AUTOMPR: AUTOMATIC DETECTION OF STANDARD PLANES IN 3D ECHOCARDIOGRAPHY

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ABSTRACT

3D echocardiography is one of the emerging real-time imaging modalities that is increasingly used in clinical practice to assess cardiac function. It provides for evaluation a more complete heart representation in comparison to conventional 2D echocardiography. However, one of the drawbacks is the time it takes the clinician to navigate the 3D volumes to the anatomy of interest and to obtain standardized views that are similar to the 2D acquisitions. We propose an automated supervised learning method to detect standard multiplanar reformatted planes (MPRs) from a 3D echocardiographic volume. Extensive evaluations on a database of 326 volumes show performance comparable to intra-user variability and the execution time of the algorithm is about 2 seconds.

***Index Terms*—** Three-dimensional echocardiography, multiplanar reformatted/reconstruction (MPR), standard views

1. INTRODUCTION

In the past few years, three-dimensional (3D) real-time imaging systems have advanced rapidly and emerged in the market. The acquisition methods are continuously improving in terms of spatial and temporal resolution. 3D echocardiography is more and more used in clinical practice to evaluate both morphology and pathology. Research studies have shown that automated three-dimensional analysis provides more precise information about the pathophysiology of the heart than conventional analysis of 2D views and is of particular help for volume and ejection fraction (EF) calculation [1, 2, 3, 4, 5]. However, interpretation and quantitative analysis of the 3D volumetric data is more complex and time consuming than for conventional two-dimensional (2D) echocardiography, which limits 3D echocardiography applications in clinical diagnosis. Therefore, automatic detection of anatomical structures in 3D volumetric data is extremely important to guided navigation and to have a fast quantitative analysis.

Standard views are used to visualize the cardiac structures and are the starting point of many echocardiographic examinations [6]. In a 3D volume, such views can be reconstructed as multiplanar reformatted/reconstruction (MPR) planes. Finding the standard 2D planes in a 3D volume can improve consistency among users and can be used to adjust the on-line acquisition parameters for better image quality. For example, as shown in Fig. 1, all four chambers, i.e., left and right ventricles, and left and right atria, are present in the apical four chamber (A4C) view. In the apical three chamber (A3C) view, the left ventricle, the left atrium, and the aorta are present. Although 3D echocardiographic volumes provide much richer information of the heart than 2D echocardiographic images, the heart can be located in different positions with various orientations within each volume in different exams. Therefore, it is time consuming for users to navigate through a 3D volume to search the target structure. A major barrier for using 3D echocardiography for quantitative analysis of heart function in routine clinical practice is the absence of accurate and robust detection methods necessary to make the analysis automatic [7].

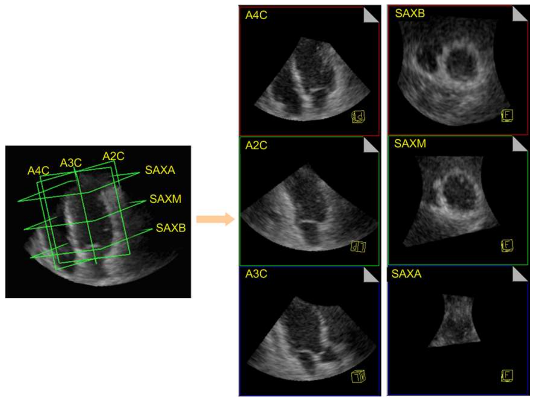

Fig. 1. Standard planes in an echocardiographic volume.

In addition to the ultrasound operator's capability, other factors including transducer selection, instrument settings, patient comfort and positioning, and the patient's breathing pattern, will affect the quality of the recording. This leads to large appearance variations and inconsistent image qualities (see Fig. 3 for examples), which makes the automatic detection task much more difficult. Moreover, although the volumes were captured through apical windows, the initial configuration of planes significantly varies as demonstrated in Fig. 4. To automate the clinical workflow and facilitate the subsequent processing tasks such as endocardial wall motion analysis, it is an essential component to automatically detect standard cardiac MPR planes from a 3D volume. In order to achieve fast, accurate, and consistent MPR detection, we propose a method and system that is able to detect MPR planes from a 3D echocardiographic volume in a fully automatic mode. Specifically, six major MPR planes as shown in Fig. 1 are detected in the prototype system: (1) A4C: apical four chamber plane; (2) A2C: apical two chamber plane; (3) A3C: apical three chamber plane; (4) SAXB: short axis basal plane; (5) SAXM: short axis middle plane; (6) SAXA: short axis apex plane. To our best knowledge, this is the first fully automatic MPR detection system on three-dimensional echocardiography data.

2. METHODOLOGY

2.1. Knowledge-based Probabilistic Model

We address the problem of MPR plane detection from 3D volumes by using a database-driven knowledge-based approach [8]. Knowledge is embedded in large annotated data repositories where expert clinicians manually indicate the standard MPR planes. Features that are relevant to the MPRs are extracted and learned in a machine algorithm based on the experts' annotations, resulting in a probabilistic model for MPRs, see Fig. 2. The algorithm uses the learned model to search for targets (MPR planes) in the hypothesis space. Online detection algorithm searches through multiple hypotheses to identify the ones with high probabilities.

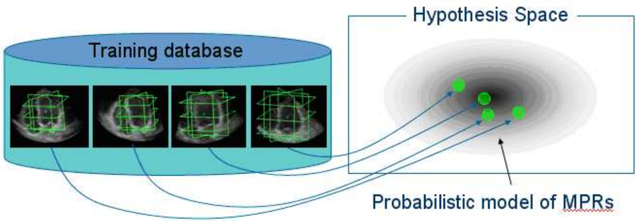

Fig. 2. Probabilistic learning for AutoMPR. A hypothesis space is constructed and learned for each standard MPR plane.

2.2. Marginal Space Learning and Hierarchical Search

We consider each MPR plane not only in an abstract 2D domain, but a 3D volume sample, where three-dimensional context information is preserved and guide the detection process. MPR plane detection is to estimate the pose parameters for each plane. The pose parameters of a 3D rigid body consists of 9 components, including 3 translations (x, y, z), 3 orientations (e.g., Euler angles w.r.t. each axis), and 3 scales along each axis. Because searching in a high resolution 3D volume is prohibitive for online applications. For example, a volume of $100 \times 100 \times 100$ voxels will have $10^6 = 100 \times 100 \times 100$ hypotheses for position. If combining orientation and scale, a combinatorial hypothesis search space increases dramatically. Therefore, we designed a series of detectors that estimate plane parameters at a number of sequential stages in the order of complexity, i.e., translation, orientation, and scale, as the parameter degrees of freedom increase [9]. Different stages utilize different features computed from 3D volume data. Multiple hypotheses are maintained between algorithm stages, which quickly removes false hypotheses at the earlier stages while propagates the right hypotheses to the final stage. Only one hypothesis is selected as the final detection result.

The plane detectors are discriminative classifiers that are trained on the registered 3D echocardiographic volume, which are used to determine if a given sub-volume sample is positive or negative. Positive/negative samples correspond to correct/incorrect plane parameters (configurations). The detectors are trained on a large number of annotated 3D echocardiographic volumes. We control the training sets for the detectors at different levels depending on the complexity of the detection task. At the coarse level, the negatives are far from the positives and randomly sampled across all reasonable plane configurations, while maintaining a relative large gap from the positives. At the fine level, negatives are selected only within a neighborhood of the positives in accordance to the search strategy, while decreasing the gap in between.

We use a probabilistic boosting tree (PBT) [10] for each detector. The classifier is a tree-based structure with which the posterior probabilities of the presence of the plane of interest are calculated from given data. Therefore, each plane detector not only provides a binary decision for a given sample, but also a confidence value associated with the decision. The nodes in the tree are constructed by a combination of simple classifiers using boosting techniques [10].

Each detector selects a set of discriminative features that are used to distinguish the positive target from negatives from a large pool of features. For the classifiers at the translation stage, we choose Haar wavelet-like features [11], which are calculated efficiently using integral image-based techniques. Due to inconsistent imaging conditions of ultrasound in real applications, we normalize the features within each sample by subtracting the average and dividing the standard deviation. For the classifiers at the orientation and scale search stages, steerable features [9] are applied, because their computation does not require volume rotation and re-scaling, which are computationally expensive, especially when the hypothesis search space is large.

All 6 MPR planes are simultaneously searched in a coarse-to-fine strategy through a multi-scale hierarchical search as follows:

(1). An A4C detector is learned and applied at a coarse level in a low-resolution volume (downsampled from the original volume) and is used to limit the search region for fine plane parameter estimation.

(2). Because the six target MPR planes have anatomic regularities with each other and with respect to the left ventricle (LV), based on the A4C candidate detected in step (1), we compute initial plane parameters (position, orientation, and scale) for A2C, A3C, SAXB, SAXM, and SAXA. These are based on learned statistics of the pose parameters for each plane relative to A4C and are precalculated from the annotations in the training database.

(3). At higher resolutions, a plane detector for more accurate parameter estimation trained for each MPR plane is applied to search the best candidate only in a small neighborhood around their initial detection results obtained in step (2) to ensure efficiency.

3. EXPERIMENTS

We collected a set of 326 3D echocardiographic volume sequences from different patients. For each sequence, the end diastole (ED) frame (a 3D volume) was extracted and added into our experimental database. For each volume, six standard planes (A4C, A2C, A3C, SAXB, SAXM, and SAXA) were manually annotated by clinical experts and used as groundtruth for evaluation.

To measure the difference between two planes, two error metrics are applied, i.e., angle and distance. The angle between two planes is defined as the angle between two plane normals. The distance between two planes is measured as the distance of an anchor on one plane to the other plane, where the anchor is the LV center (for A4C, A3C, A2C, and SAXM) or the intersection between the LV long axis and the MPR (for SAXB and SAXA). Based on the groundtruth annotations, the LV long axis is computed as the average of the two intersections of A4C-A2C and A4C-A3C, and the LV center is calculated as the intersection between the LV long axis and SAXM.

A 4-fold cross-validation scheme was applied for evaluation. The entire dataset of 326 volumes was randomly partitioned into four quarters. For experiment, three quarters (244 volumes) were for training and the remaining one quarter (82 volumes) was used as unseen data for testing. In total, there are four experiments so that each volume has been used once for testing. AutoMPR performance is summarized based on all 4 folds and provided in Table 1. Examples of the detection results are shown in Figs. 3 and 4. MPRs in 3D echocardiography data present ambiguities due to data quality, leading to difficulties for accurate identification. Fig. 5 gives visual examples of above-average detection errors. Preliminary intrauser variability involving two experts yielded an average angle error of about 8.2 degrees and average distance error of about $3.2mm$.

Table 1. 4-fold AutoMPR cross validation evaluation. Angle difference is in degree and distance is in mm.

(a) Overall performance

	Avg. angle error	Avg. distance error
mean	11.3	3.7
std	8.0	2.1
median	9.3	3.3

(b) Performance breakdown (apical planes)

	A4C		A2C		A3C	
	Angle	Dist.	Angle	Dist.	Angle	Dist.
mean	13.2	3.5	15.2	2.9	14.5	3.4
std	12.5	3.4	13.0	2.8	13.2	3.9
median	10.4	2.7	11.6	2.2	10.9	2.3

(c) Performance breakdown (short axis planes)

	SAXB		SAXM		SAXA	
	Angle	Dist.	Angle	Dist.	Angle	Dist.
mean	8.2	3.6	8.2	4.3	8.2	4.5
std	6.2	3.1	6.2	3.5	6.2	3.5
median	6.8	2.9	6.8	3.7	6.9	3.7

4. CONCLUSIONS

We have presented a method and developed a fully automatic system for detecting standard MPR planes from 3D echocardiographic volumetric data. This automated system significantly reduces the burden of searching anatomic structures for human echocardiography examiners across a large variety of different volumes. With the detected standard MPRs, advanced quantitative analysis can proceed automatically, such as ejection fraction analysis. A multi-scale hierarchical search strategy is applied in the AutoMPR system. Experimental results on a 326 volume database are very promising.

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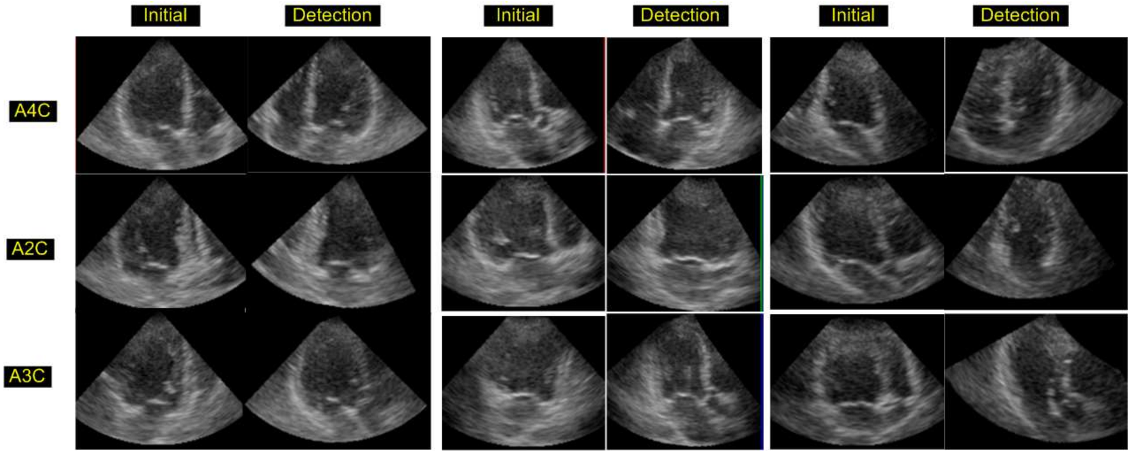

Fig. 4. Examples of initial and detected planes by AutoMPR. Initial plane configuration is fixed and defined by the acquisition probe location and orientation.

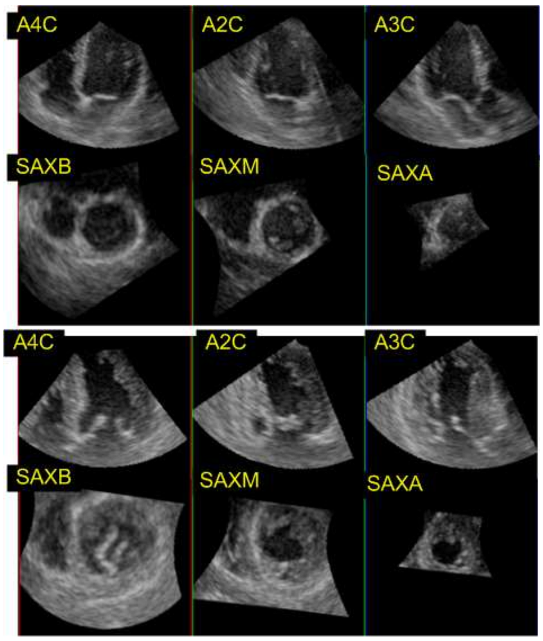

Fig. 3. Examples of AutoMPR detection results.

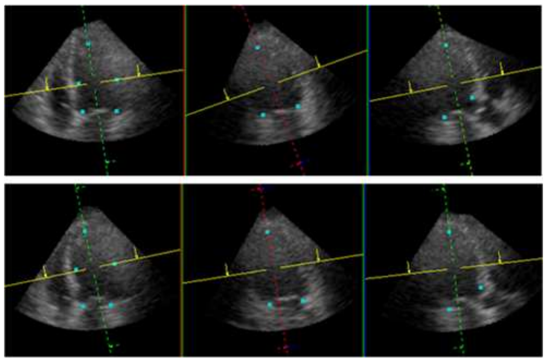

Fig. 5. Examples of above average detection errors. The angle difference between the detected MPRs (bottom) and the groundtruth (top) is $23.4°$, $16.6°$, and $20.0°$ for A4C, A2C, and A3C (from left to right), respectively.

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