Reaching intra-observer variability in 2-D echocardiographic image segmentation with a simple U-Net architecture

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Introduction

Problem

- Delineation of cardiac structures in 2-D echocardiography
  - ✓ Endocardial contour of the left ventricle (LV-Endo)
  - ✓ Epicardial contour of the left ventricle (LV-Epi)

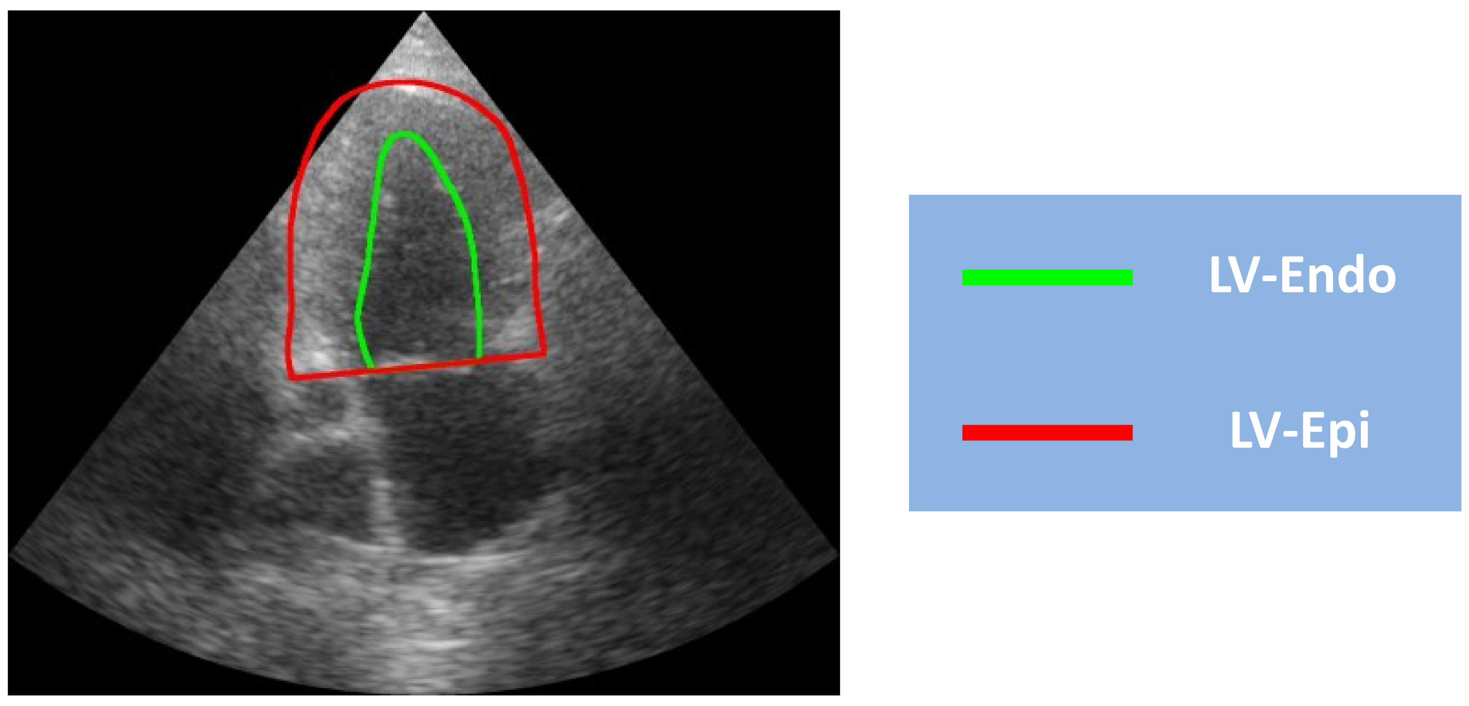


Figure 1: Segmentation of the LV-Endo and LV-Epi on a 2-D echocardiographic image.

GOAL

- Automate the segmentation task using a simple network architecture.
- Reach intra-observer variability on both geometric and clinical metrics.

Methods

CAMUS Dataset

- One of the largest echocardiographic open dataset
- 500 patients
  - ✓ 2000 End-diastole/End-systole Apical 2/4-chamber view images
- 10-fold cross validation

Model #1

- 5-layer U-Net
- 7M parameters

Model #2

- 5-layer U-Net + Deep supervision
- 7M parameters

Model #3

- 5-layer U-Net + Deep supervision + Data augmentation in training
- 7M parameters

Model #4

- 8-layer U-Net + Deep supervision + Data augmentation in training + Patch-wise approach
- 30M parameters

Training Scheme

- Batch size of 2
- 250 iterations per epoch

} To boost the generalization ability

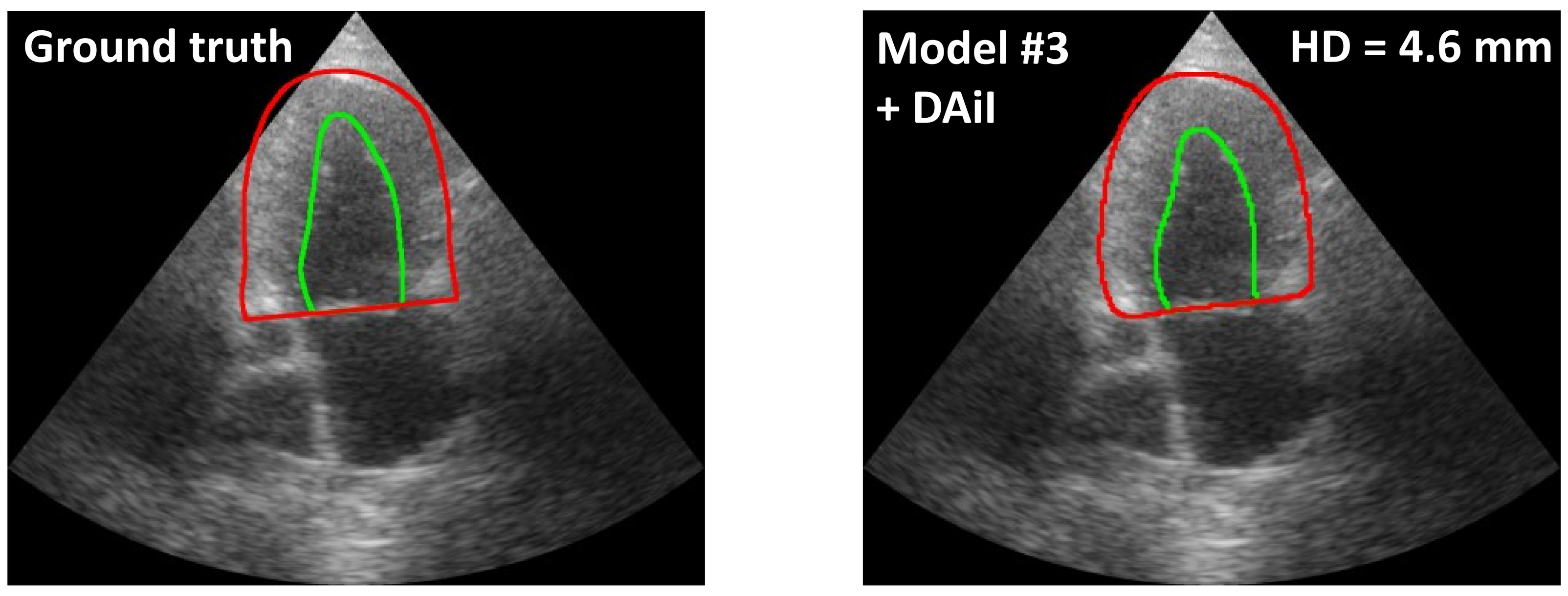
- Input image resized to 256 × 256 pixels for Model #1 to #3
- Model #4 uses a patch size of 1024 × 640 pixels

Model #3 and #4 were evaluated twice, with and without Data augmentation in inference (DAiI).

Results

Methods	LV-Endo & LV-Epi		End-diastolic volume		End-systolic volume		Ejection fraction	
	HD±σ (mm)	ASSD±σ (mm)	Corr	MAE±σ (mL)	Corr	MAE±σ (mL)	Corr	MAE±σ (%)
Intra-observer	4.7 ± 2.0	1.5 ± 0.7	0.978	6.5 ± 4.4	0.981	4.5 ± 3.9	0.895	4.7 ± 4.1
CLAS	4.8	1.5	0.958	-	0.979	-	0.926	-
Model #1	5.4 ± 3.2	1.6 ± 0.9	0.960	8.0 ± 7.3	0.960	6.6 ± 6.0	0.839	5.1 ± 4.3
Model #2	5.3 ± 3.1	1.6 ± 0.9	0.965	8.0 ± 7.4	0.965	6.3 ± 5.6	0.831	5.0 ± 4.7
Model #3	4.8 ± 2.5	1.4 ± 0.7 (**)	0.972	7.2 ± 5.9	0.972	5.7 ± 4.9	0.847	4.9 ± 4.2
Model #3 + DAiI	4.5 ± 2.1 (**)	1.4 ± 0.7 (***)	0.974	6.8 ± 6.1	0.974	5.6 ± 4.8	0.863	4.6 ± 4.0
Model #4	4.5 ± 1.9 (*)	1.4 ± 0.7 (**)	0.972	6.7 ± 5.9	0.972	5.5 ± 5.1	0.84	4.9 ± 4.3
Model #4 + DAiI	4.4 ± 1.9 (***)	1.4 ± 0.7 (***)	0.972	6.6 ± 5.7	0.972	5.5 ± 4.8	0.843	4.7 ± 4.4
nnUNet	4.3 ± 1.9 (***)	1.3 ± 0.6 (***)	0.976	6.5 ± 5.6	0.976	5.3 ± 4.6	0.876	4.4 ± 3.6

Table 1: Comparison of geometric and clinical scores between different models. CLAS: Best reported algorithm on CAMUS dataset.
(HD: Hausdorff distance; ASSD: Average symmetric surface distance; Corr: Correlation; MAE: Mean absolute error)
Statistical test: Left-tailed two sample t-test conducted between each model and intra-observer variability for all metrics, (*): p-value < 0.05; (**): p-value < 0.01; (***): p-value < 0.001.



- From Model #3 onwards, intra-observer variability was reached in terms of geometric metrics.
- High correlation between the estimated and the ground-truth volumes, (*Corr* > 0.97).
- Less accurate volumes and intra-observer variabilities than with CLAS due to temporally inconsistent segmentations.

Conclusions

Keys to reach intra-observer variability

- Data augmentation both in training and inference
- Reduced batch size and number of iterations per epoch to improve the generalization ability

References

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- Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., & Maier-Hein, K. H. (2020). "nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation". Nature Methods, 1-9.
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