

Real-time AI-empowered echocardiography in Intensive Care Units

Miguel Xochicale

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1 Introduction

In the last decades the use of echocardiography is a crucial clinical approach in Intensive Care Units (ICU) because of the advances of smaller US clinical devices, US image quality and its real-time capabilities to access cardiac anatomy [Feigenbaum, 1996,

Vieillard-Baron et al., 2008, Singh and Goyal, 2007, Campbell et al., 2018]. However, despite the previous advances there is still challenges on finding standard views from experienced sonographers that sometimes such quantifications are qualitative and subjective [Feigenbaum, 1996]. Similarly, automatic quantification of left ventricular ejection fraction (LVEF) is still challenging at the point of care due to variation of protocols, skills levels [Field et al., 2011] and the nature of providing feedback on real-time [Liu et al., 2021].

2 AI-empowered methods

2.1 Image Quality Assessment

[Labs et al., 2021] considers chamber clarity, depth gain, on-axis attributes, apical foreshortenedness.

2.2 Clustering techniques

Zhang et al. mentioned that 23 view classes from 7168 individually labeled videos that were classified with a 13-layer CNN to then viewed with the use of t-Distributed Stochastic Neighbor Embedding [Zhang et al., 2018]. Kusunose et al. mentioned that other authors have reached an accuracy of 91-94 for 15-view classification while their work mentioned a 98.1 accuracy for five-predefined views [Kusunose, 2021].

2.3 Auto-encoders

Laumer et al. proposed a novel autoencoder-based framework to learn human interpretable representation of cardiac cycles from cardiac ultrasound data [Laumer et al., 2020],

Ouyang et al. presented echo-dynamic dataset as the first annotated medical video dataset with 10,036 videos. Additionally, authors reported the use of three CNN architectures varying filters in each layer to assess ejection fraction to near-expert performance. It is worthwhile to note that authors got best performance with mean absolute error of 5.44% using clip length of 16 and frame rate of 4. Such error is near-expert performance as they can get 4-5% for skilled echocardiographers in controlled settings [Ouyang et al., 2019].

Ghorbani et al. applied convolutional neural networks of cardiac ultrasound to identify local structures, estimate cardiac function and predict pathologies. Their deep learning model, EchoNet, can identify up to 10 cardiac biometrics which results in decreasing repetitive task in the clinical flow, provide interpretation to less experienced cardiologist, and predict phenotypes. This work can predict age, sex, weight and height from echocardiogram images. Authors mention that the increase of data does not improve model training. The homogenisation of cardiac views prior to model training improved training speed and computation time [Ghorbani et al., 2020]

2.4 Segmentation

With the challenges of limited sampling of cardiac cycles and the considerable inter-observer variability, Ouyang et al. presented a CNN model with residual connections and spatiotemporal convolutions that surpass human performance of segmentation of left ventricle, estimation of ejection fraction and assessment of cardiomyopathy. Their model

reached Dice similarity coefficient of 0.92, predicts ejection fraction with mean absolute error of 4.1% and classify heart failure based on reduced ejection fraction [Ouyang et al., 2020].

2.5 Contrastive Learning

Methods on Contrastive Learning apparently address the challenge of required labelled data to identify pathologies in the images of detect certain cardiac views. Recently, Chartsias et al. use contrastive learning to train imbalanced cardiac datasets and they compared a naive baseline model to achieve a F1 score of up to 26% [Chartsias et al., 2021] Saeed et al. recently investigated contrastive pretraining to improve the DeepLabV3 and UNET segmentation networks of cardiac structures in ultrasound imaging. Authors showed comparable results with state-of-the-art fully supervised algorithms and presents better results compared to EchoNet-Dynamic and CAMUS [Mohamed et al., 2021]

2.6 AI-guided US imaging

Near-human quantification of LV and EF has been investigated, however Asch et al. pointed out that boundary identification is prone to errors when low quality images or artifacts are used Asch et al. pointed out that data and materials were not publicly available and they made use of AutoEF by CaptionHealth Co. Authors used a database of 50000 echocardiography datasets over a period of 10 years of various clinical US systems. The training datasets included multiple views of 2 and 4-chamber views and LV EF values where clinicians use conventional methods (biplane Simpson technique) [Asch et al., 2019].

Asch et al. [Asch et al., 2021].

Hong et al. reported the evaluation of image quality assessment to demonstrate that AI can recognise nuances of varying image during scanning [Hong et al., 2021]

Narang et al. reported the acquisition of 10 echocardiography views of novice users using deep-learning-based software [Narang et al., 2021]. Narang et al. mentioned that CNN were used with stacks of networks and transformations. The AI-guided software consists of three estimates: (1) quality image assessment, (2) "6-dimensional geometric distance with position and orientation between the current probe location and the location anticipated to optimise the image"; and (3) corrective probe manipulation. [Narang et al., 2021] Authors mention that algorithms do not use trackers, fiducial marks or additional sensors to make guide estimations [Narang et al., 2021].

Cheema et al. reported the use of AI-enabled guidance to sonographer which was created from the use of 500000 hand movements. Cheema et al. reported that such feature was the first cardiac authorised by Food and Drug Administration in 2020. Authors presented five cases COVID-19 intensive care unit (ICU) to illustrate "how decision making affect in patient care" and how the use of AI-enabled provided real-time guidance to acquire desired cardiac UL with the steering of user's transducer position and hand movement [Cheema et al., 2021].

2.7 Annotation tools

Recently, Smistad et al. 2021 published the first web-based tool for annotation of medical ultrasound video to do image classification, segmentation, bounding box and landmark annotation [Smistad et al., 2021c]. AW tool has been used since 2016 at different projects to perform segmentation of the left ventricle, cardiac view classification, and detection of nerves and blood vessels [Smistad et al., 2021c].

2.8 3D US

Considering that 3D left ventricle (LV) can provide full volume information of the heart than 2D echocardiography, Dong et al. proposed a real-time framework VoxelAtlasGAN that made use of cGAN [Dong et al., 2018]. VoxelAtlasGAN framework with mean surface distance of 1.85 mm, mean hausdorff distance of 7.66mm, mean dice 0.953 and correlation of EF 0.918 and the mean inference speed of 0.1 s demonstrated potential for clinical application [Dong et al., 2018]. Dong et al. in 2020 applied transformers to obtain translations parameters that passed to VoxelAtlasGAN [Dong et al., 2020]. AtlasNET framework ended up with "mean surface distance, mean hausdorff surface distance, and mean dice index were 1.52 mm, 5.6 mm and 0.97 respectively" [Dong et al., 2020]

Smistad et al. 2021 made use of CETUS 3D US LV segmentation dataset and weakly annotated datasets for real-time 3D left ventricle segmentation and estimation of ejection fraction [Smistad et al., 2021b]. Authors presented the impact of pre-training that resulted in an improvement of Dice score. It is important to note that VoxelAtlasGAN and AtlasNet by Dong et al. presented a better dice score. Smistad et al. 2021 concluded that a limited labelled datasets of 15 patients demonstrate good accuracy and models were able to generalise to new data and ultrasound scanners [Smistad et al., 2021b].

2.9 Transformers

2.10 Others

Rank-2 non-negative matrix factorization [Yuan et al., 2017] to generate End-Systole and End-Diastole for apical 4 view. Recently Robust Non-negative Matrix Factorization seems to be implement low-computation cost algorithms to automatic segment mitral valve [Dukler et al., 2018].

Salte et al. classified three standard apical views from data of 200 patients to perform strain measurements with deep learning architectures [Salte et al., 2021]. Salte et al. made use of the work [Østvik et al., 2021] inception and dense network were used to classify, recurrent network to detect event timing and u-net-based network for segmentation [Salte et al., 2021]. Authors compared the results with the commercially available semiautomatic speckle-tracking software (EchoPAC v202), reporting evidence of the comparable GLS measurements to other semiautomatic methods [Salte et al., 2021].

3 Spatiotemporal Features

3.1 Deep Residual Learning

Ouyang et al. benchmarked various spatiotemporal convolutions (Sports-1M, Kinetics, UCF101, and HMDB51) [Ouyang et al., 2019] based on deep residual learning (He et al. 2015 and Tran et al. 2018).

3.2 LSTM

Recently, Smistad et al. 2021 presented the use of LSTM to address the single frame segmentation of end-diastole and end-systole to address segmentation flickering and reduce temporal errors [Smistad et al., 2021a]. One of the challenges is architecture design to add ConvLSTMs to which authors experiment at the location at the endocenter, decoder, last

layer and in bottleneck, to which authors mention that the use of the ConvLSTM layers in the encoder of the temporal NN gave the best results [Smistad et al., 2021a]. Authors mention that interpolation of the annotations of the entire cardiac cycle did not capture the complex motion with the use of 7 frames to which they suggest to use advanced speckle tracking such as Echo-PWC-Net [Østvik et al., 2021].

4 Open datasets

4.1 2D echocardiography

4.1.1 CAMUS

CAMUS dataset, Cardiac Acquisitions for Multi-structure Ultrasound Segmentation, was published in 2019 by Leclerc et al. 2019 [Leclerc et al., 2019]. CAMUS is the largest publicly-available and fully-annotated dataset of two and four-chamber acquisition from 500 patients. Datasets is categorised in image quality (good, medium, and poor) and LV_{EF} ($\leq 45\%$ (pathological risk), $\geq 55\%$, else). The dataset reflects a daily clinical practice data where images quality and a range of pathological cases. Dataset was collected with GE Vivid E95 ultrasound scanners (GE Vingmed Ultrasound, Horten Norway) with a GE M5S probe (GE Healthcare, US). The datasets is available electronically to download at <https://www.creatis.insa-lyon.fr/Challenge/camus/>.

4.1.2 EchoNet-Dynamic

Ouyang et al. published a large datasets of 10,030 annotated echocardiogram videos [Ouyang et al., 2019, Ouyang et al., 2020]. Datasets were labelled left ventricle volumes by sonographers to calculate ejection fraction. Datasets were acquired by skilled sonographers using iE33, Sonos, Acuson SC2000, Epiq 5G or Epiq 7C ultrasound machines and processed images were stored in a Philips Xcelera system. The datasets is available electronically to download at <https://echonet.github.io/dynamic/index.html#dataset>.

4.2 3D echocardiography

4.2.1 CETUS

CETUS dataset, Challenge on Endocardial Three-dimensional Ultrasound Segmentation, was published in 2016 by Bernard et al. [Bernard et al., 2016]. CETUS contains 45 sequences of 3D ultrasound volumes of one cardiac cycle from 45 patients were equally acquired from three different hospitals with three different brands of ultrasound machines (GE, Philips and Siemens) [Bernard et al., 2016]. The studied population of 45 participants is composed of 15 healthy subjects, 15 with previous myocardial infarction, 15 with dilated cardiomyopathy. The datasets is available electronically to download at https://www.creatis.insa-lyon.fr/EvaluationPlatform/CETUS/about_database.html.

5 Methods and materials

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