Multi-label 4-chamber segmentation of echocardiograms using Fully Convolutional Network

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Abstract

Precise segmentation of the heart is crucial for reliable calculation of clinical indices such as chambers' volumes and ejection fraction (EF). Currently, in echocardiography, cardiac segmentation is manually performed through a tedious and time-consuming process. More importantly, this process is prone to inter- and intra-user variability. Motivated by current methods limitations, we have employed Fully Convolutional Networks to semantically segment heart chambers. Our model was trained with more than 900 images from 70 subjects and tested on 449 images from 30 patients. Further, it was evaluated using multiple evaluation metrics including Dice similarity coefficient and Hausdorff distance. The proposed model has shown robust and good accuracy.

1 Introduction

Echocardiography has been the preferred imaging modality to study the heart chambers for routine screening purposes due to its portability, real-time application, and overall cost. However, it suffers from subjective interpretation Hoffmann et al. [1996] and inter- and intra-observer variability. Thus, the assessment of 2D echocardiograms has yet remained unsatisfactory, with chambers' volumes commonly calculated by manually tracing their boundaries Furiasse and Thomas [2015].

Precise segmentation of the heart's chambers is crucial for reliable calculation of clinical indices, diagnosis and transcatheter procedures. Previous attempts to automate cardiac segmentation were mainly focused on left ventricle (LV) due to the emerging needs for assessment of left heart function. However, recent attentions to the significance of other chambers such as the right ventricle (RV) and left atrium (LA) in progression of heart disease, and in particular, structural heart problems, necessitate approaches for accurate automated segmentation of multiple heart chambers.

Motivated by the clinical unmet needs for accurate and automated analysis of echocardiograms and current limitations, we have employed the latest deep learning algorithms to develop a fully automated four-chamber segmentation method for 2D echocardiograms.

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2 Method

2.1 Dataset

The segmentation method was validated using a dataset of more than 1000 annotated images from 100 normal subjects, who had undergone clinically-indicated standard transthoracic echocardiography using commercially available systems. Echocardiography records were available from Loma Linda University. The dataset includes apical 4-chamber long axis views. We partitioned our data to $70\%-30\%$ as training and test dataset, including 946 and 449 images, respectively. Manual segmentations of images as gold standard labels have been provided by a board-certified cardiologist.

2.2 Network architecture and parameters

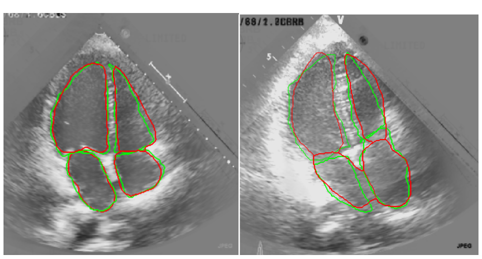
To investigate the power of deep fully convolutional networks, we chose the FCN-VGG Long et al. [2015] Net with 16 layers based on its promising results in image segmentation challenges. VGGNet. Simonyan and Zisserman [2014] was developed by K. Simonyan and A. Zisserman of the Visual Geometry Group (VGG) from the University of Oxford as a CNN model. Then it was converted to FCN-VGG as the fully connected layers convolutionized in different versions with different stride sizes in deconvolution layers. Here we chose 8-pixel size strides for our task. For FCN-8s, the model's final output was a product of upsampling of the third pooling layer, (upsampling of the fourth pooling layer) x 2 and (upsampling of the seventh convolutional layer) x 4, which performs better for object segmentation Long et al. [2015], Ahmad et al. [2018].

To effectively train such a deep neural network, a considerable amount of data was required. To tackle this problem we used both transfer learning and real-time data augmentation. Thus, during the whole heart semantic segmentation training process, we performed real-time random augmentation, by displacing the center point up to 30 pixels, zooming up to 15% shear distorting the mean and SD up to .15, rotating up to 30 degree and adding Gaussian noise with .15 SD. The outputs of the FCN network are probability map for each pixel.

Further, the weights associated to FCN-VGG pre-trained models were subsequently used to fine-tune the deep learning method. A softmax classification layer was exploited to generate the probability map. Finally the whole networks were trained via a mini-batch gradient descent method by minimizing a pixel-wise cross-entropy (multinomial logistic) loss function on the 4-chamber echocardiogram dataset.

3 Results

After training for 40 epochs, Dice coefficient and Haussdorf distance -as evaluation metrics- were calculated as 91.35% (SD=3.7) , 12.1 mm for LV, 84.96% (SD=7.7) , 17.4 mm for RV, 89.72% (SD=5.8) , 9.8 mm for LA, and 91.01% (SD=4.4) , 10.6 mm for the RA, respectively.



(a) (b)

Figure 1: Automatic (red) and manual (green) segmentation results for two Long axis 4-chamber cardiac ultrasound (a) good result (b) poor result

Table 1: Comparison of segmentation performance between our method and state-of-the-art techniques

		Dice (%)	HD (mm)	# of images
LV	Chen, H. et al. [2016]	87.9	--	3,118 images
LV	Carneiro et al. [2013]	90.7	--	132 images
LV	Belous et al. [2013]	90.09 ± 0.03	16.0	35 subj
LV	Smistad et al. [2017]	87.0 ± 6	5.9	52 images
LV	Mod- FCN-VGG8s	**91.35 ± 3.7**	12.1	449 images
RV	Mod- FCN-VGG8s	**84.96 ± 7.7**	17.4	449 images
LA	Mod- FCN-VGG8s	**89.72 ± 5.8**	9.8	449 images
RA	Mod- FCN-VGG8s	**91.01 ± 4.4**	10.6	449 images

Figure 2. illustrates the correlation graphs between the automatic and manual area-based results using the test dataset, for LV, RV, LA and RA, respectively. A correlation with the ground truth contours of 0.95, 0.88, 0.95 and 0.93 for LV, RV, LA and RA was achieved.

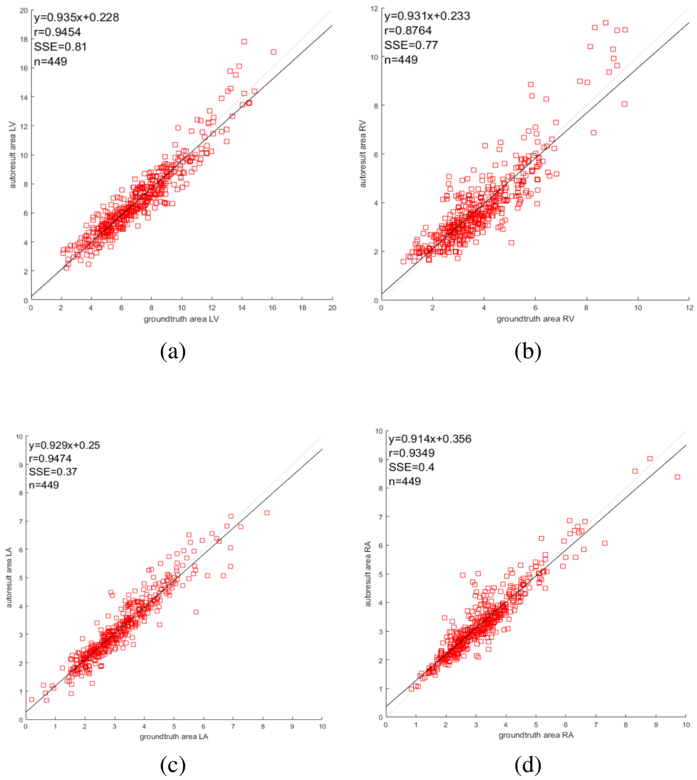


Figure 2: Correlation graphs for (a) LV (b) RV (c) LA (d) RA

4 Conclusion

This study verifies that the challenging problem of automatic cardiac segmentation in echocardiograms can be solved as a semantic segmentation problem using latest deep-learning algorithms. Considering the room for improvement, as shown in Figure 1, employing hybrid models such as Avendi et al. [2016] work will be the subject of future research. To the best of our knowledge, this study is unique with respect to the whole heart segmentation in noisy 2D echocardiograms.

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