Left-Ventricular Volume Estimation in Contrast-Enhanced Echocardiography Using Deep Learning

1st Jieyu Hu
Department of Circulation and Medical Imaging,
Norwegian University of Science and Technology
Trondheim, Norway
jieyu.hu@ntnu.no

2nd Erik Smistad
Department of Circulation and Medical Imaging,
Norwegian University of Science and Technology,
SINTEF Medical Technology
Trondheim, Norway
erik.smistad@ntnu.no

3rd Bjørnar Grenne
Department of Circulation and Medical Imaging,
Norwegian University of Science and Technology,
St. Olavs Hospital
Trondheim, Norway
bjornar.grenne@ntnu.no

4th Espen Holte
Department of Circulation and Medical Imaging,
Norwegian University of Science and Technology,
St. Olavs Hospital
Trondheim, Norway
espen.holte@ntnu.no

5th Håvard Dalen
Department of Circulation and Medical Imaging,
Norwegian University of Science and Technology,
St. Olavs Hospital
Trondheim, Norway
havard.dalen@ntnu.no

6th Lasse Lovstakken
Department of Circulation and Medical Imaging,
Norwegian University of Science and Technology
Trondheim, Norway
lasse.lovstakken@ntnu.no

***Abstract*—Accurate estimation of left ventricular (LV) volume is important for the diagnosis and management of cardiac disease. Contrast-enhanced ultrasound (CEUS) helps improve the visualization of the endocardial borders and is essential for patients with poor image quality. This study aims to develop automated CEUS segmentation and volume estimation, evaluate the inter-observer variability, and compare its accuracy to automated B-mode segmentation for patients with suboptimal image quality.**

We included N=105 patients (492 contrast images) with diverse cardiac conditions to develop a U-Net-based CNN for LV segmentation. We evaluated the inter-observer variability between two annotators, and with an existing B-mode pipeline for reference, we evaluated LV volume for both automated B-mode and CEUS towards the manual CEUS reference for the same patients.

Results showed good accuracy in LV segmentation and volume estimation on CEUS images, with an average Dice score of 0.92±0.04, similar to the inter-observer variability at 0.92±0.03. Compared to manual volume measurements, our automated approach had an average bias of –10.0 mL (-7.0%) and a standard deviation of 17.6 mL (17.3%). A significantly higher standard deviation (26.6 mL, 27.1%) was found for automated B-mode measurements, mainly due to indistinct borders and subpar segmentation.

Our study demonstrates the potential of LV volume estimation using contrast echocardiography images.

***Index Terms*—Echocardiography, Contrast-Enhanced echocardiography, Left ventricular volume, segmentation, deep learning**

I. Introduction

Accurate left ventricular (LV) volume measurements are needed for determining the ejection fraction (EF), an important metric for diagnosing and overseeing cardiac disease. Despite the advancements in image quality, a significant number of patients still yield suboptimal images, and often necessitate the application of ultrasound contrast agents to improve heart visualization [1].

Contrast-enhanced ultrasound (CEUS) markedly enhances the visualization of the endocardial borders and improves the clarity and reliability of image interpretation. Notably, the inter- and intra-observer variability of EF measurements obtained from CEUS has demonstrated greater consistency than those from non-contrast echocardiography and is comparable to Magnetic Resonance Imaging (MRI) [2].

Manual measurements of LV volume are time-consuming and prone to the annotators' expertise and available time in the busy echo laboratory. To battle these challenges, image analysis approaches have been proposed to automatize the measurement process, and in recent years deep learning based approaches have shown the ability to fulfill this task, aiming to reduce the variability and facilitate the workflow [3]–[5]. There are also some studies focused on myocardial function [6] and myocardial segmentation [7], [8] for CEUS.

In this work, we develop methods for automated CEUS segmentation and volume estimation and compare its accuracy

Author accepted manuscript version of the publication in
2023 IEEE International Ultrasonics Symposium (IUS)
Published version: https://doi.org/10.1109/IUS51837.2023.10308094

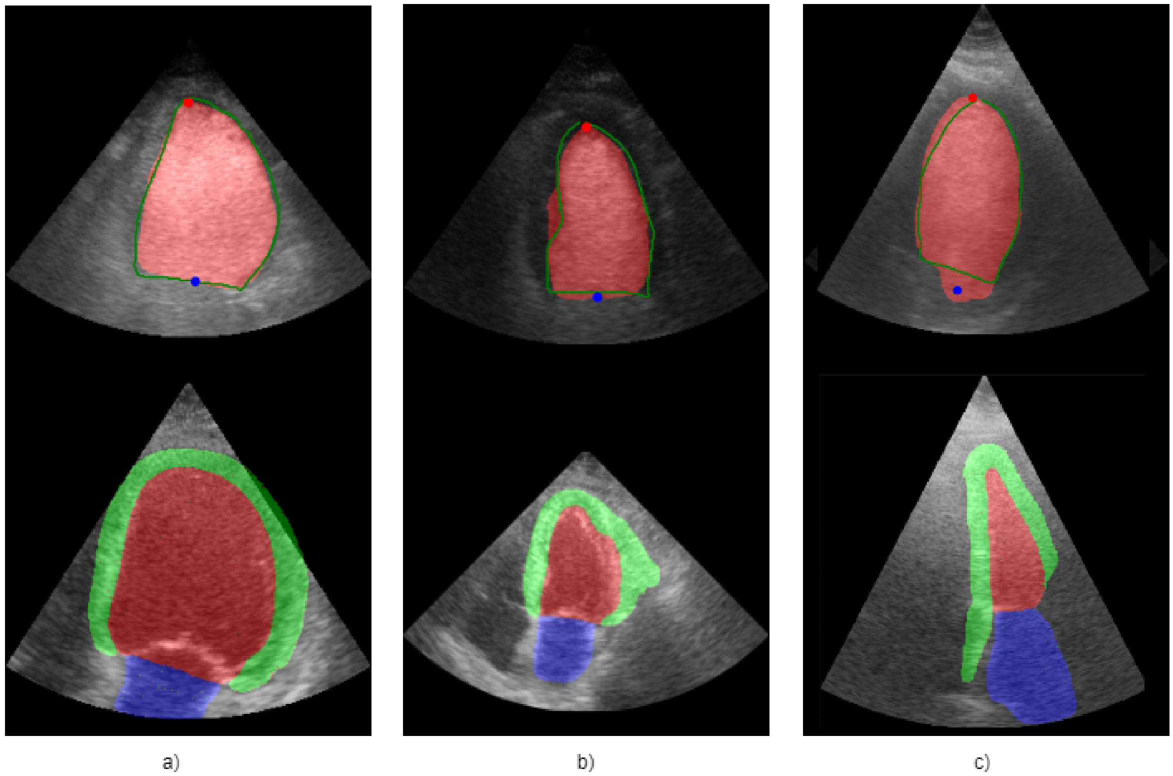

Fig. 1. Representative examples for good, average, and poor segmentations in CEUS and B-mode images for the same patients (Upper: CEUS, LV prediction masks in red and reference contours in green; Lower: B-mode, LV prediction masks in red, myocardium in green and left atrium in blue)

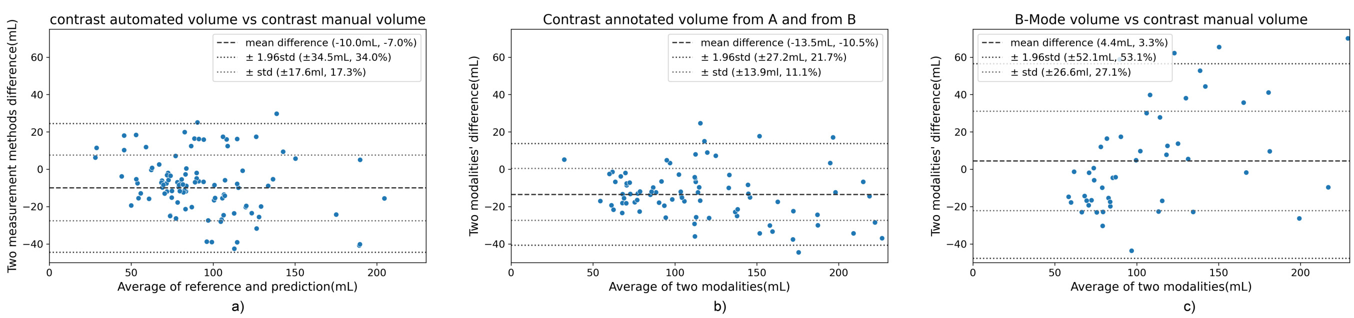

Fig. 2. Bland-Altman plots for LV volume estimations comparisons: a) Between our proposed automated method and manual measurements for CEUS. b) Inter-observer comparison of manual measurements from CEUS. c) Between results from the B-mode automated pipeline and manual measurements in CEUS for the same patient.

to manual measurements, inter-observer variability, as well as automated B-mode segmentation for patients with suboptimal image quality.

II. Methods

A. Dataset and materials

We analyzed 493 CEUS recordings obtained from N=105 patients, comprising both apical 2-chamber (A2C) and 4-chamber (A4C) views, from a Norwegian hospital database. The annotations were contributed by a team of clinical experts. For each recording, the annotations were made by two distinct clinical experts for 2 to 4 frames. This included the end-diastole (ED) frame, one systolic frame, the end-systole (ES) frame, and an additional ED frame. The ED and ES frames were selected before mitral valve closure as recommended in [9]. Of the initial 105 patients, B-mode recordings were available for 72 patients, captured during the same examination as the contrast recording.

For analysis, the dataset was partitioned into training, validation, and testing subsets, with distributions of 70%, 10%, and 20%, respectively. This dataset underwent a 5-fold cross-validation for evaluation, separated on a patient level.

B. Network architecture

To enable real-time performance when used bedside, we aimed to find a compromise between speed and accuracy, and therefore used a light-weight U-Net as described in [3], which has 1.9 M parameters, but was shown to have very similar performance as larger networks. The architecture consists of Convolutional2D, ReLU, and max pooling layers. The encoder has 2D convolutional layers with channel numbers as [32, 32, 64, 128, 128], reaching an 8x8 latent space with 128 channels, and the decoder is characterized by channels ([128, 128, 64, 32, 16]), using up-sampling2D layers. Each upsampling step is concatenated with the corresponding encoder layer with skip connections to retain high-resolution features. The same network architecture was used in both B-mode and CEUS segmentation.

C. Inter-observer variability

In echocardiographic studies, our reference measurements are made from subjective annotations, an absolute 'ground truth' for LV segmentation is not available. Assessing inter-observer variability is then important and provides a benchmark measure when evaluating the LV segmentation in a clinical context. For a subset of 85 recordings from 33 patients, we compared the manual contrast annotations made by two distinct annotators. The level of agreement was quantified using the Dice score, while the volume differences were computed from the contours using the method of disc summation (MOD).

D. Automated B-mode volume estimation

An automated LV volume estimation pipeline for B-mode images was proposed in our previous work [5]. For an input B-mode recording, a timing network identifies the ED and ES frames, then the segmentation network predicts the contour. Finally, the volume was calculated based on the MOD.

III. Results

A. Segmentation Accuracy and Volume Estimation

The results showed good accuracy for segmentation of the LV and for volume estimation using CEUS images. The approach yielded an average Dice score of 0.92 ± 0.04, which corresponds to a very high overlap between the predicted and reference masks. No significant differences were observed between ES/ED frames and those outside the ES/ED, further attesting to the model's robustness. To validate the consistency of our approach, we further evaluated the network on a set of 120 frames from 23 patients in our dataset. These frames were annotated by a different annotator, which was not used in the training set. The CEUS segmentation network maintained an average Dice score of 0.92 ± 0.04, which suggests that the model agrees with both annotators. Figure 1-a, -b, and -c displays representative examples for good, average, and poor segmentation in CEUS and B-mode images for the same patients.

For the volume estimation, we found an average bias of -10.0 mL (-7.0%) and a standard deviation of 17.6 mL (17.3%). The standard deviation can be attributed to two main factors: firstly, the segmentation errors resulting from the network; secondly, the reference data were obtained from multiple annotators, which introduces a potential variability in the reference itself. Figure 2-a shows a Bland-Altman plot comparing our proposed method for estimating LV volume to manual measurements for CEUS.

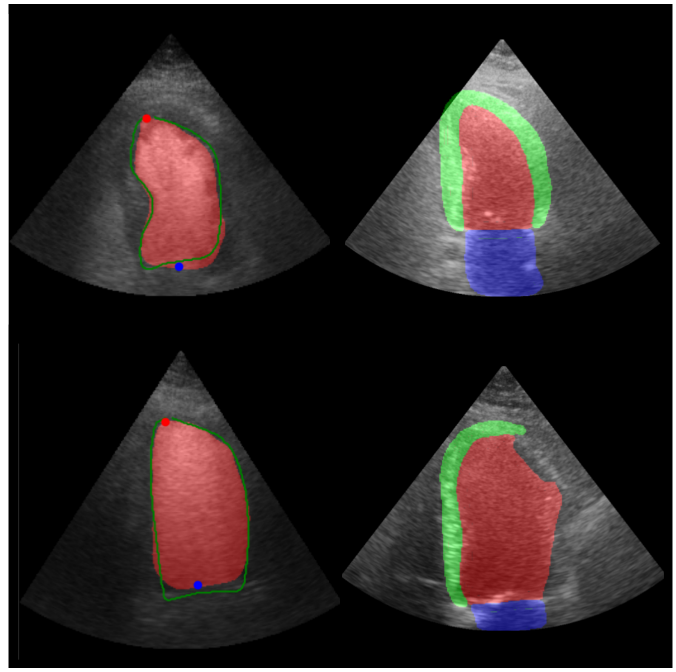

Fig. 3. Cases where B-mode failed to segment accurately endocardium, but the contrast segmentation network managed on CEUS. Each row represents a segmentation result from the same patient for CEUS and B-mode.

B. Inter-observer Variability

The inter-observer variability was evaluated using the Dice score between annotation masks from two annotators for 85 frames from 23 patients. The analysis revealed a Dice score of 0.92 ± 0.03, indicating substantial agreement in the manual contour tracing of the endocardium. In terms of volume estimation, a bias was observed. The average volume difference between the two annotators was –13.5mL (-10.5%). It's also noteworthy that the standard deviation associated with this volume estimation was 13.9mL, 11.1% of the estimated volume. This finding reveals that the inter-observer variability is comparable to the results of our automated segmentation algorithm. It suggests that our segmentation tool offers a reliable means of LV volume estimation despite minor variations in the manual annotations. Figure 2-b presents the Bland-Altman plot comparing manual measurements from one annotator to another.

C. Comparison to B-mode Automated Pipeline

When comparing LV volume from the same patient using automated segmentation in B-mode to manual measurements in CEUS, we obtained a mean bias of 4.4 mL, representing

3.3% of the volumes, and a standard deviation of 26.6 mL (27.1%). The higher standard deviation could be due to indistinct borders and variability in segmentation. For example, we noticed differences in shape between B-mode and CEUS recordings from the same patient, as shown in the first case of Figure 1. Figure 2-c depicts the Bland-Altman plot, providing a visual representation of the comparison. Figure 3 shows examples where the B-mode images are unclear, while the contrast segmentation network managed to segment accurately on CEUS.

IV. Discussion

Our study shows that reliable left ventricular (LV) volume estimation can be obtained in contrast-enhanced echocardiographic images. The high Dice scores achieved in our study attest to the robustness of the automated algorithms for LV segmentation in contrast images but should be further evaluated in a larger data material. The observed bias and standard deviation point to potential improvement for future work.

Evaluating inter-observer variability helped to better understand the current acceptance in clinical practice, and thus provides an important benchmark for the automated approach. Our method obtained a Dice score consistent with the inter-observer variability, while the standard deviation of our volume estimations was higher than the inter-observer variability, the two are still comparably close, as shown in the Bland-Altman (Figure 2).

When comparing the automated LV volume acquired from B-mode to manual measurements, the standard deviation is notably high, especially for larger volumes. In future work, MRI could be used as the reference to assess the performance of both B-mode and CEUS images.

Limitations of the current work include the use of a relatively small dataset from a single center and from a single vendor. Future work should evaluate the proposed approach using more data, from multiple vendors and sites to prove its applicability in general.

V. Conclusion

Our study demonstrates the potential of LV volume estimation using contrast echocardiography images. Offering automated LV volume estimation for both CEUS and B-mode images could enhance the robustness of results and broaden its applicability in clinical practice.

References

[1] Medical Advisory Secretariat. Use of contrast agents with echocardiography in patients with suboptimal echocardiography: an evidence-based analysis. Ont Health Technol Assess Ser. 2010;10(13):1-17.

[2] Senior R, Becher H, Monaghan M, Agati L, Zamorano J, Vanoverschelde JL, et al. Clinical practice of contrast echocardiography: recommendation by the European Association of Cardiovascular Imaging (EACVI) 2017. Eur Heart J Cardiovasc Imaging. 2017;18(11):1205-1205af.

[3] Leclerc S, Smistad E, Pedrosa J, Ostvik A, Cervenansky F, Espinosa F, et al. Deep Learning for Segmentation Using an Open Large-Scale Dataset in 2D Echocardiography. IEEE Trans Med Imaging. 2019 Sep;38(9):2198-2210.

[4] Asch FM, Poilvert N, Abraham T, Jankowski M, Cleve J, Adams M, et al. Automated Echocardiographic Quantification of Left Ventricular Ejection Fraction Without Volume Measurements Using a Machine Learning Algorithm Mimicking a Human Expert. Circ Cardiovasc Imaging. 2019 Sep;12(9).

[5] Smistad E, Østvik A, Salte IM, Melichova D, Nguyen TM, Haugaa K, et al. Real-Time Automatic Ejection Fraction and Foreshortening Detection Using Deep Learning. IEEE Trans Ultrason Ferroelectr Freq Control. 2020 Dec;67(12):2595-604.

[6] Guo Y, Du G, Shen W, Du C, He P, and Siuly S, Automatic myocardial infarction detection in contrast echocardiography based on polar residual network. Comput Methods Programs Biomed. 2021 Jan;198:105791.

[7] Li M, Zeng D, Xie Q, Xu R, Wang Y, Ma D, et al. A deep learning approach with temporal consistency for automatic myocardial segmentation of quantitative myocardial contrast echocardiography. Int J Cardiovasc Imaging. 2021;37:1967–1978.

[8] Zeng D, Li M, Ding Y, Xu X, Xie Q, Xu R, et al. Segmentation with Multiple Acceptable Annotations: A Case Study of Myocardial Segmentation in Contrast Echocardiography. In: Information Processing in Medical Imaging. IPMI 2021. Lecture Notes in Computer Science, vol 12729. Springer, Cham.

[9] Lang RM, Badano LP, Mor-Avi V, Afilalo J, Armstrong A, Ernande L, et al. Recommendations for cardiac chamber quantification by echocardiography in adults: an update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging. J Am Soc Echocardiogr. 2015 Jan;28(1):1-39.e14.