AutoGate: Fast and Automatic Doppler Gate Localization in B-Mode Echocardiogram

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Abstract. In this paper, we propose an algorithm for fast and automatic Doppler gate localization in spectral Doppler echocardiography using the B-mode image information. The algorithm has two components: 1) cardiac standard view classification and 2) gate location inference. For cardiac view classification, we incorporate the probabilistic boosting network (PBN) principle to local-structure-dependent object classification, which speeds up the processing time as it breaks down the computational dependency on the number of classes. The gate location is computed using a data-driven shape inference approach. Clinical evaluation was performed by implementing the algorithm on an ultrasound system. Experiment results show that the performance of the proposed algorithm is comparable to the Doppler gate placement by an expert user. To the best of our knowledge, this is the first algorithm that provides a real time solution to the automated Doppler gate placement in the clinical environment.

1 Introduction

Spectral Doppler echocardiography is widely used to assess cardiovascular function and pathology such as valvular regurgitation and stenosis. It employs the Doppler effect of ultrasound waves to determine the velocity of blood or other moving structures[1]. To acquire a Doppler echocardiogram, a sonographer needs to place the sample volume of the ultrasound beam, indicated by the Doppler gate on the screen, at the location where the blood velocity needs to be measured. The optimal location of the sample volume can be inferred from the B-mode image.

We propose a fast and robust algorithm for automatic Doppler gate localization, which will be referred as (**AutoGate**) for the rest of the paper. **AutoGate** employs data-driven machine learning techniques customized for medical image analysis tasks such as left ventricle (LV) detection in noisy echo images using binary classification, multi-class classification, shape inference etc. The benefit

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of automatic placement of the Doppler gate can be summarized into two aspects: improving workflow by eliminating time consuming manual Doppler gate adjustments and reducing the user dependency of the exams.

The proposed **AutoGate** algorithm has two main components: (i) fast cardiac view classifier and (ii) gate location inference model. To automate the gate localization, we should first identify the cardiac view of the B-mode because in each standard cardiac view, there are different valves and different optimal locations for the Doppler gate. Once the view is determined using the view classifier, **AutoGate** invokes the inference model to estimate the final gate location. We base the inference model on the database-guided segmentation approach proposed in [2]. It is trained to build a function which computes the LV shape and the gate location using an image patch. We simultaneously infer the LV shape and the gate location using the shape inference algorithm [2].

There are some previous works that directly deal with automatic view classification of echocardiogram [3][4][5][6][7]. We propose a fast cardiac view classification algorithm based on the Local Structure Dependent Classification approach (called *fLoDeC*) by adopting the basic algorithm of *CardiacVC* proposed in [3] and Probabilistic Boosting Network (PBN) framework proposed in [8]. Due to the use of PBN, *fLoDeC* is more scalable than *CardiacVC*. In other words, the computation time is affected less for *fLoDeC* than for *CardiacVC* as the number of object classes increases.

We performed experiments for four cardiac standard views: apical four chamber (A4C) view, apical two chamber (A2C) view, apical three chamber (A3C) view, and apical five chamber (A5C) view. A gate is located on mitral valve (MV), tricuspid valve (TV), or aortic valve (AV) depending on the view type.

2 Object Detection and Classification

In this section we propose a generic algorithm of fast object detection and classification called *fLoDeC*. The basic framework of this algorithm is to anchor a relatively stable (rigid) local structure of each object class. We use the LV as the local structure. A global structure is then extracted based on the anchored local structure and further classified using multi-class classifiers. *fLoDeC* uses the same idea of local-structure-dependent detection and classification from *CardiacCV* [3], but it incorporates the PBN principle [8] to achieve further speed-up. The diagram in Fig. 1 illustrates how *fLoDeC* is constructed using the PBN framework.

Based on the diagram in Fig. 1-(a), the *fLoDeC* algorithm is summarized as follows. Each local structure detector (LSD_i), where $i \in [1, C]$, is independently applied to an echocardiogram. The LSD_i provides positive candidates of the local structure of the i^{th} object class. The training data for the global structure classifiers are constructed based on these positive candidates by applying LSD_i to not only the images of the i^{th} object class but also those of the other classes. Therefore, the global structure training data set is local-structure-dependent, based on which we learn a multiclass global structure classifier ($MGSC_i$). The

Fig. 1. Multiple object detection and classification using local structure dependent classification approach. **LSD**: Local Structure Detector, **LSC**: Local Structure classifier, **MGSC**: Multi-class Global Structure Classifier.

final classification result is computed by integrating the classification results provided by $\{MGSC_1, \dots, MGSC_C\}$.

To anchor the local structures, all the *LSD*'s should exhaustively search the image to detect their own local structures. The search space for LV is of five dimensions: (x, y) location, width, height and angle, represented as (x, y, w, h, θ) . This is the most time consuming part of *fLoDeC* because each local structure detector should be applied in the five dimensional search space independently. The computation time linearly depends on the number of object classes.

To lessen the above linear computational dependency on the number of classes, the *fLoDeC* algorithm tackles the problem by replacing the local structure detection part, inside the dashed box in Fig. 1-(a), with the PBN structure shown in Fig. 1-(b). In this framework, we train one multi-class local structure classifier (*MC_LSC*), and configure it to multiple levels in a hierarchical structure, $MC_LSC_1, \dots, MC_LSC_n$. To classify a local structure, it should be supplied from MC_LSC_1 to MC_LSC_n sequentially. Each local detector, LSD_i , is also re-configured as a hierarchical structure by decomposing it into multiple levels of weak detectors in the same manner as *MC_LSC*. The decomposed $MC_LSC_1, \dots, MC_LSC_n$ and $LSD_{1i}, \dots, LSD_{ni}$ are grouped in a graph structure shown in Fig. 1-(b). The essence of this approach can be summarized into two aspects: 1) apply only the few selected local structure detectors based on the *MC_LSC*, and 2) the graph structure further enables the negative exclusion as soon as possible from early layers.

The final view classification result, $\hat{c}$, given a candidate image I , can be computed via the MAP rule:

$$\hat{c} = \arg \min_{i \in [1, C]} \{P(c_i|I) = \sum_{j=1}^C P_{MGSC}(c_i|j, I) P_{LSD}(j|I)\}, \quad (1)$$

where $P_{MGSC}(c_i|j, I)$ is the posterior probability of being class c_i from $MGSC_j$ and $P_{LSD}(j|I)$ is the prior probability from LSD_j .

2.1 Cardiac View Classification of Four Apical Views

We will discuss about how the cardiac view classifier in **AutoGate** is implemented using *fLoDeC* presented in Sec. 2. We focus on the echocardiograms of four apical views, namely A4C, A2C, A3C and A5C.

To construct *fLoDeC* to deal with the four views, we train one LV classifier (MC_LSC), four LV detectors, LSD_{A4C} , LSD_{A2C} , LSD_{A3C} and LSD_{A5C} , as local structure detectors, and four global view classifiers, $MGSC_{A4C}$, $MGSC_{A2C}$, $MGSC_{A3C}$ and $MGSC_{A5C}$. Each local structure detector is trained based on Probabilistic Boosting Tree (PBT) [9] which treats this detection problem as a two-class classification problem (positive class versus negative class). The LV-classifier and the four cardiac view classifiers are trained using the multi-class logit boosting based image classification approach [3][10]. The weak classifiers in (MC_LSC) and LSD 's are divided into several parts to form the PBN framework shown in Fig. 1-(b).

3 Automatic Gate Localization Based on Learning-Based Approach

Once the view is determined, we need to find the best location of the Doppler gate. It is, however, a hard problem because the gate is usually located on the path of blood flow which is a space free of any visible structures on the B-mode image. To tackle this, we utilize anatomy structure such as the LV and valves annuli to infer the target gate location. The LV shape and its corresponding gate locations are annotated by experts using points (17 points for the LV and one point for each gate) as shown in 2. In this figure, the yellow dots represent an LV shape and the red circles with a dot represent gate locations. In the A4C view, two gate locations are computed: one for mitral valve and the other for tricuspid valve. Only one Doppler gate for mitral valve is computed in the A2C view. Two gate locations, one for the mitral valve and the aortic valve, are annotated in the A3C view and the A5C view.

With these annotations, the gate locations, even though ambiguous, can be inferred using the other heart anatomical structures such as the LV, the aortic valve annulus, the tricuspid valve annulus, etc.

We employ the database-guided segmentation algorithm proposed in [2] to infer LV shape and gate location simultaneously. Each training image is represented using a very high dimensional numerical feature vector. Its shape (including both the LV shape and gate locations) is represented as a set of landmark points. The training data are clustered into several clusters in the shape space. The algorithm selects a small number of useful features based on boosting framework by maximizing the Fisher separation criterion of the clusters.

If the view is determined as $\hat{c}$, the LV image patch computed by $LSD_{\hat{c}}$ is used as an input for the shape inference model to locate the Doppler gate. The LV

Fig. 2. Annotation of LV shape (yellow dots) and gate location (red circle with yellow dot inside)

shape and the image appearance around the LV collaboratively contribute to the final gate locations.

4 Performance Evaluation

4.1 Offline Clinical Evaluation

For offline evaluation, we collected training data and test data separately. **AutoGate** was built using the training data and compute the classification accuracy and gate localization using both data sets. Table 1 shows two confusion matrices of the classification accuracy for training and test data which are very diverse in terms of not only image quality but also heart pathology. The average classification accuracy of training data is over 96%, and that of test data is close to 95%. As shown in Table 1, most of the classification error comes from the misclassification of A5C to A4C. It is because some A5C views have a very small aorta structure which makes them very similar to the A4C view.

Table 2 shows the distance of the gate location between **AutoGate** and expert’s annotation. As shown in the table, **AutoGate** localizes the gate location very comparable to experts.

Fig. 3 shows the valve localization results by applying the offline version of the **AutoGate** algorithm to dicom videos. The small two horizontal lines within the pan box indicate the gate location. In this figure, ED and ES stand for End of Diastole and End of Systole, respectively. The view classification result is illustrated using blue bars along with probabilities of being A4C, A2C, A3C and A5C (from left to right) below each picture.

Table 1. Confusion matrix of view classification results. The numbers in a parenthesis represents the number of training/test data.

Training Data (%)					Test Data (%)				
	A4C	A2C	A3C	A5C		A4C	A2C	A3C	A5C
A4C(408)	97.5	0.2	0.5	1.7	A4C(23)	100.0	0.0	0.0	0.0
A2C(296)	0.3	99.7	0.0	0.0	A2C(24)	0.0	96.0	4.0	0.0
A3C(410)	1.0	3.7	94.6	0.7	A3C(25)	0.0	8.0	96.4	0
A5C(200)	8.0	0.0	0.0	92.0	A5C(24)	13.0	0.0	4.0	83.0

Table 2. Gate localization error between **AutoGate** and an expert for test data. ”-” indicates ”Not Applicable”.

	Mitral Valve		Tricuspid Valve		Aortic Valve	
	Mean (mm)	Std (mm)	Mean (mm)	Std (mm)	Mean (mm)	Std (mm)
A4C	4.2	2.5	3.4	2.5	-	-
A2C	5.9	2.4	-	-	-	-
A3C	3.5	2.2	-	-	3.4	2.3
A5C	3.6	3.6	-	-	2.4	2.4

Fig. 3. Valve localization results in offline environment. MV and TV represent Mitral Valve and Tricuspid Valve, respectively. ED and ES stand for End diastole and End Systole, respectively.

4.2 Online Clinical Evaluation

For clinical evaluation, we implemented an online version of the **AutoGate** algorithm on a SIEMENS ACUSON *SEQUOIA*TM ultrasound machine. The Doppler gate was automatically placed in the optimal location as soon as the user entered the Spectral Doppler mode of imaging. In case of ambiguity for cardiac views where more than one valve was present the user had the ability to select the desired valve through a button on the system console.

The results are summarized in Fig. 4 showing scatter plots of MV peak velocity measurements. The scatter plot on the left shows peak velocities computed by placing a gate using **AutoGate** (x-axis) and mean peak velocities computed after placing a gate twice by a expert (y-axis). The scatter plot on the right shows intra-user variability. As shown in the scatter plots, the correlation coefficient between **AutoGate** versus the expert is 0.951 which is comparable to the intra-expert variability of 0.966. It is also reported by the evaluator that the gate placement by **AutoGate** was appropriate 100% of the time. Minor adjustments were done 30% of the time but with no significant effect on spectral Doppler strip.

Fig. 5 shows Doppler echocardiogram of Left Ventricular Outflow Tract (LVOT) using **AutoGate** in (a) and by expert in (b), and that of Mitral valve inflow using **AutoGate** in (c) and by expert in (d). Note the similarity of the two spectra.

Fig. 4. Correlation coefficient of MV inflow peak velocity

Fig. 5. Spectral Doppler signal captured after placing Doppler gate by **AutoGate** or an expert. (a) LVOT signal from **AutoGate**, (b) LVOT signal from Expert, (c) MV Inflow signal by **AutoGate**, (d) Mitral Valve Inflow signal by Expert.

5 Conclusion

We have proposed a fast algorithm of automatic Doppler gate localization, **AutoGate**, based on the B-mode image in echocardiography. To improve the scalability, we developed a faster version of the local-structure-dependent classification algorithm *fLoDeC*, which alleviates the linear dependency on the number of object classes, by employing the Probabilistic Boosting Network (**PBN**) principle. *fLoDeC* anchors the LV structure and classifies the cardiac view faster than *CardiacAC*[3], which is the most time consuming part of the **AutoGate** algorithm. The final gate location is computed by utilizing explicit anatomical structure of the heart such as Left Ventricle (LV) and valves.

In term of performance, **AutoGate** performs very comparable to the manual gate localization by an expert, and is expected to improve work flow for spectral Doppler measurements. To the best of our knowledge, this is the first successful attempt to provide a feasible solution to automated Doppler gate placement in the real time clinical environment.

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