Segmentation of parasternal long axis views using deep learning

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***Abstract*—Accurate segmentation of the parasternal long axis (PLAX) ultrasound view of the heart is essential for automating the many clinical measurements performed in this view.**

In order to efficiently annotate all the important structures in the PLAX view in a standardized way, a new specialized annotation tool was developed. Using this tool, the left ventricle (LV) lumen, myocardium, left atrium (LA), aorta, right ventricle (RV) and left ventricular outflow tract (LVOT) were annotated in images from 53 subjects and used for training a fully-convolutional encoder-decoder neural network.

Using cross-validation, the Dice score, mean absolute difference (MAD), and Hausdorff distance were measured for each structure. The results show varying accuracy for the different structures with mean Dice between 0.80 and 0.95, and MAD between 0.9 and 1.8 millimeters. The myocardium and LVOT seems to be most difficult to segment (Dice: 0.80, 0.84, MAD: 1.3, 1.2), while the LV, aorta and RV achieves quite good accuracy (Dice: 0.93-0.95, MAD: 0.9-1.3). Overall, the accuracy of the LV, LA and myocardium seem similar to that achieved in previous studies on images from apical views of the heart. However, more data is needed to increase the robustness of the method and to validate the method further.

I. Introduction

The parasternal long axis (PLAX) ultrasound view of the heart is one of the most important standard views for clinical decision-making and is used for several ultrasound measurements such as wall thickness and diameters of the left ventricle (LV), aorta and LV outflow tract (LVOT). To automate such measurements, accurate image segmentation of this view is crucial.

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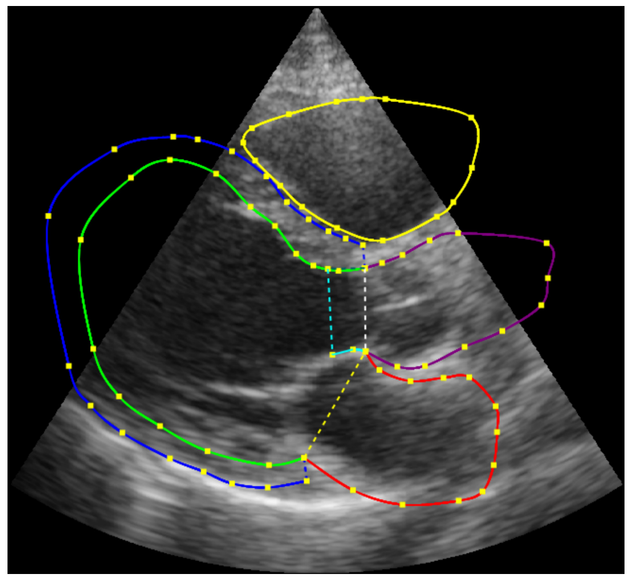

Fig. 1. Screenshot of the web-based PLAX annotation tool developed in Annotation Web. Annotations outside of ultrasound sector were not included. The colored lines are: Green: Endocardium, Blue: Epicardium, Red: Left atrium, Yellow: Right ventricle, Purple: Aorta, Cyan: left ventricular outflow tract, White (dashed): Aorta annulus plane, Yellow (dashed): mitral annulus plane.

While the segmentation of apical views have been widely studied, especially with deep learning in recent years ([1]–[4]), only a few studies on PLAX view segmentation exists. Filho et al. [5] used self-organizing maps to segment a section of the posterior myocardium in the PLAX view. Zhang et al. [2] used convolutional neural networks to segment the LV, left atrium (LA), right ventricle (RV), myocardium and aorta, but not the LVOT from PLAX views.

Another approach to automatic diameter measurements in the PLAX view is to automate the caliper placements directly by predicting their location in the image as done by Gilbert et al. [6]. However, we believe a segmentation approach has the advantage that a segmentation can be used to measure diameters at multiple location instead of just one single diameter measurement, thereby making the measurements more robust.

Measurements can also be estimated directly from the images without performing segmentation using deep learning. Such black-box measurements, however, have very limited explainability, while automatic segmentation-based measurements can be easily visualized, explained and corrected manually if needed.

The goal of this study was to achieve accurate segmentation of the LV, LA, RV, aorta, myocardium and LVOT using a single deep convolutional neural network.

II. Methods

A. Dataset and annotation

In order to efficiently annotate the 6 structures, LV, LA, RV, aorta, myocardium and LVOT, in a standardized way, a specialized PLAX annotation method was developed in the open-source Annotation Web system [7]. Annotation Web enables clinicians to efficiently annotate large amounts of ultrasound recordings in a regular web browser without any manual installation or transfer of data. The PLAX tool enables experts to delineate the endocardial and epicardial borders of the LV, as well as the LA, aorta, LVOT and RV using cubic Hermite splines. The annotator places the control points for the splines, which can be moved afterwards, for each structure. The tool ensures that the mitral valve plane is well defined and connected to the LA, and similarly the aortic valve plane is connected to the aorta and the LVOT region as shown in Fig. 1. Using this annotation tool, two clinical experts annotated ultrasound recordings from 53 subjects from the HUNT population dataset. For each recording, 5 time points of the cardiac cycle were annotated consisting of one end-diastolic (ED) frame, one systolic frame, one end-systolic (ES) frame, one diastolic frame, and finally a new ED frame to mark the end of the cycle.

B. Neural network architecture

The neural network architecture used in this study was the fully-convolutional encoder-decoder network described in [1] which was created for real-time segmentation of apical views. This architecture has six levels and uses max pooling in the encoder and 2×2 repeat upsampling in the decoder. Two 3×3 convolution layers are used at each level, together with ReLU activation. The final layer uses softmax activation. Network input is an ultrasound image of size 256×256 pixels, and the output segmentation has the same size. The network has about 2 million parameters.

Annotations and segmentations outside of the scan sector were excluded, as many of the structures in the PLAX view are only partially shown inside the scan sector. Rotation, intensity, shadow and jpeg augmentations were applied during training to reduce overfitting. The network was trained with batch size 8 and a Dice loss function.

III. Results

The segmentation accuracy was evaluated using 9-fold cross-validation. For each structure, the Dice score, mean absolute difference (MAD) and Hausdorff distance were calculated and are displayed in Table I. For comparison, a row was added to the table with Dice scores of the LV, LA and myocardium for apical two- and four-chamber views from a previous study [4] where a dataset of 500 patients was used. A row with the results from Zhang et al. [2] was also added for comparison. Fig. 2 shows best, median and worst case segmentation results on the entire dataset in terms of Hausdorff distance. Figures 3 and 4 show boxplots of the Dice scores and Hausdorff distances respectively for each structure.

IV. Discussion

The new specialized annotation tool enabled the two experts in this study to efficiently annotate $5 * 53 = 265$ images in a standardized way. This tool is open-source and available on GitHub for others to use for annotating their own data.

Even though this is considered quite a small dataset in the world of deep learning, with augmentations the trained neural networks achieved good accuracy on average in a 9-fold cross-validation. The results in Table I show varying accuracy for the different structures with mean Dice between 0.8 and 0.95, and MAD between 0.9 and 1.8 millimeters. The myocardium and LVOT seems to be most difficult to segment, while LV lumen, aorta and RV achieves quite good accuracy. Still, one should remember that the Dice score is easily affected by the size of the structure. E.g. small structures get a bigger reduction in Dice score for an error of fixed size than a large structure. For instance, the LVOT which is the smallest segmentation region has the lowest Dice score, but has the smallest Hausdorff distance of all structures (Table I). The two boxplots in figures 3 and 4 reveal the large spread and number of outliers for each of the six segmented structures. This shows that the method can be improved in terms of robustness.

Comparing with the work of Zhang et al. [2], their reported Dice scores on the PLAX view are quite similar (see bottom row Table I). However, no information regarding the spread (e.g. standard deviation) of the results were provided, only an average score for each of the structures. Thus, it is difficult to compare the robustness of the methods in these two studies. They used 130 images for training, however it is not stated where in the cardiac cycle the images were taken from nor how many patients were included.

We plan to annotate more data and thereby hopefully improve the accuracy and robustness. Next, we will work towards using this segmentation method to automate measurements such as wall thickness and diameters of the LV, aorta, and LVOT in real-time while scanning.

V. Conclusion

A method for automatic segmentation of the left ventricle, myocardium, left atrium, left ventricular outflow tract, aorta and right ventricle in the parasternal long axis ultrasound view was developed. An accuracy comparable to that of previous

TABLE I
RESULT OF 9-FOLD CROSS-VALIDATION ON THE 53 SUBJECT DATASET WITH DICE SCORE, MEAN ABSOLUTE DIFFERENCE (MAD) AND HAUSDORFF DISTANCE FOR EACH STRUCTURE. THE BOTTOM ROWS CONTAIN SEGMENTATION DICE SCORES ON THE 500 PATIENT APICAL VIEWS CAMUS DATASET [4], AND DICE SCORES FROM PLAX VIEWS IN THE STUDY OF ZHANG ET AL. [2] FOR COMPARISON.

Metric	**Left Ventricle**	**Myocardium**	**Left Atrium**	**Aorta**	**Right Ventricle**	**LVOT**
Dice	0.95 ± 0.03	0.84 ± 0.07	0.91 ± 0.06	0.94 ± 0.03	0.93 ± 0.04	0.80 ± 0.12
MAD (mm)	1.3 ± 0.6	1.3 ± 0.6	1.8 ± 1.1	0.9 ± 0.5	1.2 ± 0.6	1.2 ± 0.7
Hausdorff (mm)	5.9 ± 4.1	7.2 ± 6.0	7.8 ± 6.2	4.6 ± 6.9	5.9 ± 6.1	3.1 ± 2.0
Dice score on apical views ([4])	0.93 ± 0.05	0.86 ± 0.06	0.89 ± 0.09	NA	NA	NA
Dice score on PLAX from Zhang et al. [2]	0.94	0.86	0.93	0.93	0.92	NA

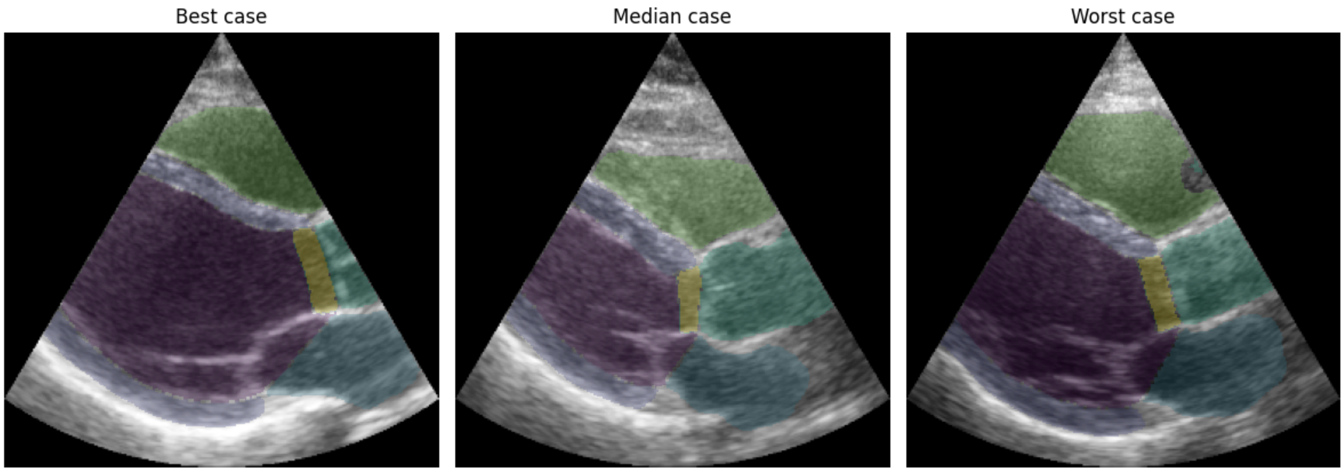

Fig. 2. Best, median and worst case segmentation results of entire dataset according to Hausdorff distance.

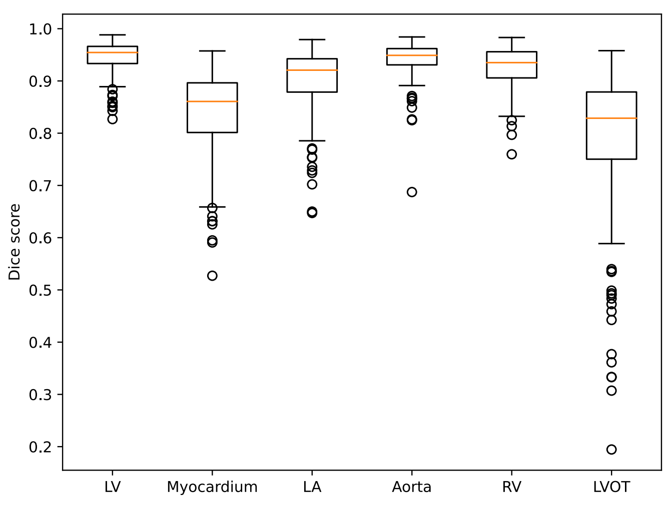

Fig. 3. Boxplot of Dice scores for each of the six structures.

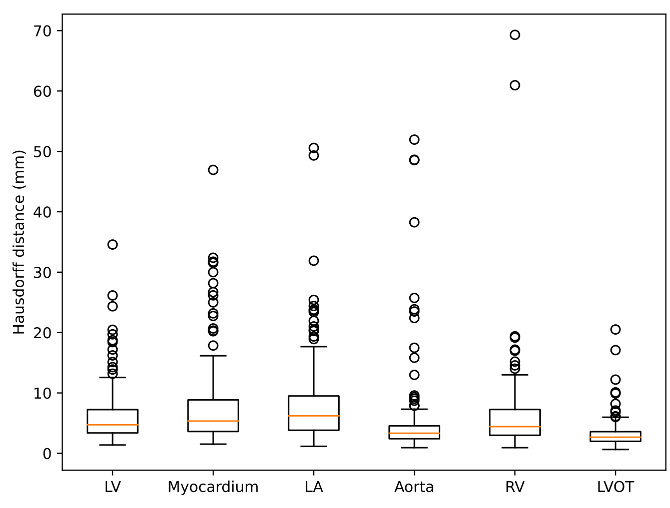

Fig. 4. Boxplot of Hausdorff distances for each of the six structures.

work on segmentation of apical views was achieved. The segmentation will be further used to automate measurements and analysis of the parasternal long axis view.

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