Real-time AI-empowered echocardiography in Intensive Care Units

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Contents

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]. Despite the previous advances, the current pratcies of clinical ultrasound are user and patient dependant which can lead to diagnostic uncercaintiy. Some of these challenges are related to the finding standard views from experienced sonograpehrs that sometimes such quantifcations are qualitative and subjective [Feigenbaum, 1996].

Further challenges are in "low- and middle-income countries (LMICs)" where limited number of expert clinitians can perform such US imaging analysis.

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 proving feedback on real-time [Liu et al., 2021]. Studies in the management of tetanus in low- and middle-income countries (LMICs) emphasised the importance and requirement of duration of hospitalisation and mechanical ventilation requirements [Hao et al., 2021].

Ghorbani et al. in 2020 reported the first deep learning model to predict age, sex, weight and height from echocardiogram images and make use of such models to understand how models predicts systematic phenotypes which are difficul for human interpreters [Ghorbani et al., 2020]. Authors trained CCN models with 2.6 million echocardiogram images from 2850 patients with the extraction of labels local strucutre and features (e.g. pacemaker lead, dilation of left atrium, hypertrophy for left ventricular) and labels from the physician-interpreted report (e.g, catheters, pacemaker, and defibrillator leads).

2 Challenges in Echochardiography in the ICU

The following points summaries various challenges of performing echochardiography [Khamis et al., 2017

1. Intra-view variability of echochardiograms (physiological variations of subjects and adquisition parameters) and sonographer expertise,
2. Inter-view similarity of echochardiograms (similar views of valve motion, wall motion, left ventricle, etc) and transducer position during adquision,
3. Redudant information in the clinical echo system (icons, date, frame rate, etc).

Zhang et al. mentioned the challenges of having A4c view with partially osbcured left atrium which might not help to compute left atrial volumes but would help to estimate LV volumes, mass, ejection and longitudinal strain [Zhang et al., 2018].

3 AI-empowered methods

3.1 Image Quality Assessment

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

3.2 Classification of echochardiograms

Khamis et al. considered 309 clinical echocardiogram of apical viewss which were visiually classified and labelled by two experts into three classes: 103 a2c views, 103 a4c views and 103 alx views to then applied spatio-temporal feature extraction (Cuboic Detector) and supervised learning dictionary (LC-KSVD) resulting in an overall recognition rate of 95% [Khamis et al., 2017].

Zhang et al. performed view classification with 277 echochardiograms to create a 23-class models (including a4c no occlusions, a4c ocluded LA, a4c ocluded LV, etc) using 13-layer CNN with 5-fold cross-validation for accuracy assement and resulting in 84% for overall accuracy where challenges for partial obscured LVs for a2c, a3c and a4c [Zhang et al., 2018]. Similarly, Zhang et al. applied U-net to segment 5 views (a2c, a3c, a4c, PSAX, PLAX) and CNN model for 3 chardiac disseases with the use of A4c captuting most of the information for the diseases.

3.3 Clustering techniques

Zhang et al. mentioned that 23 view classes from 7168 individually labeled videos that ware classified with a 13-layer CNN to then viewed with the use of t-Distributed Stochastic Neighbor Embedding [Zhang et al., 2018]. Zhang et al. made use of 277 echochardiograms collected over a 10-year period for view classification. Kusunose et al. mentioned that other authors have reached an acciracy of 91-94 for 15-view classification while their work mentioned a 98.1 accuracy for five-prederminted views [Kusunose, 2021].

3.4 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 arquitectures varing 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 lenght of 16 and frame rate of 4. Such error is near-expert perfonace as they can get 4-5% for skilled echochardiographers in cotrolled 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 phenotipes. This work can predict age, sex, weight and heigth from echocardiogram images. Authors mention that the increase of date does not improve model traiining. The homogenisation of cadiac views prior to model training improved training speed and computaitonla time [Ghorbani et al., 2020]

3.5 Segmentation

With the challenges of limited sampling of cardiac cycles and the considerable interobserver variability, Ouyang et al. presented a CNN model with residual connections and spatiotemporal convolutions that surpase human performance of segmentaion of left ventricle, estimation of ejection fraction and assessment of cardiomyophaty. Their model reached Dice similarity coefficient of 0.92, predicts ejection fraction with mean absolute error of 4.1% and clasify heart failure based on reduced ejection fraction [Ouyang et al., 2020].

Meyer et al. used Prominence Iterative Dijkstra's algorithm (ProID), based on the identification of ventricle boundaries with iterative Dijkstra's algorithm, for ventricle detection and volumen estimation [Meyers et al., 2021]. ProID employs echochardiogram-specific cost-matrix to address contrast-to-noise and resolution limitations problems [Brindise et al., 2020

3.6 Contrastive Learning

Methods on Contrastive Learning apparently address the challenge of required labelled data to identify pathologies in the images of dectect 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 structers 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]

3.7 AI-guided US imaging

Near-human quantification of LV and EF has been investated, however Asch et al. pointed out that buoundary 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 databes of 50000 echocardiography datasets over a period of 10 years of varios clinical US syustems. The training datasets included multiople views of 2 and 4-chamber views and LV EF values where clininias use conventional methods (biplane Simpson technique) [Asch et al., 2019].

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

Hong et al. reported the evalition of imagin quality asssement to demostrated that AI can recognise nuaces of varing imaing during scanning [Hong et al., 2021]

Narang et al. reported the adquisiton of 10 echocardiography views of novices users using deep-learning-based software [Narang et al., 2021]. Narang et al. mentioned that CNN were used with stacks of networks and transofrmations. The AI-guided software consist of three estimates: (1) quality image assement, (2) "6-dimensional geometric distance with postion and orientation between the current probe location and the locattion 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 made guide estimations [Narang et al., 2021].

Cheema et al. reported the use of AI-enabled guidance to sonoographer which was created from the use of 500000 hand movmentes. Cheema et al. reported that such feature was the first cardiac aotorhisedd by Food and Drug adminstation in 2020. Authors presented five cases covid-19 intensive care unit (ICU) to illustrate "how desition making affect in patient care" and how the use of AI-enabled provided real-time guidance to acquire desired cardiac UL with the sterting of user's transducer position and hand movevemnt [Cheema et al., 2021].

3.8 3D US

Considering that 3D left ventricle (LV) can provide full volume information of the hearth than 2D echordaiography, 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 demostrated potential for clinical applicaiton [Dong et al., 2018]. Dong et al. in 2020 applied tranformers to obtain translations parematers that passed to VoxelAtlasGAN [Dong et al., 2020]. AlasNET 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 annorated datasets for real-time 3D left ventricle segmentation and estiomation of ejection fraction [Smistad et al., 2021b]. Authors presented the impact of pre-training that resulted in an improvement of Dice score. It is imporant to note that VoxelAlasGAN and AtlasNet by Dong el al. presented a better dice score. Smistad et al. 2021 concluded that a limited labelled datasets of 15 patiens demostrate good accuracy and models were able to generalise to new data and ultrasoudn scanners [Smistad et al., 2021b].

3.9 Transformers

Rubin et al. noted the shortcoming of transformers of extensive compation for training that lead to use detection transformer (DETR) which make smaller models reducing model size and acceleration inference [Rubin et al., 2021]., Rubin et al. considered the detection of needles in real-time ultrasound video sequences 12,000 needle insertions (2 million of individual frames). Video sequences (up to 60 sec in time) were divided into 30-frame clips (1 sec in time).

Reynaud et al. 2021 adapted Residual Autoencoder Network and BERT model to predict ejection fraction which is different from what is commonly use with segmentation methods [Reynaud et al., 2021]. Reynaud et al. applied their model to Echonet-Dynamic dataset which only constains 10,030 echocardiograms containing one to three or more cadiac cycles with only cardiac cycle with ES and ED annorations. Due to the distribution between ES and ED, the sequence legnth was 128 frames. As Echonet-Dynamic datasets contains unlabelled ES and ED, Reynaud et al. applied (a) Guided Random Sampling (b) Mirroring Methods. Code is available at `https://github.com/HReynaud/UVT`.

3.10 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 peformf straing measurements with deep learning arquitectures [Salte et al., 2021]. Salte el al. made use of the work [Østvik et al., 2021] inception and dense network were used to clasity, recurrent network to detect event timing and u-net-based network for segmentation [Salte et al., 2021]. Authors compared the results with the commenrially avaible semiautomatic speckle-tracking software (EchoPAC v202), reporting evinde of the comparable GLS measurmentes to other semiatuomatic methods [Salte et al., 2021].

4 Spatiotemporal Features

4.1 Deep Residual Learning

Ouyang et. al. benmarked 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).

4.2 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 fricklering and reduce tmeporal errors [Smistad et al., 2021a]. One of the challenges is architecture design to add ConvLSTMs to whcih authors experiment at the location at the endocer, decoder, last layer and in bottlenet, to which authors mentiosn 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 annorations of the entire cardiac cycle did not captured the complex motion witht he use of 7 frames to which they suggest to use advance speckle tracking such as Echo-PWC-Net [Østvik et al., 2021].

Lu et al. made use of U-Net and LSTM to model Left Ventricular cardiac motion [Lu et al., 2020].

5 Tools and open datasets

5.1 Annotation tools

Recently, Smistad et al. 2021 published the first web-based tool for annoration of medical ultrasound video to do image classification, segmentation, bouding 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 vesels [Smistad et al., 2021c].

5.2 Open datasets

5.2.1 CAMUS (2D US)

CAMUS dataset, Cardiac Acquisitions for Multi-structure Ultrasound Segmentation, was publised in 2019 by Leclerc et al. 2019 [Leclerc et al., 2019]. CAMUS is the largest publicy-available and fully-annotated dataset of two and four-chamber adquistion from 500 patients. Datasets is cathegorised in image quality (good, medium, and poor) and LV_{EF} ($\leq$ 45% (phatological risk) , $\geq$ 55%, else). The dataset reflects a daily clinical practice data where images quality and a range of phatological 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/`.

5.2.2 EchoNet-Dynamic (2D US)

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`.

5.2.3 CETUS (3D US)

CETUS datset, 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 infartation, 15 with dilated cardiography. The datasets is available electronically to download at `https://www.creatis.insa-lyon.fr/EvaluationPlatform/CETUS/about_database.html`.

5.3 Synthetic cardiac motion

Alessandrini et al. in 2018 published "a open access library of 105 synthetic sequences encompassing i) healthy and ischemic motion patterns, ii) most common apical probe orientations iii) vendor specific image quality from 7 different systems" [Alessandrini et al., 2018]. See previuos work of Alessandrini et al. in 2015 [Alessandrini et al., 2015].

6 Methods and materials

7 Datasets

7.1 VITAL

86 patients of average age (?) ? male and ? female were collected by four clinicians of ? years of expience collected echochardiography datasets. The collection was done with the clinical device GE Venue Go machine and GE convex probe C1-5-D.

7.2 Ethics statement

This study was approved by ... and the ethics committee ... All participants gave written informed consent to participate before enrollment.

8 Potential future work

2D velocity vector fields of flow blow can help to detect abnormal flow patterns as done in fetal and neonatal echochardiograhy [Meyers et al., 2021]. Use LV A4C echos that can create synthetic Ulstraound images for GE Vivid E9, Hitachi Prosound U7, Philips iE 33 Vision, Siemens SC2000, and Toshiba Artida ultrasound systems [Brindise et al., 2020].

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