on image contrast and its following. The method used can figure out the bright blood vessels and avoids those with low contrast.

Lankton and Tannen baum [20] implemented a novel localization framework that permits the region-based energy to be basic in a whole variable way. As the objects with heterogeneous statistics can be fully segmented among the localized energies increasing the sensitivity to start-up the efficiency is maintained.

Tian et al. [21] also join the region and corner information to build a signed pressure force performance in account of improvising the segmentation where the parameters are tuned for better results.

A combined segmentation and representation algorithm for the testing of skin aging by 50 MHz high-frequency ultrasound images are implemented. The used segmentation method permits a well defined formation of the signal's statistics in the dermis as a representation of in depth. The procedure of statistical calculating that combined into a single aging score. The segmentation process is related to tailored recursive non-linear filters or layer. Here at this stage the epidermis and the dermis combination are segmented with a non-parametric real format contour indulging a texture criterion, an epidermis initializing map and the geometric constraint of horizontal continuity with its format. The algorithm also gets applied to both 2D and 3D also [35].

For breast density measurement a better segmentation algorithm is formulated in several other methods [36]. In general the segmentation methods use filter, region growing, thresholding and other various edge operation which are not enough because of noise and attenuation lacking. To overcome this K-means clustering and Maximum Expectation of Posterior Mardinal (MEPM) were used for better computational cost, pixel. The main advantage is usage of 3D next pixel as statistical Bayesian prior statistical Bayesian prior for grouping the data same as the tissue format.

Also the Kc clustering is a common method [25] in image segmentation particularly in noisy data. Here both the techniques are been compared and according to the accuracy; efficiency the best ultrasound segmentation result is taken in which Maximum Expectation of Posterior Mardinal (MEPM) plays a far way better than K-means algorithm in ultrasound image [37].

All know that angiograms are widely used for vascular and non-vascular pathology by every neuro surgeons helps to clear the blockage of diabetes, hypertension, cerebro vascular diseases and strokes. In favour of blood vessel segmentation a new Allen Cahn (AC) equation to segment blood vessels in angiograms is been implemented [38]. The process formulates joints length with double well potential and regularize by combining both local and global parts to solve low contrast issue and even finer detection is enabled [39].



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II. METHODOLOGIES FOR IMPROVED SEGMENTATION

A. LCH (LIKELIHOOD CAHN-HILLIARD) -EXACT SEGMENTATION

Image segmentation is basic task for better image processing and computer vision. A common approach is to decompose an image origin into homogeneous regions in image features divided by sharp features are processed. The main aim is on Phase separation where the two divisions of a binary fluid continuously extracts and create a new form origin in every component.

Segmentation of cardiac Lesions in 2-D and 3-D Ultrasound Images by a Coherent common Rayleigh Mixture Model is done. Also, the divisions of multiple-tissue images are arranged as a coherent finite mixture of Rayleigh distributions. Spatial coherence inherent to biological tissues is modelled by indulging local dependence among the combined components. A real Bayesian algorithm mixture along with a Markov chain Monte Carlo technique is then implemented to combine and estimate the parameters and a vector label including each voxel to a tissue element. And also to execute samples a hybrid metropolis among Gibbs sampler is used to the posterior distribution of the Bayesian model. Then by this model the estimated parameters are activated by the created samples.

Then the end results are tested on the synthetic info enhancing the performance of the estimation strategy. Thereby, the method is applied to the various medical field like tumor segmentation, cancer cells detection in higher level frequency 2 D and 3D ultrasound images[26].

B. SLICE-BASED DNL WITH DEEP SUPERVISION for efficient Cather segmentation

To increase the cardiac interventions efficiency and for faster and exact segmentation in 3D ultrasound a deep supervision technique is implemented. A catheter segmentation technique entirely related to Deep Neural Convolution learning (DNL) is found. For further enhancement a pre-trained model that process the 3D ultrasound volumes slice by slice is structured by skipping the links with F-score loss performance [27]. The method proposed have capacity to demolish the contextual data and higher the voxel of catheter detection challenging ex-vivo dataset (92 3D US images) from hearts with an RF ablation catheter inside [29]. But the DNL implementation the highest performance of segmentation is achieved.

On this slice based semantic segmention involving the 3D and 2D convolutional network and deep super vision technique converting 2D slices to 3D is optimised [30].



Figure 2. Proposed catheter segmentation method.



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From the above diagram the input 3D volume is decomposed into adjacent 2D slices along the axial axis. The input volume is first decomposed into small patches [33]. The 3D patch here is then divided as the 3D U-Net that leads to a smaller VOI output. The segmented VOIs are stitched as the full 3D US volume. Finally, catheter model-fitting is applied to localize the catheter in the noisy 3D segmentation domain [34]. An F-score type loss performance is added that views the network on execution finding and segmenting the catheter on challenging ultrasound images on enhancing the real positive rate.

Result Analysis



In the above analysis the segmentation efficiency and the noise decrease is rated. These estimation are made among the K-means MPEM algorithm, Catheter DNL methods and the LCH (LIKELIHOOD CAHN-HILLIARD) multi-grid segmentation is made. From all the discussed terms and techniques these three are considered to be best one.

III. CONCLUSION

In this survey various methodologies like LCH, K-means clustering algorithm combined with Expectation of Posterior Mardinal (MEPM) and Catheter disseminated necrotizing leukoencephalopathy (DNL) method that performs a deep learning of convolution network are discussed. Here the variation formulation Log-likelihood distance among the intensity distribution of ultrasound image is discussed [35]. Here the Allen-Cahn equation focussing at defining diffuse interface phase field evolutions is discussed the new approach LCH (LIKELIHOOD CAHN-HILLIARD) exact method is utilized much for betterment of segmentation. Then comparisons among the various algorithms are made and best is estimated. These estimation are made among the K-means Maximum Expectation of Posterior Mardinal (MPEM) algorithm, Catheter disseminated necrotizing leukoencephalopathy (DNL) methods and the LCH multi-grid segmentation is made. From all the discussed terms and techniques these three are considered to be best one.



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REFERENCES

[1] X. Yuan, N. Situ, G. Zouridakis, A narrow band graph partitioning method for skin lesion segmentation, Pattern Recognition, vol. 42, pp. 1017-1028.2009

[2] M. Mete, N. M. Sirakov, Dermoscopic diagnosis of melanoma in a 4D space constructed by active contour extracted features: Computerized Medical Imaging and Graphics, vol. 36, pp. 572-579, 2012.

[3] M. Pereyra, N. Dobigeon, H. Batatia, J. Tourneret, Segmentation of skin lesions in 2D and 3D ultrasound images using a spatially coherent generalized rayleigh mixture model, Medical Imaging, IEEE Transactions on, pp. 1509-1520, 2012.

[4] B. Sciolla, L. Cowell, T. Dambry, B. Guibert and P. Delachartre, Segmentation of Skin Tumors in High-Frequency 3-D Ultrasound Images, Ultrasound in Medicine & Biology, vol. 45, no. 1, pp. 227-238, 2017.

[5] Y. Sun, C. Beckermann, Sharp interface tracking using the phase field equation: Journal of Computational Physics, vol. 220, pp. 626-653, 2007. [6] S. M. Allen and J.W. Cahn, A microscopic theory for anti-phase boundarymotion ad its application to anti-phase domain coarsening, Acta Metall, vol. 27, pp. 1085-1095, 1979.

[7] C. M. Elliott, The Cahn-Hilliard model for the kinetics of phase separation, International Series of Numerical Mathematics vol. 88, pp. 36-73, 1989.

[8] E. G. Morton, Generalized Ginzburg-Landau and Cahn-Hilliard equations based on a microforce balance, Physica D: Nonlinear Phenomena vol. 92, pp. 3-4, 1999.

[9] S. Esedoglu and Y. H. R. Tsai, Threshold dynamics for the piecewise constant Mumford-Shah functional, Journal of Computational Physics vol. 211, pp. 367-384, 2006.

[10] Y. Li and J. Kim, Multiphase image segmentation using a phase-field model, Computers and Mathematics with Applications vol. 62, pp. 737-745, 2011.

[11] S. Zhao, M. Zhou, T. Jia, P. Xu, Z. Wu, Y. Tian, Y. Peng and J. S. Jin, Multi-branched cerebrovascular segmentation based on phase field and likelihood model, Computers & Graphics vol. 38, pp. 239-247, 2014.

[12] M. H. R. Cardinal, J. Meunier, G. Soulez, R. L. Maurice, E. Therasse and G. Cloutier, Intravascular Ultrasound Image Segmentation: A Three-Dimensional Fast-Marching Method Based on Gray Level Distributions, IEEE Transactions on Medical Imaging, vol. 25, no. 5, pp. 590-601, 2006. [13] G. Slabaugh, G. Unal, M. Wels, T. Fang and B. Rao, Statistical Region-

Based Segmentation of Ultrasound Images, Ultrasound in Medicine & Biology, vol. 35, no. 5, pp. 781-795, 2009.

[14] B. Sciolla, J. L. Digabel, G. Josse, T. Dambry, P. Delachartre, Joint segmentation and characterization of the dermis in 50 Mhz ultrasound2D and 3D images of the skin, Computers in Biology and Medicine, vol. 00, pp. 1-17, 2018.

[15]C. Peters and R. L. Chevalier, "Congenital urinary obstruction: pathophysiology and clinical evaluation," in Campbell-Walsh Textbook of Urology, 10th ed., Philadelphia, PA: Elsevier, 2012, pp. 3028-47.

[16] J. J. Cerrolaza, N. Safdar, E. Biggs, J. Jago, C. A. Peters, and M. G. Linguraru, "Renal segmentation from 3D ultrasound via fuzzy appearance models and patientspecific alpha shapes," IEEE Trans. Med. Imaging, vol. 35, no. 11, pp. 2393-2402, 2016.

[17] L. X. Gong, S. D. Pathak, D. R. Haynor, P. S. Cho, and Y. Kim, "Parametric shape modeling using

deformable superellipses for prostate segmentation," IEEE Trans. Med. Imag., vol. 23, no. 3, pp. 340 349, Mar. 2004.

[18] C. Knoll, M. Alcaniz, V. Grau, C. Monserrat, and M. Carmen Juan, "Outlining of the prostate using snakes with shape restrictions based on the wavelet transform," Pattern Recognit., vol. 32, no. 10, pp. 1767-1781, Oct. 1999.

[19] Sum K, Cheung PY. Vesselextraction under non-uniformillumination: a level set approach. IEEE TransBiomedEng2008;55(1):358-60.

[20] Lankton S, TannenbaumA. Localizingregion-basedactivecontours. IEEETrans Image Process2008;17(11):2029-39.

[21] Tian Y, Duan F, Zhou M, Wu Z. Active contour model combining region and edge information. Mach Vis Appl 2013;24(1):47-61.

[22] L. A. Christopher, E. J. Delp, C. R Meyer, and P. L. Carson, ""3-D Bayesian ultrasound breast image segmentation using the EMMPM algorithm"," in Proceedings of the IEEE Symposium on Biomedical Imaging, 2002.

[23] L. A. Christopher, E. J. Delp, C. R. Meyer, and P. L. Carson, ""New approaches in 3D Ultrasound segmentation"," in Proceedings SPIE and IST *Electronic Imaging and Technology Conference*, 2003. [24] M. L. Comer and E. J. Delp, ""The EM-MPM algorithm for segmentation of textured images: Analysis and further experimental results"," *IEEE*

Transactions on Image Processing, pp. vol. 9, no. 10, 2000.

[25] P R Bakic et al., "Comparison of 3D and 2D Breast Density Estimation from Synthetic Ultrasound Tomography Images and Digital Mammograms of Anthropomorphic Software Breast Phantoms," in SPIE Medical Imaging: Physics of Medical Imaging, Lake Buena Vista, FL, 2011. [26] Marcelo Pereyra*, Nicolas Dobigeon, Hadj Batatia, and Jean-Yves Tourneret "Segmentation of Skin Lesions in 2-D and 3-D Ultrasound Images Using a Spatially Coherent Generalized Rayleigh Mixture Model" 2012[27]J. M. Waller, H. I. Maibach, Age and skin structure and function, a quantitative approach (i): blood flow, ph, thickness, and ultrasound echogenicity, Skin Research and Technology 11 (4) (2005) 221-235.

[28] D. J. Tobin, Introduction to skin aging, Journal of tissue viability.

[29] M. Farage, K. Miller, P. Elsner, H. Maibach, Intrinsic and extrinsic factors in skinageing: a review, International Journal of Cosmetic Science 30 (2) (2008) 87-95.

[30] D. Parkin, D. Mesher, P. Sasieni, 13. cancers attributable to solar (ultraviolet) radiationexposure in the uk in 2010, British journal of cancer 105 (2011) S66-S69.

[31] J.-M. Morel, S. Solimini, Variational Methods for Image Segmentation, Birkhäuser, 1994.

[32] T. Brox, J. Weickert, Level set segmentation with multiple regions, IEEE Trans. Image Process. 15 (10) (2006) 3213-3218.

[33] T.F. Chan, L.A. Vese, A multiphase level set framework for image segmentation using the Mumford and Shah model, Int. J. Comput. Vis. 50 (3) (2002)

271-293

[34] G. Chung, L. Vese, Image segmentation using a multilayer level-set approach, Comput. Vis. Sci. 12 (2009) 267-285.

[35] L. He, S.J. Osher, Solving the Chan-Vese model by a multiphase level set algorithm based on the topological derivative, in: Proceedings of the

International Conference on Scale Space Variational Methods in Computer Vision, 2007, pp. 777-788.

[36] Y.M. Jung, S.H. Kang, J. Shen, Multiphase image segmentation via Modica-Mortola phase transition, SIAM J. Appl. Math. 67 (2007) 1213-1232.



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[37] J. Lie, M. Lysaker, X.C. Tai, A variant of the level set method and applications to image segmentation, Math. Comp. 75 (2006) 1155–1174.
[38] F. Li, C. Shen, C. Li, Multiphase soft segmentation with total variation and H1 regularization, J. Math. Imaging Vision 37 (2010) 98–111.
[39] H. Li, X.C. Tai, Piecewise constant level set method for multiphase motion, Int. J. Numer. Anal. Model. 4 (2) (2007) 291–305.
[40] C. Samson, L. Blanc-Feraud, G. Aubert, J. Zerubia, A level set model for image classification, Int. J. Comput. Vis. 40 (3) (2000) 187–197.
[41] X.C. Tai, O. Christiansen, P. Lin, I. Skjaelaaen, Image segmentation using some piecewise constant level set methods with MBO type of project, Int. J.

Comput. Vis. 73 (2007) 61-76.

[42] X.-F. Wang, D.-S. Huang, A novel multi-layer level set method for image segmentation, J. Univers. Comput. Sci. 14 (14) (2008) 2428–2452.
[43] S.M. Allen, J.W. Cahn, A microscopic theory for antiphase boundary motion and its application to antiphase domain coarsening, Acta Metall. 27 (1979)

1085–1095.

[44] Y. Li, H.G. Lee, D. Jeong, J.S. Kim, An unconditionally stable hybrid numerical method for solving the Allen–Cahn equation, Comput. Math. Appl. 60

(2010) 1591–1606.

[45] J.W. Cahn, On spinodal decomposition, Acta Metall. 9 (1961) 795-801.