AUTOMATIC SEGMENT-LEVEL ASSESSMENT OF REGIONAL WALL MOTION ABNORMALITY FROM ECHOCARDIOGRAPHY IMAGES

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ABSTRACT

Regional wall motion assessment is critical for the diagnosis of coronary artery diseases, and is commonly performed using echocardiography images in clinical practice. However, manual assessment of regional wall motion is time-consuming and requires expertise. Currently, various works have been proposed to detect the existence of regional wall motion abnormality, whereas they do not provide a segment-level assessment which is essential for detailed diagnosis and treatment. In this paper, we propose a deep learning-based framework for automatic segment-level assessment of regional wall motion abnormality. We collected a dataset consisting of 198 patients each with three views in three modes. Experimental results show that our framework can detect segment-level abnormality with an excellent performance of sensitivity, specificity, and accuracy rates of 93.85%, 99.99%, and 99.73%, respectively, which has demonstrated the potential in clinical application. The dataset and code used in our study are released to the public [1].

***Index Terms*—** Regional wall motion abnormality, Segment-level assessment, Echocardiography, Deep neural networks, Machine Learning

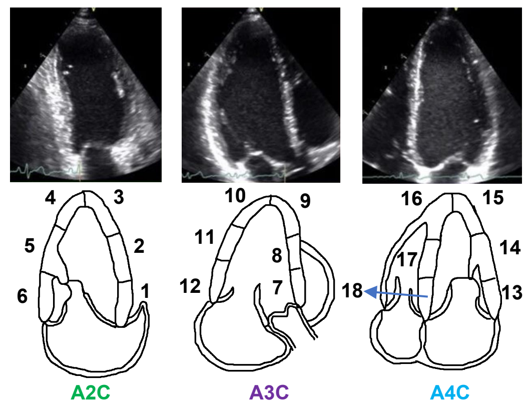

Fig. 1. Segment illustration of left ventricles in three views including apical 2-chamber view (A2C), apical 3-chamber view (A3C), and apical 4-chamber view (A4C). Each view corresponds to six segments and there are totally 18 segments.

1. INTRODUCTION

Coronary artery disease (CAD) is the third leading cause of death worldwide and kills 17.8 million people each year [3]. The assessment of left ventricular systolic function and particularly regional wall motion abnormality has become increasingly important in determining the severity and prognosis of CAD [9]. Currently, echocardiography has been widely used for evaluating regional wall motion abnormalities [7]. However, manual assessment requires extensive experience, hence is subjective, time-consuming, and hard to reproduce [11]. Therefore, there is a growing appreciation for automatic assessment of regional wall motion abnormalities.

To solve this problem, several studies have adopted deep learning to perform detection of regional wall motion abnormalities from echocardiography [7, 10, 12]. Kusunose et al. [10] used deep neural networks to detect whether the regional wall motion is normal or abnormal, which was evaluated on a dataset consisting of 400 patients each with short-axis views. Huang et al. [7] adopted a similar approach. A recent work by Sanjeevi et al. [12] extracted temporal information to enhance the detection performance.

Note that in clinical practice, the regional wall in echocardiography views is further divided into multiple segments for precise diagnosis [2]. As shown in Fig. 1, left ventricles are shaped like a cup in which the basal and the apical parts correspond to the lip and the bottom of the cup, respectively. Left ventricles are first divided into three circles: the basal circle, the mid circle, and the apical circle. For each circle, it is further divided into six segments with roughly equal length: anterior, anteroseptal, inferoseptal, inferior, inferolateral, and anterolateral segments. Therefore, there are totally 18 segments in the regional wall, and each of the three views (A2C, A3C, and A4C) can detect six segments. In clinical practice, echocardiography images are assessed using three modes: two-dimensional (2D), myocardial contrast echocardiography (MCE), and left ventricle opacification (LVO), all

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of which are used to evaluate regional wall motion abnormalities. 2D mode is the most commonly used one as it is sufficient to fulfill the need of diagnosis for most patients, while LVO mode and MCE mode are less common because they are invasive and usually more expensive [4].

In this paper, we propose a deep learning-based framework for automatic segment-level assessment of regional wall motion abnormality from echocardiography images. Particularly, there are three modules in the proposed framework: regional wall contour segmentation, distance feature extraction, and abnormality prediction. We collected a dataset of 198 patients each with three views (including A4C, A3C, and A2C) in three modes, including 2D mode, MCE mode, and LVO mode. Experimental results show that our framework can detect segment-level abnormality with excellent performance in sensitivity, specificity, and accuracy being 93.85%, 99.99%, and 99.73%, respectively, which demonstrates its potential to be applied in clinical practice.

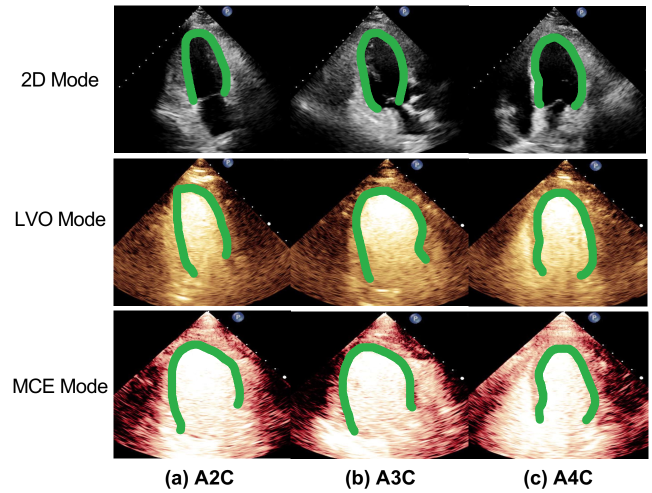

Fig. 2. Examples in our dataset.

2. DATASET

Our dataset consists of 198 patients where for each patient three views (A4C, A3C, and A2C) in three modes (2D mode, MCE mode, and LVO mode) are included as shown in Fig. 2. Thus, there are totally 1,782 echocardiography videos, with the varying frame size of $640 \times 480 \times (71-510)$. A total of 9881 frames of echocardiography images in three modalities are collected, in which, there are 3,091, 3,391 and 3,399 frames in the 2D mode, LVO mode, and MCE mode, respectively. For each video, six frames (two end-systolic frames, two end-diastolic frames, and two frames between the end-diastolic and end-systolic frames) are selected for annotation, and the regional wall contour of the left ventricle is labeled as shown in Fig. 2. A total of 3,564 segments are labeled in all the 198 patients, among which 45 segments are abnormal. Note that such low incidence rate is a reflection of the real-life statistics of clinical practice at our center. All labels were annotated by four experienced sonographers, and each taking about 5 minutes to finish.

3. METHOD

Overview: As shown in Fig. 3, the proposed framework includes three modules: regional wall contour segmentation, distance feature extraction, and abnormality prediction. The regional wall contour segmentation module obtains the segmentation of the regional wall contour of the left ventricle, and then the distance feature extraction module calculates the maximum distance between the segments in the end-diastolic and end-systolic phases, which are finally fed into the abnormality prediction module to make a diagnosis using machine learning models (e.g. random forest). Note that there are three modes in the input, and the final prediction is an ensemble of the prediction in all the three modes. Additionally, single mode images can be also taken as input, and the only modification being the removal of the final ensemble. Note that in clinical practice, the single 2D mode is more common as it can provide accurate diagnoses for most patients.

Regional wall contour segmentation: We adopt nnU-Net [8] for the segmentation of regional wall contour. The input is a 2D echocardiography image with a normalized size of 480×360 including 2D mode, LVO mode, and MCE mode. We don't utilize temporal information since a single 2D input can yield good segmentation results, as demonstrated in the experimental section. For conditions with interrupted walls, we use region growing and skeletonization algorithms to obtain a rough wall. Particularly, the two ends of the interrupted wall are grown using morphology operation, and once they meet, the skeleton of the combined wall is extracted as the refined wall. We adopt only one nnU-Net to process the three modes of an image while the same configuration applies to single mode images as well.

Distance feature extraction: Four steps are performed. First, frame extraction is used to obtain the two frames in the end-diastolic phase and the end-systolic phase. Particularly, by connecting the two endpoints of the boundary, a closed shape is formed, which roughly corresponds to the boundary of left ventricle. The area of this shape is used to determine which frames correspond to the end-diastole (the largest area in a period) and the end-systole (the smallest area in a period). Second, due to the heart motion, the regional walls in the two frames are not aligned, and registration (mainly rotation and translation operations) of the two walls are performed. Specifically, principal component analysis is adopted to get the primary principal directions ($D1$ and $D2$ in Fig. 3) of the segmented walls which are used for rotation to make the two walls share the same primary principal directions. The middle points ($P1$ and $P2$ in Fig. 3) of the two endpoints at the basal segments of the two walls are then used for transla-

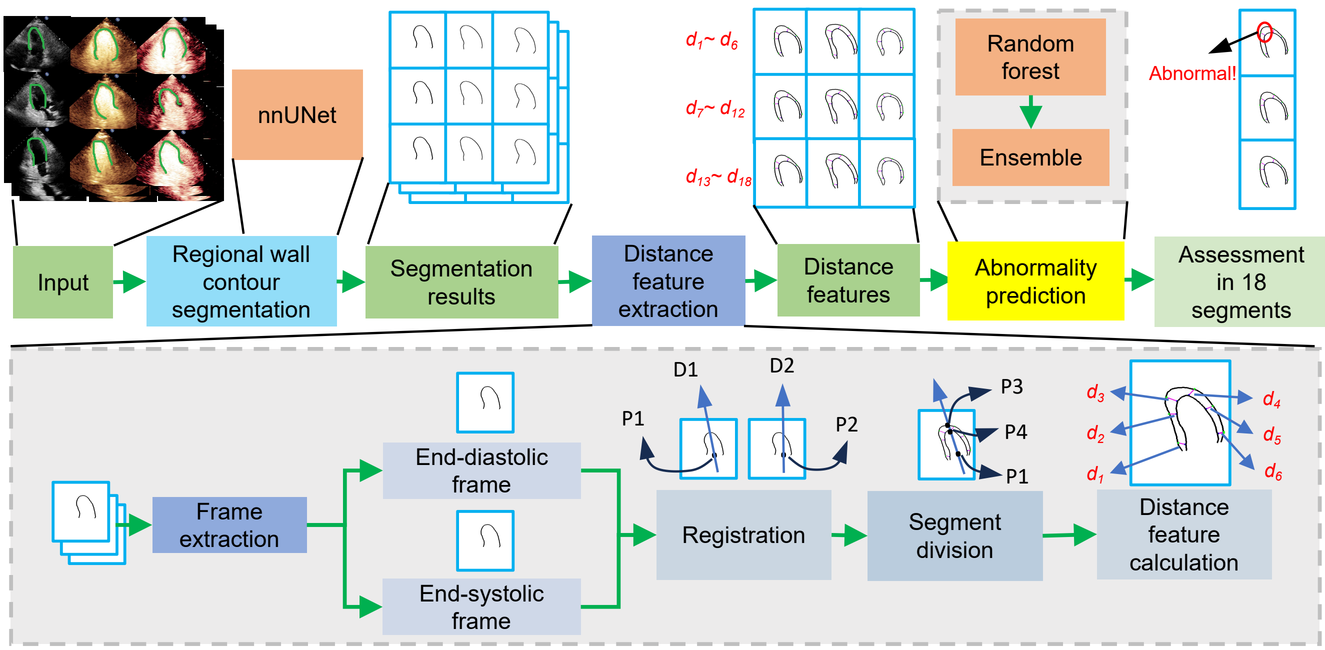

Fig. 3. Detailed structure of the proposed framework.

tion. Third, the segment division is calculated. Each wall is divided into two parts based on the Intersection point of the wall and the shared primary principal direction (e.g., $P3$ and $P4$ in Fig. 3) that crosses the middle point ($P1$ in Fig. 3). Each part is then further divided into three segments of equal length. Lastly, the maximum distance of the points in the corresponding segments is calculated as the distance feature of the current segment. Totally, there are six distance features (d_1-d_6) to be extracted for each echocardiography video.

Prediction: Machine learning algorithms, particularly random forest, are used to make the prediction. The input contains three sets of distance features extracted from the three modes including 2D mode, MCE mode, and LVO mode, respectively. Each set includes 18 distance features from three views. As the size of the dataset is limited, only one prediction model is implemented for all the modes, which indicates that the model can be used for all the three modes.

4. EXPERIMENTS

Experiment Setup: All experiments were conducted on an Nvidia A40 GPU with 48GB of memory. This allowed for efficient processing and operation of data-heavy tasks. We were keenly aware of the inherent challenges of our project, given that there were only 45 abnormal segments among the total of 3,564 segments, leading to a high degree of imbalance in the training data. For effective evaluation, we adopted k-fold cross-validation, and considering the limited number of abnormal segments, $k = 2, 3, 4, 5$ were used to obtain the average performance. In each cross-validation setting, 9,881

Table 1. Segment-level assessment performance of regional wall motion abnormality in sensitivity (Sens), specificity (Spec) and accuracy (ACC) of the proposed framework.

Mode	Sens	Spec	ACC
2D	77.47%	100%	99.715%
LVO	81.11%	100%	99.76%
MCE	77.78%	99.94%	99.72%
Ensemble	93.85%	99.99%	99.73%

Table 2. Segmentation results of nnU-Net and 2D U-Net in Dice score and Hausdorff distance (pixels).

Mode	nn U-Net		2D U-Net	
	Dice	Hausdorff	Dice	Hausdorff
2D	0.62	25.95	0.57	23.29
LVO	0.72	13.66	0.66	30.53
MCE	0.73	7.22	0.68	34.99

2D images were split by the ratios of 1-$1/k$-0.1, 0.1, and $1/k$ for training, validation, and testing, respectively. Note that the partitioning was conducted to ensure the ratio of cases with abnormal wall motion in each set to be roughly equal. For the evaluation metrics of our experiment, we used the Dice score and Hausdorff distance, both of which are widely used.

Quantitative results: The quantitative results are shown in Table 1. Overall, our framework using the ensemble of the three modes can obtain the performance in sensitivity, specificity, and accuracy of 93.85%, 99.99%, and 99.73%, respectively. For the all-three modes, our framework using the 2D

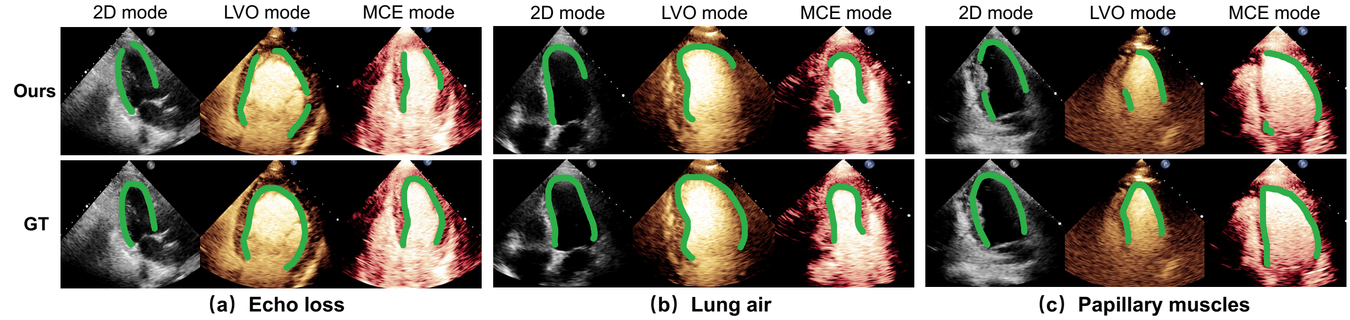

Fig. 4. Bad segmentation results due to (a) echo loss, (b) lung air, and (c) papillary muscles. GT stands for ground truth.

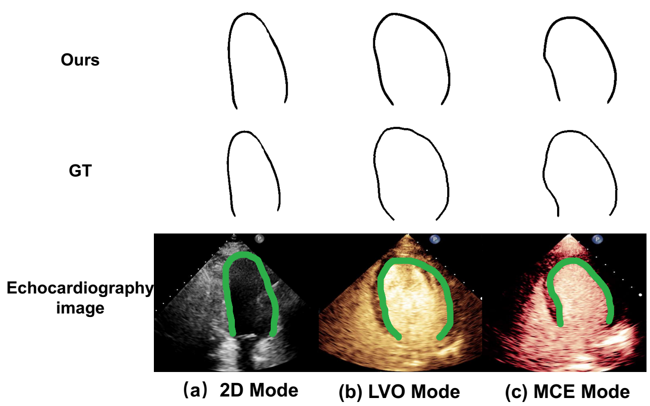

Fig. 5. Examples of good segmentation by our framework.

mode achieves a similar performance to the MCE mode, using the LVO mode obtains a higher performance especially on sensitivity. A possible reason for this observation is that the boundaries of the left ventricle are enhanced by the LVO mode. The segmentation results of nnU-Net and 2D U-Net in our framework are shown in Table 2. The averaged Dice score and Hausdorff distance of the nnU-Net and 2D U-Net are 0.69 and 0.64, 15.71 pixels and 29.54 pixels, respectively, which are relatively low.

Qualitative results: Examples of good and poor segmentation results are shown in Fig. 4 and Fig. 5, respectively. Our framework performs exceptionally well when the image quality is high and devoid of complex context, cleanly segmenting the left ventricular contour without any breaks as shown in Fig. 5. However, when these conditions are not met, the segmentation results can be unsatisfactory as demonstrated in Fig. 4. For example, in Fig. 4(a), the apical segment is not detected because of the blurred border in the echocardiography image. In Fig. 4(b), there are segmentation breaks in the basal segments and mid segments. This type of error leads to an inaccurate differentiation between the end-systolic and end-diastolic volumes and thus the misclassification of regional wall motion abnormalities.

In terms of segment-level assessment of regional wall motion abnormality, most detection errors are due to segmentation errors as shown in Fig. 4. There are mainly three causes that may lead to segmentation errors including echo loss [5], lung air [14], and papillary muscles [13]. Fig. 4(a) shows several examples of missing wall due to echo loss. Particularly, the apical part suffers from a blurring boundary which can not be easily detected. Note that echo loss is caused by a variety of reasons including tissue density, acoustic frequency and wrong operation [6]. In clinical practice, sonographer experts may obtain the wall contour based on their experience. We may add an image quality assessment module to filter out low-quality images like the ones with echo loss to mitigate this problem. Fig. 4(b) shows some examples with interrupted wall contours at the mid-segment regions of the heart due to lung air. As the density of the lung air and the background is very close (especially in the 2D mode), the boundaries of the heart will disappear from the echocardiography images (especially in the 2D mode), making the segmentation much more difficult. Fig. 4(c) shows examples of segmentation errors at the basal segments due to papillary muscles. Since papillary muscles move during acquisition, the shape and location of papillary muscles can vary. They may appear in some frames and disappear in others. The shape of wall contours with papillary muscles is quite different from those without as shown in Fig. 4(c).

5. CONCLUSION

In this paper, we proposed a deep learning-based framework for automatic segment-level assessment of regional wall motion abnormality from echocardiography images. We collected a dataset of 198 patients each with three views and in three modes. Results show that our framework can detect the segment-level abnormality with an excellent performance in sensitivity, specificity, and accuracy of 93.85%, 99.99%, and 99.73%, respectively. We believe the proposed framework has strong potential for clinical applications. However, the performance especially the sensitivity is low. So we have published our dataset and code to the public [1] to facilitate further research in this important topic.

6. ACKNOWLEDGMENTS

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7. COMPLIANCE WITH ETHICAL STANDARDS

This work and the collection of data of retrospective data on implied consent received Research Ethics Committee (REC) approval from Guangdong Provincial People's Hospital under Protocol No. KY-N-2022-048-01. It adheres to all relevant ethical regulations. Deidentification was carried out by converting all CT files into NIfTI format and removing sensitive patient information, including names, birth dates, admission years, admission numbers, and CT numbers. Only de-identified retrospective data were used for research, without the active involvement of patients.

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