Automated Tracking of the Tricuspid Valve Plane in Long-axis Cine Images with a 2-step Deep Learning Pipeline

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Purpose

Right ventricular (RV) dysfunction is associated with increased morbidity and mortality in patients with varied cardiovascular diseases[1], and it is commonly assessed by echocardiography, by measuring the tricuspid annular plane systolic excursion (TAPSE) and the peak diastolic velocity (RV e') of tricuspid annular (TA) motion[2]. However, very small changes in beam angle and changes in imaging window can significantly impact the evaluation of RV size and function[3]. Cardiovascular magnetic resonance (CMR) is not clinically utilized to measure such parameters but it is considered the reference standard for cardiac volume assessment. Only a few studies were reported to track the TA motion, but still required manual initialization or adjustment[4]. In this study we have developed a fully automated, fast and accurate method for TA motion tracking in long-axis cine images of the 4-chamber view, with a 2-step deep learning pipeline. This builds on our recent work to track the mitral valve[5], with a similar deep learning pipeline.

Methods

A group of 120 patients (54 females, age 55.6±14.7 years), scanned on a 1.5T clinical scanner for diverse clinical indications were retrospectively enrolled in an IRB-approved study. Four chamber cines were acquired with a balanced steady-state-free-precession sequence with 30 timeframes per cardiac cycle, spatial resolution was 2x2x8 mm^3, TR/TE/Θ: 3ms/1.5ms/60º. The software Segment[6] was used to manually annotate the TA points in all patient data as a reference. A residual neural framework of 50 layers (ResNet50)[7] was adapted to perform a regression task for both points in each image, using MATLAB Deep Learning Toolbox. The method used two trained networks and followed a 2-step deep learning pipeline. Step 1 used a trained network to predict the TA points in the first time frame of the cine series, with an accuracy sufficient to use the location of the TA points to reorient the long-axis cines into a standardized orientation, as part of the pre-processing. This step standardized the input image with a fixed size, cropping, resolution and heart orientation. Step 2 used another trained network to locate the TA points in all pre-processed frames, with a high accuracy, which were then reconverted to their original coordinates. The dataset was randomly split into two sets: 94 subjects for training and validating the neural network, and 26 test subjects for evaluating performance.

Results

The differences between the automatic method and ground truth annotations were (mean±SD) -1.95±1.93 mm (r = 0.90), and 0.40±1.56 cm/s (r = 0.80), for TAPSE, and RV e', respectively. The regression and Bland-Altman plots for these metrics are shown in Figure 1. The TAPSE results can be compared to an interobserver error of -0.5±1.4 mm (r = 0.95), reported for TAPSE measurement[8], with a semi-automated method. The Euclidean distance error after the first step was 6.15±4.07 mm, and after the second step was 3.63±3.38 mm.

Discussion

The proposed deep learning method, trained with 94 patient cine data sets, allowed a fast and accurate tracking of the TA points even in subtle changes, relevant for velocity analysis, that are difficult to manually track. The addition of a pre-processing step to standardize the images significantly improved the accuracy. Quantitative analysis using derived clinical parameters and Euclidean distance error showed that the agreement between predicted and manual annotations was good. In conclusion, a deep learning approach for automatic delineation of TA points for RV diastolic evaluation in CMR long-axis cine images was developed. The method is able to carefully track these points with high accuracy and in a timely manner. This will improve the feasibility of MRI methods which rely on valve tracking, such as measurement of RV e', or slice-following phase-contrast, and increase their utility in a clinical setting.

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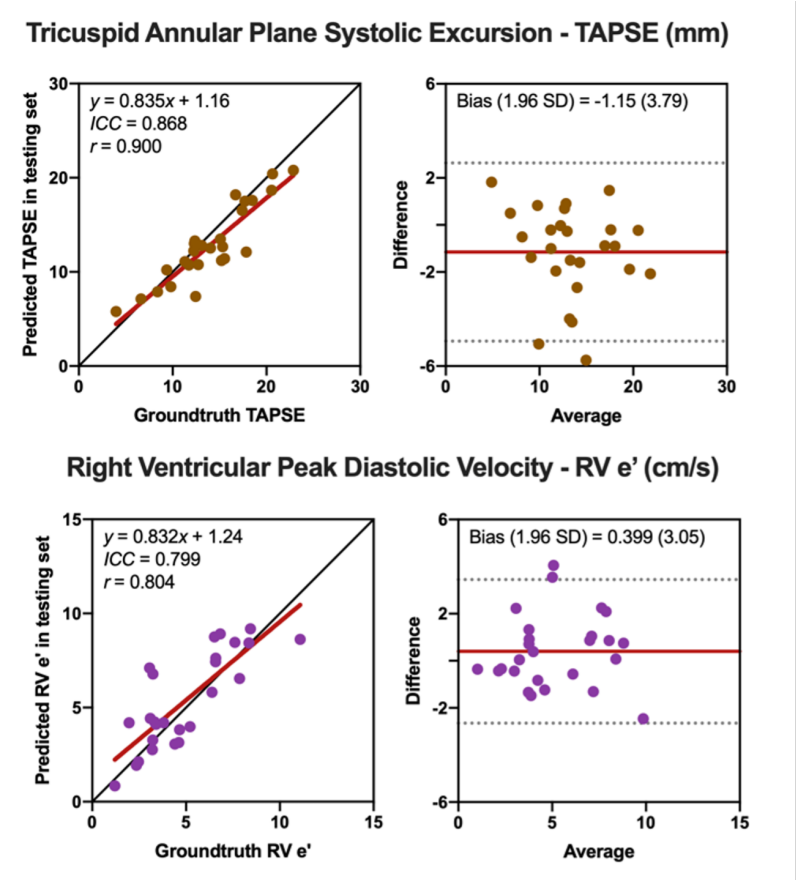


Figure 1. Correlation and Bland-Altman plots of TAPSE and RV e' between automated and groundtruth measures in the testing set.