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A Review on Ventricular Segmentation for Cardiac MR Images

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Abstract

Cardiac MRI is most comprising process for both functionality estimation and anatomized structure of the heart. The delineation of various ventricles are obtained from experienced physicians. Therefore an efficient method being invented which can replace human observer variability. Fully automatic delineation algorithms are on high demand. Sectionalization of Left and Right Ventricles is imperative part in quantitative analysis in CMRI. This work presents study of various techniques used for right, left and biventricular delineation with performance evaluation parameters such as Dice Metric, Haussdorff Distance and Ejection Fraction. The result of LV delineation is quite solved as compared to RV and Bi-ventricle segmentation. The irregular shape of RV affects the accuracy of models. The robustness and efficiency of various algorithms is challenging due to lack of publically available huge data sets for healthy and pathological patients.

Keywords*— Left Ventricle, Right Ventricle, Dice Metric, Haussdorff Distance, Ejection Fraction*

I. Introduction

The major cause of death in all over the world is cardiovascular diseases. The maximum ailments of the heart are observed are like coronary heart disease related to the blood vessels supplying to the heart muscle, peripheral arterial disease related to the blood vessels heart disease. Cardiac MR Images are very useful for anatomical study and quantitative analysis of various parts of heart. CMR still have limitations in visualizing the underlying anatomy due to imaging artifacts due to as continuous cardiac activity, poor resolution, human dependent errors such as shadows, signal drop-out. By acquiring multiple anatomical scans these problems can be avoided. Though imaging artifacts gets reduced by discarding unwanted images but expensive in the form of time. Also it can cause imprecise measurements. Cardiac image segmentation analysis could provide more accurate and reliable assessment of the anatomical parameters. The main challenge in this situation is to get proper assessment in a segmentation process which dominates heart rate variation and image artifacts also.

The segmentation is used to simplify change the representation of an image into something that is more meaningful and easier to analyze. But, segmentation of the ventricle still remains a challenge because of the high speed movement of the heart, blood flow and image noise interference and its variable and irregular structure, and thin wall and ill-defined boundaries.

The main purpose of medical image analysis is to separate out a particular organ so that the medical expert's can center on it for further diagnosis decisions. Three ways of medical image segmentation is employed in previous work. The simplest way is an edge based method in which object is identified after filtering process from original image. In threshold based methods a global threshold is decided to detach foreground object from background image. By finding discontinuities in intensity levels of an interested region from an image is called as region based methods. Clustering based methods are divided into two processes, first is feature extraction and other is to measure its distance with the extracted feature to classify the pixels. Providing prior knowledge of an object location is in the process of segmentation is applied in Multi Atlas segmentation [18].

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II. CARDIAC ACQUISITION PLANES

Instead of commonly used body planes (coronal, axial and sagittal) the CMR images are acquired along several oblique directions aligned with the structures of the heart.

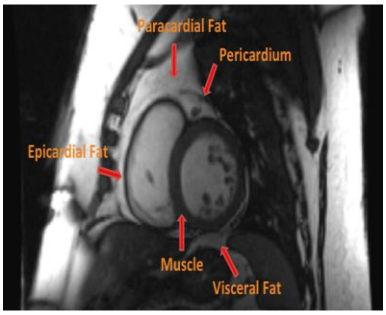

Figure 1: Short Axis View of Human Heart

Fig. 1 shows human heart structure in short axis view, which represents pericardium view, Epicardial view with left and right ventricles both. The central circular portion of left ventricle is surrounded by crescent shaped right ventricle. Therefore these ventricles can be separately segmented or combinable segmented. Imaging in these standard cardiac planes ensures efficient coverage of relevant cardiac territories (while minimizing the acquisition time) and enables comparisons across modalities, thus enhancing patient care and cardiovascular research. The optimal cardiac planes depend on global positioning of the heart in the thorax. This is more vertical in young individuals and more diaphragmatic in elderly and obese. These planes are often categorized into two groups. Figure 2 and three shows the short and the long axis planes of MR images.

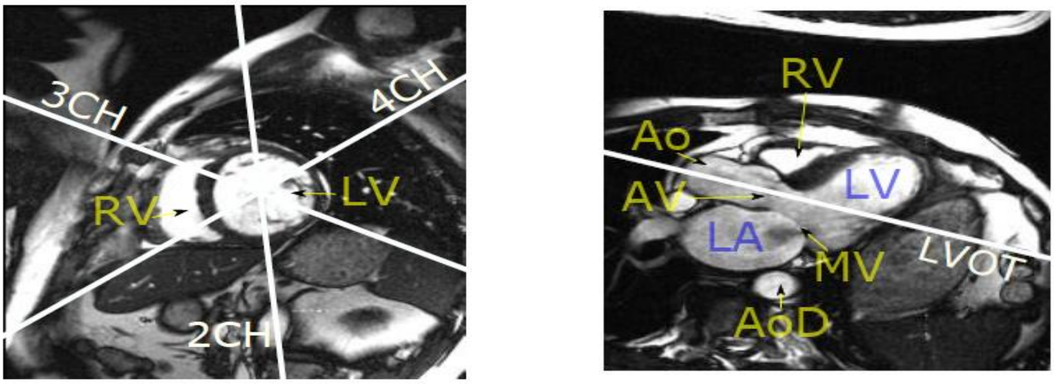

Figure 1: Basal Short Axis View and Mutual Orientation of the Long Axis Planes

The long axis planes are radially distributed around the myocardium to ensure the optimal coverage of the heart.

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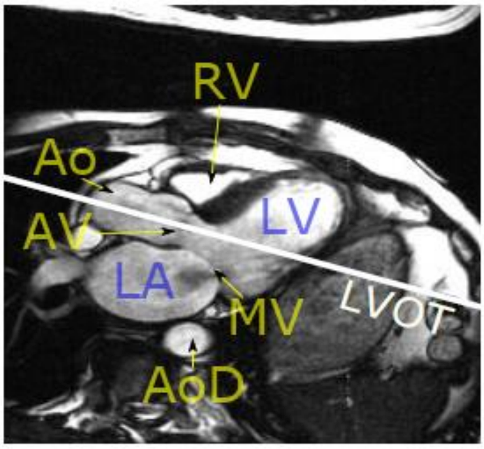

Figure 3: Long Axis View of Cardiac MR Images

III. PERFORMANCE PARAMETERS

2.1 Evaluation Parameters

Performance of the right ventricle segmentation system will be measured on the basis of following parameters:

- **Dice metric /coefficient (DM)**

It finds similarity between manual and automated segmentation. It measures the overlap (*Ama*) between manually segmented (*Am*) and automatically segmented contour area (*Aa*). DM always ranges between [0, 1]. The larger DM value is, the higher consistency between manual and automated segmentation.

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

Figure no 3 shows graphical representation of Dice Metric measurement. Here Blue circle-shows manual Segmentation volume V_m and Orange circle shows volume of automated Segmentation V_a. V_{am} represents volume of intersection area of both segmentations[2][7][8].

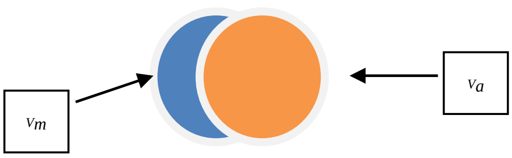

Fig. no.3 Graphical Representation of DM measurement

- **HAUSDORFF DISTANCE (HD)**

HD is a symmetric measure of distance between automatic and manual segmentation. It denote the minimum distance (MD) from a point (*p*) on automated contour (*a*) to its nearest point (*p*) of manual contour (*m*) as followed.

HD is measured in mm. It is maximum of two values.When HD increases performance reduces[2][4][5].

$$HD(Ca,Cm)= \max(\max_i(\min_j (d(Pa,Pm))_{i,j}),\max_j(\min_i(d(pa,pm)))_{i,j}) \qquad eq.(2)$$

Where d(.) is Euclidean Distance

- **Ejection Fraction:**

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Clinical Indices for functional analysis of right ventricle will be identified using ejection fraction. It is ratio of difference in end diastolic volume and end systolic volume with end diastolic volume [2].

$$\text{Ejection Fraction} = \frac{EDV - ESV}{EDV} x100\% \qquad eq(3)$$

- **Bland Altman Plot:**
  It is plotted for difference between automatic measurement and ground truth against ground truth results.

IV. OVERVIEW OF DELINEATION METHODS

3.1 Left Ventricle Delineation Methods

Manual segmentation is a time consuming process takes at least 20 minutes per ventricle by experts. In commercial software processing time is reduced but still requires modifications. This paper provides challenges in cardiac segmentation methods, state-of-art cardiac segmentation methods and future aspect towards LV and RV segmentation. LV segmentation problem is partially open for basal and apical segmentation, as mid ventricle segmentation provides appropriate results. Very less attention is for RV segmentation due to its varying size, non defined borders, thin and irregular structured nature. Delineating RV at apical slices is critical issue. Identification of ED and ES frames and volumetric measurement is a challenging task in image processing and pattern recognition for short axis MR images. [2].
An automatic LV segmentation method was implemented by author, which was combination of two algorithms. A level set method was employed for endocardium delineation and fuzzy C Means (FCM) was used for epicardium delineation with clinical indices such as ejection fraction and volumes. Method was applied on short axis MR images on the dataset provided by MICCAI and results provide good contours 0.9429 dice metric on middle slice with more stability in low constrast background. This author was also implemented a fast technique of two algorithms. FCM used to segment out ROI in the form of clusters and connected component labeling was used to separate ROI from non ventricle regions.

Table no. 1: Survey of Left Ventricle Segmentation Methods with Parameters [15][16]

Sr. No.	*Method used*	*Dice Metric*	*Computation Time (sec)*	*Accuracy*
1	*Local Adaptive K Means Clustering & CCL*	*0.992*	*0.01-0.1*	*-*
2	*Level Set and FCM*	*0.932*	*0.7*	*-*
3	*Deep Learning with Deformable model*	*0.96*	*-*	*-*
4	*CNN*	*-*	*-*	*98.66*
5	*U-Net*	*0.92*	*-*	*-*

Table 1 shows comparison between performances of various algorithms with their selected performances. These results are not comparable to each other as authors have implemented different data sets of short axis cine MR images.

3.2 Right Ventricle Delineation Methods

A fully automatic learning based method implemented using Convolution neural network and stacked autoencoder for RVsegmentation. They have used MICCAI 2012 challenge database of cardiac MR short axes Images of 32 subjects. Fast, robust results have employed as good as human annotator. This work provides average Dice metric 82.5% and Haussdorff Distance 7.85 mm. Problems of RV segmentation methods such as leakage and shrinkage of contours are overcame with this method.

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Validation of data set formed on a dataset and not on patients with abnormalities; also improvement in result is expected in terms of accuracy and computational time. Results of this method are implemented on offline dataset, but still it is required to apply on more number of subjects for validation[7]. Table 2 describes method employed for RV segmentation with its evaluation parameters.

Table 2: Survey of RV delineation Methods for short axis MR images with different data sets [7][8]

Sr. No.	*Method used*	*Dice Metric*	*HD (mm)*	*Accuracy*
1	***Gradient Vector Flow***	***-***		***Better***
2	***A fully Automatic FCN model***	***Endocarium-0.84 RV Epicardium-0.86***	***Endocardium-8.86 Epicardium- 9.3***	
3	***Deep Learning model***	***0.82***		
4	***CNN with autostack encoder***	***0.82***		

This paper present a new method for segmentation of RV named as point correspondence method . This non rigid registration method can track any curve in the image sequence. Need of intensity information or shape information is not required. It also avoids requirement of huge training set. Author suggests a more flexible approach of finding only one point of RV for whole segmentation. In this paper 32 short axis cardiac MR images were used for comparison with manual segmentation. This algorithm segments both endocardial and epicardial borders of right ventricle with dice metric 0.79 to 0.84. The performance of algorithm is evaluated for estimating clinical measurements such as end systolic volume and ejection fraction. The average error between automatic and manual EF is 0.1874+-0.13 and standard deviation error occurred as 0.0858+-0.06 [3].
A new approach has been suggested by …. To segment right ventricle by temporal information constrained gradient vector flow. It is a model designed to search subsequent information of motion of right ventricle. One weighting parameter is employed to decide the weight of temporal information against image data itself. After quantitative analysis, here author proved GVF-T model gave better results than GVF model [8].

3.3 **Bi Ventricle Delineation Methods**

Bi-ventricle segmentation has been implemented to study morphology and function of LV and RV using Active Shape model (ASM) and Active Appearance Model (AAM). The author has implemented their algorithm on 25 normal and 25 Tetra logy of Fallot (TOF) hearts images both in Short and Long axis. This model has extracted LV and RV shape and volume based features with 90-100% sensitivity. Still these methods are affected by size of training data [1].
First 3D based near automated method was employed with 3D narrow band statistical level set and 2D edge based level set algorithm. Results were compared with manual traced ventricle edges by experts. Author implemented this method for LV endocardial and epicardial and RV endocardial segmentation on long axis images and evaluated its performance with two parameters: mean absolute distance

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(MAD) and HD. Fast, reliable detection of LV contours takes place but still problem remains with RV. It shows lowest accuracy of RV endocardial contours at apical slices [4].
To improve accuracy a semiautomatic algorithm has suggested. The algorithm was tested on multiple atlases for RV, LV and myocardium segmentation with Dice metric reported is 0.89, 0.92 and 0.82 respectively. This method shows several advantages such as shape variability identification, robust for errors with respect to single atlas segmentation. 28 subjects were under gone for evaluations with 27 images are selected as atlas set, which are labeled by experts [5].
A segmentation free method was implemented by authors [j] to provide accurate estimation of LV and RV volumes. The method was accepted by RSNA, Radiology Society of North America 2013. Ventricular volume was calculated by integrating sum of all volumes of each slice with thickness (h), where cavity area (Ai) is measured using Bayesian formulation.

$$v = \sum_{Ai} Ai\ h \qquad eq\ ()$$

56 subjects were tested for both normal and abnormal cases. Ejection fraction for LV and RV was calculated as 0.966 and 0.807. The mean and standard deviation of difference between manual ejection fraction and automatic ejection fraction were calculated and it concludes that LV results are more accurate than RV [6].

Table no.3: Survey of BiVentricle Segmentation Methods with Parameters [8][6][2]

Sr. No.		***Dice MetricParameter***					
	Method used	***LV***	***RV***	***LV Endocardium***	***LV Epicardium***	***RV Endocardium***	***RV Epicardium***
1	***Patch based fusion model for Multiatlas***	***0.93***	***-***	***-***	***-***	***0.77***	***0.814***
2	***3D narrow band level set method***	***-***	***-***	***0.9***	***0.9***	***0.8***	***-***
3	***Local PCA***	***-***	***-***	***1.08***	***1.10***	***1.58***	***1.61***
4	***Active Contour model***	***-***	***-***	***0.72***	***0.80***	***1.28***	***1.32***
5	***BDN***	***-***	***0.84***	***0.91***	***0.94***	***-***	***-***
6	***Adaptive Bayesian Model***	***0.966***	***0.807***	***-***	***-***	***-***	***-***
7	***Graph Cut method***	***-***	***0.79***	***0.80***	***0.84***	***-***	***-***
8							

Table no 3 shows survey of Bi ventricle segmentation method implemented in previous work with its evaluation parameters.

Datasets:
The MICCAI 2009 LV Segmentation Challenge dataset is comprised of 45 subjects. The expert images are generated manually for endocardial and epicardial borders on all slices [19].
A 45 patients MRI data set with various heart conditions is available. Also this sunnybrook cardiac data set contains manually delineated images, which are provided for endocardium and epicardium contours at end systole and end diastole states [20].

V. Conclusion and future Scope

Significance of this research is to review various methods to delineate left, right and bi-ventricles from cardiac cine MR images. Left and right ventricle segmentation plays important role in calculation of clinical indices such as blood volume, ejection fraction. There are many difficulties

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available in identification of ventricles such as inhomogeneity in brightness level due to blood flow, papillary muscles. The performance of various algorithms is compared using parameters such as dice metric (DM), haussdorff distance (HD). For LV assessment the maximum accuracy acquired is 98% with various models. previous results shows RV delineation is possible with maximum HD of 9.3mm and DM is 0.86. The study of bi-ventricle segmentation algorithm reveals that LV endocardium and epicardium borders got maximum 0.94 and 0.91 DM where RV endocardium and epicardium borders achieved 0.8 DM.
This survey concludes that the assessment of LV problem is quantitatively solved at certain extent but functional analysis of RV is uncovered as accuracy is not attainable. In delineation process the result of apical slices are poor as compare to mid and basal slices. Lack of availability of immense data sets of healthy and pathological patients limits robustness of be implemented algorithm. The fully automatic methods for bi-ventricle, right and left ventricle segmentation at endocardium and epicardium level are demanded with its volumetric measurements, so that today's manual delineation process can be altered by these models

References

1. Honghai Zhang, Andreas Wahle, Ryan K. Johnson, Thomas D. Scholz, and Milan Sonka*,"*4-D Cardiac MR Image Analysis: Left and Right Ventricular Morphology and Function", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 29, NO. 2, FEBRUARY 2010.
2. Caroline Petitjean, Jean-Nicolas Dacher, "A review of segmentation methods in short axis cardiac MR images", Med. Image Analysis, DOI: 2010 .12.004, 2011.
3. K. Punithakumar, Michelle Noga, Pierre Boulanger, " Cardiac Right Ventricular Segmentation via Point Correspondence", 35th Annual International Conference, IEEE EMBS, PP. 4010-4013,2013
4. 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.
5. Wenjia Bai, Wenzhe Shi, Declan P. O'Regan, Tong Tong, Haiyan Wang, Shahnaz Jamil-Copley, Nicholas S. Peters and Daniel Rueckert "A Probabilistic Patch-Based Label Fusion Model for Multi-Atlas Segmentation With Registration Refinement: Application to Cardiac MR Images", IEEE Transaction on Medical Imaging, VOL. 32, NO. 7, JULY 2013.
6. Zhijie Wang, Mohamed Ben Salah, Bin Gu, Ali Islam, Aashish Goela, and Shuo Li, "Direct Estimation of Cardiac Biventricular Volumes With an Adapted Bayesian Formulation", IEEE Transaction of Biomedical Engg. , VOL. 61, NO. 4, APRIL 2014.
7. Michael R. Avendi, Arash Kheradvar and Hamid Jafarkhani, "Automatic Segmentation of the Right Ventricle from Cardiac MRI Using a Learning-Based Approach", in Magnetic Resonance in Medicine. New York, NY, USA:Wiley, doi: 10.1002/mrm.26631, Feb. 2017.
8. Avendi, MR Kheradvar, A Jafarkhani, H "A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI", MedIA Image Anal., vol. 30, pp. 108–119, May 2016.
9. [9] Omar Emad, Inas A. Yassine, Ahmed S. Fahmy," Automatic Localization of the Left Ventricle in Cardiac MRI Images Using Deep Learning", IEEE, pp 683-686, 2015.
10. [10] Ozgun Cicek, Ahmed Abdulkadir, Soeren S. Lienkamp, Thomas Brox, and Olaf Ronneberger," 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation",June 2016.
11. Liangijia Zhu, Yi Gao, Vikram Appia, Anthony Yezz," Automatic Delineation of Myocardial Wall From CT images Via Shape Segmentation and Variational Region growing", IEEE Transaction on Biomedical Engg., VOL. 60,No.10, pp. 2887-2895, Oct. 2013.
12. Qi Dou, Hao Chen, Lequan Yu, Yueming Jin, Xin Yang, Jing Qin, Pheng-Ann Heng," 3D deeply supervised network for automated segmentation of volumetric medical images", Medical Image Analysis, Elsevier, pp.40-54, 2017.

ISSN: 2233-7857 IJFGCN

13. M. S. Nosrati and G. Hamarneh,"Incorporating prior knowledge in medical image segmentation: a survey." [Online]. Available:https://arxiv.org/abs/1607.01092, 2016
14. ArchontisGiannakidis, KonstantinosKamnitsas," Fast Fully Automatic Segmentation of the Severely Abnormal Human Right Ventricle from Cardiovascular Magnetic Resonance Images using a Multi-scale 3D Convolutional Neural Network" ,in IEEE Computer Society, pp. 42-46, 2016.
15. Zhu, Yi Gao, Vikram Appia, Anthony Yezz," Automatic Delineation of Myocardial Wall From CT images Via Shape Segmentation and Variational Region growing", IEEE Transaction on Biomedical Engg., VOL. 60,No.10, pp. 2887-2895, Oct. 2013.
16. 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 Labeling", 2nd International Conference on Signal Processing and Integrated Networks, 2015
17. Vinayak Ray, Ayush Goyal, "Image Based Sub-second Fast Fully Automatic Complete Cardiac Cycle Left Ventricle Segmentation In Multi Frame Cardiac MRI Images Using Pixel Clustering And Labelling", 2015.
18. Xulei Yang, Si Yong Yeo, Yi Su, Calvin Lim, Min Wan, Liang Zhong, Ru San Tan," Right Ventricle Segmentation by Temporal Information Constrained Gradient Vector Flow", IEEE International Conference on Systems, Man, and Cybernetics, DOI 10.1109, PP. 2551-2555, 2013.
19. Xiang-Wei Li, Yu-Xiu Kang,Ya-Ling Zhu, Gang Zheng,Jun-Di Wang," An Improved Medical Image Segmentation Algorithm Based On Clustering Techniques", 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI 2017), IEEE, 2017
20. A. Andreopoulos and J. K. Tsotsos, "Efficient and generalizable statistical models of shape and appearance for analysis of cardiac MRI," *Med. Image Anal.*, vol. 12, no. 3, pp. 335–357, 2008.
21. Jinming Duan, Ghalib Bello etc.," Automatic 3D bi-ventricular segmentation of cardiac images by a shape-refined multi-task deep learning approach", IEEE, 0278-0062, 2018
22. http://www.cardiacatlas.org/studies/sunnybrook-cardiac-data/www.healthline.com

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