

Delineation of LV using Local Motion Intensity Clustering Technique

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Abstract

Magnetic Resonance Imaging (MRI) is a powerful tool for identification of finding anatomical information and functionality of heart. The delineation of the LV in MRI images is a promising task because of repetitive and fast flow of blood in the heart. For such images noise interference is challenging problem. To Process such a challenge, an algorithm for delineating LV is proposed here. The proposed approach LMIC model connects the Local Intensity Clustering with mobility intensity information of LV. The Lucas Kanade optical flow way is used to calculate motion intensity of LV. This motion intensity is used as energy parameter for clustering purpose and further by using level set method accurate separation of LV has done. The LV can be accurately segmented by this approach. The experimentation has been using parameters such as dice metric and Hausdorff distance. Here Experimental result shows better model to delineate LV over existing methods to address the problem of image noise nosiness.

Keywords – *Delineation, Left ventricle, Local Motion Intensity Clustering*

I. INTRODUCTION

Now day's cardiovascular diseases are increasing rapidly. In the survey of heart diseases mostly the reason could be identified from morphological functional regions. CMR images are very useful for assessment of anatomical study and quantitative analysis of various parts of heart. CMR still have limitations in visualizing the underlying anatomy due to imaging artifacts such as cardiac motion, low slice resolution, lack of slice coverage or operator-dependent errors such as shadows, signal drop-out. Cardiac image segmentation analysis could provide more accurate and reliable assessment of the anatomical parameters. Variability in heart rates, sizes, positions and orientations, variations in image contrast and resolution may challenge the consistency and accuracy of any single

segmentation technique. Lots of the investigations are already been done on the LV.

II. PREVIOUS WORK

To apply 3D sectionalization of ventricles a narrow band statistical level set and 2D edge based level set method is suggested [5]. First process was performed for higher robustness and then to refine edges edge based segmentation is used for endocardial and epicardial walls of LV and endocardial walls of RV. This paper presents a more accurate automatic segmentation approach than manual work. The author also reports limitation of this method in locating apical area of ventricles [5]. A level set method is implemented to locate endocardium border of LV. Fuzzy C means algorithm is employed to find edges of epicardium here[17]. Its quantitative analysis shows than method gives good results for middle

level slices but still work is remaining for apical and basal level slices [2]. Further for LV automatic segmentation, adaptive K means clustering is employed to form clusters then connected component labeling to locate LV. The future work is expected to find LV's function to identify level of cardiac diseases [3]. Fuzzy C means strategy is used by the author to locate LV at systolic and diastolic phases both with fast computational speed. Here author suggests a new parameter for clinical diagnosis. The thickness between outer wall and inner wall changes due to blood pool which affects on epicardium wall segmentation [4]. For automatic LV identification with quantitative measurement several method are suggested based on Atlas or Deep learning or prior geometric properties [9][10][11]. But these techniques do not considered the initial problem of intensity inequality and noise problem, which also affects on the performance of the algorithm [1]. This approach is suggested to solve this problem for better improvement identification of LV.

III. METHODOLOGY

Local Intensity Clustering model is implemented for left ventricle segmentation at end systole phase. The cardiac MRI video be the input of model which will detect image sequence with systole number set in the data set. The operating procedure to estimate ventricle mobility of pixels is LK. This algorithm computes optical flow of an image to help in motion tracking. This motion parameter we have considered for further clustering. The Local clustering function classifies total intensities available in the image. Then energy minimization will be applied to get only two clusters with positive and negative values only. Then we have segmented the required LV region after erosion and dilation process. The algorithm of above methodology is given below.

Algorithm Steps;

Step 1: Input the MRI video

Step2: Detect image sequence till end systole image.

Step3: Find optical flow method to estimate motion intensity.

Step4: Apply clustering based on motion intensity information detected in step 3.

Step5: Minimize energy level to reduce number of clusters.

Step6: Get the segmented LV of test image.

Step7: Input ground truth image and segment the LV.

Step8: Analyze the segmented region with quantitative parameters such as HD and DM.

Step 9: end

A. Data Set Collection

We have collected total cardiac MRI data of 18 patients available for left ventricular chamber. This data set contains the 3D image sequence in the Pat??/img/ form where ?? presents patient number and for each patient out???.pgm 3D image of the sequences are available. Also its contains two folders named as Pat??/expert1/ and Pat??/expert2/ to provide the manual segmentation of the endocardial and epicardial border at end-systolic and end-diastolic time [3]. These images available in PGM format which are modified from DICOM for supporting 3D. Each image has a header of the form 100 x 100 indicates that the image has 100 lines, 100 columns, 255 is the maximum value of the image voxels [17]. For our work we have considered only end systolic sequence. The fig. no.2 shows input image for patient no. 2.

B. Experimental Results

We have selected MATLAB 2018 as programming tool : for this implementation. Fig. 1 shows an input image from the selected sequence of the video and Fig. 2 shows motion image generated using optical flow of sequence using Lukas Kanade Method. Here gray level

portion shows motion intensity image generated.



Fig.1 Input Image

After performing image normalization, we applied K means clustering Algorithm depending on motion feature space to get classification of intensities depends on clusters generated. To minimize classification of intensities we repeated the process till get two disjoint regions.

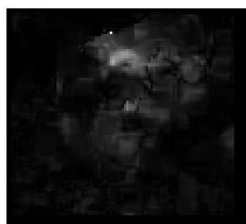


Fig. 2 Result of Optical Flow

The Fig. 3 points minimization of energy level taking place according to each iteration of clustering. Total five iterations are taken by the algorithm for the selected input. In the first iteration energy level is 30. For second iteration it is drastically reduced to 5 and then slowly reduced till fifth one.

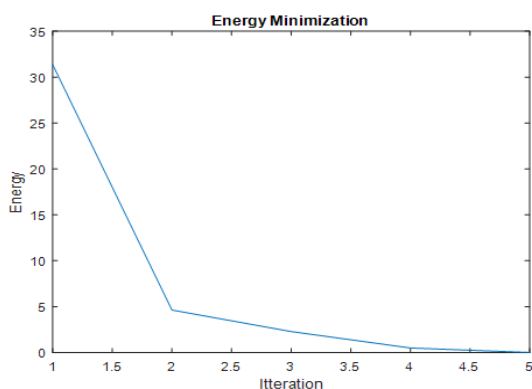


Fig. 3 Energy Minimization Process



Fig. 4 Clustering Output of Image after Energy Minimization

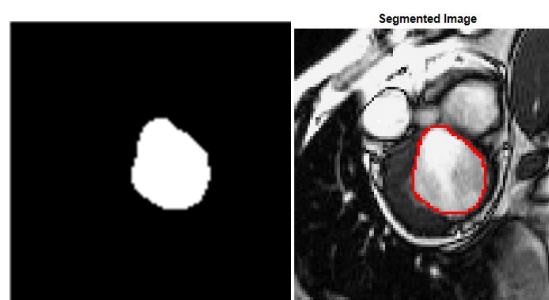


Fig. 5 Delineated LV Output in ground truth and input images

Figure 4 shows clustered output of the image after energy minimization and finally Fig 5 shows results. The image after erosion and the dilation gives us required output Image of left ventricle portion. The red color bordered portion in cardiac MR image is segmented as left ventricle.

C. Quantitative Analysis

To compare our results we used following evaluation measurement parameters.

1. Dice Metric or Dice Coefficient: It finds similarity between manual and automated segmentation. The span of DM varies between [0,1]. The DM value should be closer to one, It presents higher consistency between manual and automated segmentation [1] [4].

$$DM(Va, Vm) = \frac{2 Vam}{Va + Vm} \quad (1)$$

Where,

Vam=Area of intersection

Va= Area of Automatic contours

Vm= Area of manual contours

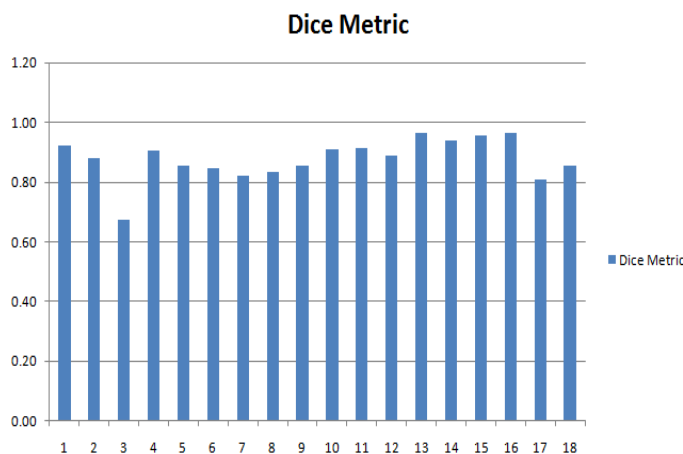


Fig. 6 Plot of DM for Various Patients

Here Fig. 6 presents results of dice metric for eighteen patient's data. The DM calculations are above 0.9 for patient no 01, 04, 10, 11 and 14 to 16 which are better than remaining DM calculations. It also shows in the range of 0.8 to 0.9 for other subjects. The poor DM was evaluated for patient no. 03 and 17.

2. Hausdorff Distance: HD is a measure of evenness distance between automatic segmented and manual segmented portion. It denotes the minimum distance (MD) from a point (p) on automated contour (a) to its nearest point (p) of manual contour (m) as followed [4].

HD is measured in mm which is maximum between two values. When HD increases performance reduces.

$$HD(C_a, C_m) = \max(\max(\min(d(P_a, P_m))), \max(\min(d(p_a, p_m)))) \quad (2)$$

Where $d(\cdot)$ is Euclidean Distance

Fig no 8 represents evaluation plot for HD in mm for the said data set. The average HD calculated is around 7.00mm, where for patient no.13, 14 and 17 it gives promising results as compare to other patients.

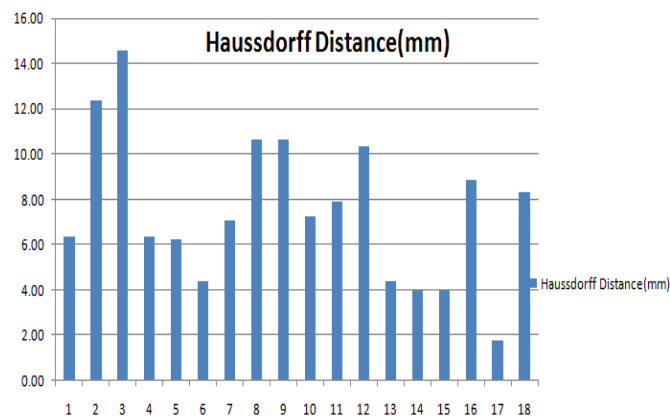


Fig. 7 Plot of HD for Various Patients

IV. CONCLUSION

This paper presents a model for LV identification from cardiac MR short-axis images at endocardium wall. This algorithm suggests solution to reduce problem of noise interference as many previous methods are based on geometric information. Here motion intensity information is easy to acquire and not requires time consuming training process, so time required for training is reduced. We have tested our results on eighteen patient's data set. Average dice metric and hausdorff distance are calculated are 0.89 and 7.00 mm respectively. This model of local motion intensity clustering provides significant image based assessment of LV structure. Experimental result shows that the edges of LV can be effectively described by using the LMIC model with a different approach of segmentation. Our work will be extended to identify LV borders at epicardium walls also. The future scope of this work is to develop fully automatic delineation methods of LV with quantitative estimation of volumetric analysis such as end systole volume, end diastolic volume, ejection fraction.

V. REFERENCES

1. Zengzhi Guo, Wenjun Tan , Lu Wang, Lisheng Xu , Xinhui Wang, Benqiang Yang and Yudong Yao "Local Motion Intensity Clustering (LMIC) Model for Segmentation of Right Ventricle in Cardiac MRI Images". DOI: 10.1109/JBHI.2018.2821709,2018

2. Li Wang, Yurun Ma, Kun Zhan, Yide Ma, "Automatic Left Ventricle Segmentation in Cardiac MRI via Level Set and Fuzzy C-Means", IEEE RAECs UIET Panjab University Chandigarh, pp. 978-1-4673-8253-3/15, 2015.
3. Anupama Bhan, Ayush Goyal, Vinayak Ray, "Fast Fully Automatic Multiframe Segmentation of Left Ventricle in Cardiac MRI Images Using Local Adaptive K-Means Clustering and Connected Component Labelling", IEEE International Conference on Signal Processing and Integrated Networks (SPIN), pp. 114-119, 2015.
4. Anupama Bhan, Ayush Goyal, Vinayak Ray, "Image - Based Pixel Clustering and Connected Component Labeling in Left Ventricle Segmentation of Cardiac MRI Images", IEEE International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), pp. 339-342, 2015.
5. G. Tarroni, D. Marsili, F. Veronesi, C. Corsi, and C. Lamberti, G. Sanguinetti, "Near-Automated 3D Segmentation of Left and Right Ventricles on Magnetic Resonance Images", 8th International Symposium on Image and Signal Processing and Analysis, PP. 522-527, 2013.
6. M. A. Simon, "Assessment and treatment of right ventricular failure," Nat Revis Cardiol, vol. 10, no. 4, 2013, pp. 204-218.
7. C. Petitjean and J. N. Dacher, "A review of segmentation methods in short axis cardiac MR images," Med Image Anal, vol. 15, no. 2, pp. 169-184, 2011.
8. C. Li, R. Huang, Z. Ding, C. Gatenby, D. Metaxas, J. C. Gore, "A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI," IEEE Transactions on Image Processing, vol. 20, no. 7, pp. 2007-2016, 2011.
9. B. D. Lucas, and T. Kanade, "An iterative image registration technique with an application to stereo vision," International Joint Conference on Artificial Intelligence Morgan Kaufmann Publishers Inc, vol. 73, no. 3, pp. 674-679, 1981.
10. H. Zhang, A. Wahle, R. K. Johnson, T. D. Scholz, and M. Sonka, "4-D cardiac MR image analysis: left and right ventricular morphology and function," IEEE Trans Med Imaging, vol. 29, no. 2, pp. 350-364, 2010.
11. C. Petitjean and J. N. Dacher, "A review of segmentation methods in short axis cardiac MR images," Med Image Anal, vol. 15, no. 2, pp. 169-184, 2011
12. <http://perso.esiee.fr/~dpt-it/a2si/heart/data/HeartDatabase.tgz>
13. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68-73.
14. I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271-350.
15. K. Elissa, "Title of paper if known," unpublished.
16. R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.
17. Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," IEEE Transl. J. Magn. Japan, vol. 2, pp. 740-741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].
18. M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.