Automated Analysis of Mitral Inflow Doppler using Convolutional Neural Networks

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Abstract

Doppler echocardiography is commonly used for functional assessment of heart valves such as mitral valve. Currently, the measurements are made manually which is a laborious and subjective process. We have demonstrated the feasibility of using neural networks to fully automate the process of mitral valve inflow measurements. Experiments show that the automated system yields comparable performance to the experts.

Keywords: Cardiac imaging, Echocardiography, Deep learning

1. Introduction

Transmitral Doppler echocardiography has become the primary mode of noninvasive assessment of diastolic filling and function. The physiology of ventricular filling is reflected by the transmitral Doppler velocity profile which is comprised of two distinct components (waves); the E-wave (early phase ventricular filling) and the A-wave (atrial phase of ventricular filling)). Accurate analysis of Doppler echocardiographic images is therefore of crucial importance. Current clinical practice requires sonographers to manually perform velocity measurements on Doppler traces , which often results in high intra- and inter-observer variability (Corriveau and Johnston, 2004). Automated systems could help standardise measurement protocol and reduce the amount of time spent on these measurements, thereby improving clinical workflow.

For normal hearts, the E- and A-waves do not overlap each other and the E-wave is higher than the A-wave. But for disease hearts, the following can occur (Park et al., 2008): (i) the E- and A-waves may overlap depending on the heart condition; (ii) the E-wave is lower than or of the same height as the A-wave; and (iii) only the E-wave is present with no A-wave. The has contributed to the significant variation in the envelope shape of the mitral inflow, which has made it the most challenging echocardiographic Doppler modality to analyse automatically. Very limited previous attempts have therefore used the ECG information to locate the waves and isolate the heartbeats (Elwazir et al., 2020). As the first study of its kind, we have investigated the feasibility of using deep convolutional neural networks to fully automate the process of mitral valve inflow measurements, without the need for the ECG signals and suing the Doppler data only.

2. Method and dataset

A random sample of 500 echocardiographic examinations of different patients was extracted from Imperial College Healthcare NHS Trust's echocardiogram database. The acquisition of the images was performed by experienced echocardiographers and according to standard protocols, using ultrasound equipment from GE and Philips manufacturers. Ethical approval was obtained from the Health Regulatory Agency (Integrated Research Application System identifier 243023). Mitral inflow Doppler images were then annotated manually by expert cardiologists, selecting the E- and A-wave peak coordinates. DICOM-formatted images of varying image sizes images were zero-padded to the size of 1024x1024 pixels. The cardiologist's annotations of the images were used as the ground truth (400 for training, and 100 for testing).

A schematic diagram of the full deep learning pipeline is illustrated in Figure 1. In order to detect/isolate heartbeats, Faster-RCNN object-detection architecture was used. All overlapping bounding box predictions are processed using non-maximum suppression method. Predicted bounding boxes with probability over 70% are then passed to a landmark detection model based on architecture proposed in (Wei et al., 2016). The predicted heatmaps are then used to extract the location of the E- and A-waves for all the heartbeats present in the Doppler image. TensorFlow was used to implement the models, running on Nvidia RTX3090 GPU.

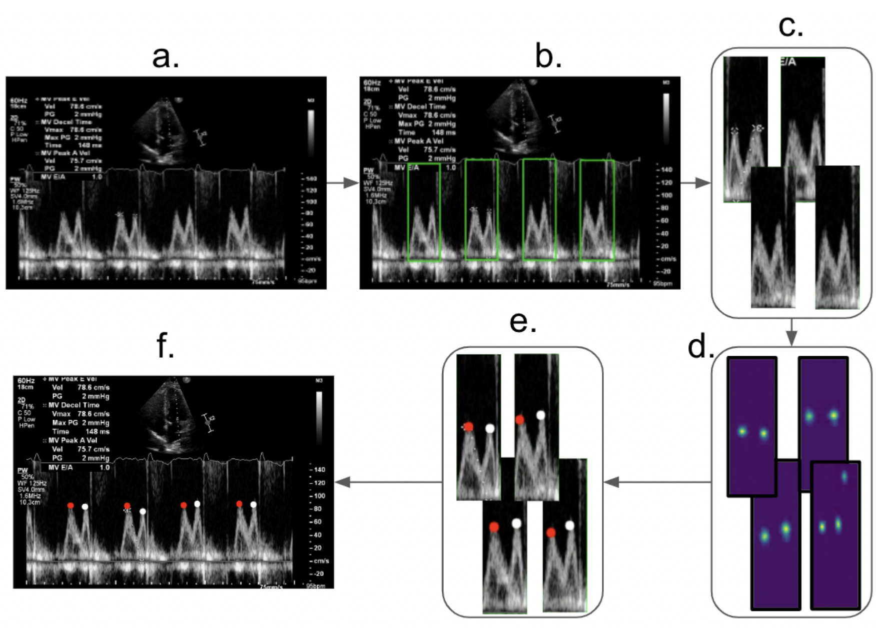

Figure 1: Full pipeline. a) Original Doppler image as input with no pre-processing. b) Faster-RCNN detects/seperates every heartbeat present in the image. c) Isolated heartbeats are cropped. d) Landmark detection model predicts heatmaps. e) E- and A-wave peak points are obtained from the heatmaps. f) Peak velocities from all heartbeats are put back on the Doppler image.

3. Results

Figure 2 upper row shows Bland-Altman plots for the pool of heartbeats across all patients. Bias for the automated measurements versus the expert measurements was less than 1 cm/s for both E- and A-wave peak velocities. The lower row shows the same plots, but for a patient-by-patient analysis, where all heartbeats present in a Doppler image for each patient are averaged. The standard deviation in both beat-by-beat and patient-by-patient analyses for the A-wave was larger; indicating that this peak was harder to detect/measure than the E-wave. The image datasets, code, and trained networks generated/developed in this study are made freely-available for future benchmarking (intsav.github.io/doppler).

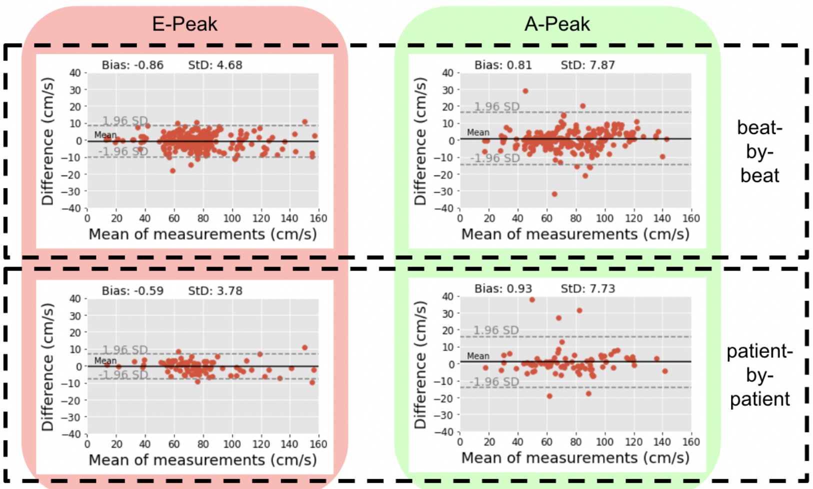

Figure 2: Bland-Altman plots for automated vs. manual measurements.

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