Automating 3D Echocardiographic Image Analysis

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Abstract

A major barrier for the use of 3D echocardiography as a quantitative tool in routine clinical practice is the absence of accurate and robust segmentation and tracking methods necessary for fully automated analysis. In previous work [1] we demonstrated LV automatic tracking is feasible provided a good segmentation and a correct initialisation for the tracker. In this article we present a fully automated 3D echocardiographic image processing protocol for assessment of left ventricular (LV) function. We use a **hybrid segmentation method** that combines a) local boundaries obtained with phase-based **acoustic feature detection** [2], with b) global image information provided by a new **multi-scale fuzzy-clustering** segmentation algorithm based on combined ideas from [3] and [4]. We fit and track the LV surface using a **4D spline continuous transformation** [5]. We compare **volume curves and ejection fraction** (EF) results obtained using 3D image sequences that have been processed manually, in semi-automatic manner, and in fully automated fashion. **Minimal user interaction** is necessary and the protocol is viable for routine clinical practice.

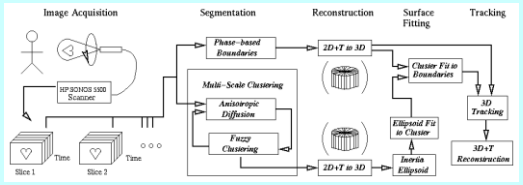
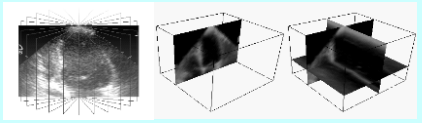


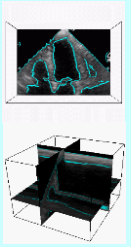
Image acquisition

3D transthoracic data was acquired on a HP SONOS 5500 ultrasound machine using a rotating transducer. Data is stored as a sequence of **2D echograms (2D+T image)**, one for each of 12 different probe angles, with a frame rate of 25 frames per second. Scanning was performed using ECG and respiration gating, on an **apical view** (i.e. the probe was located at the apex and roughly aligned with the LV long axis).



Phase-based boundary detection

Acoustic reflection from endocardial borders varies according to the relative angle between the boundary and the transducer. The net effect is to produce a **border with variable intensity** contrast around its length, difficult to detect using an intensity-gradient based approach. For this reason we employ a phase-based spatio-temporal feature detection method [2], which finds candidate endocardial border points according to their phase signature (edge shape). A measure of the **feature asymmetry on 2D+T images** is produced for endocardial borders.

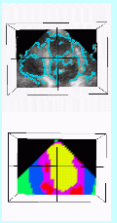


Multi-scale clustering for LV cavity detection

Because ultrasound images have a low signal-to-noise ratio (specially in regions of the LV wall parallel to the insonification beam), obtaining boundary points all over the endocardium is difficult even with the phase-based method. In order to obtain an estimate of the endocardial wall, in *every region* of the LV cavity, we developed a complementary region-based segmentation method that exploits a priori knowledge about the ellipsoidal shape of the LV.

Multi-scale clustering for LV cavity detection (cont.)

We use a multi-scale fuzzy clustering algorithm that does not rely exclusively on the local differential structure of the data but takes into account the global characteristics of the image. In this way, a **continuous approximation of the LV cavity** boundary is provided even in regions of the images with low contrast and low signal-to-noise ratio. This also diminishes the effect of outliers detected by the phase-based method that correspond to noise or to other anatomical structures. The results of the clustering method are then used to initialize the surface fitter and can also be used to filter out edge detection outliers (see section on future work).



Fuzzy clustering:

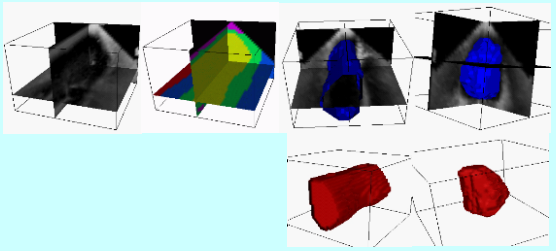
We use a fuzzy c-means clustering algorithm to divide the image domain into a pre-determined number of regions (clusters). The image attributes we use for this classification are **intensity**, and position in an **elliptic-cylindrical coordinate** system [3], which is a natural choice for the 2D+T LV long-axis images.

Scale-space generation:

In order to overcome the problematic effect of intensity fluctuations of the noisy ultrasound images, the clustering process is performed at different levels of resolution in a scale-space of the image. The scale-space is generated using the **knowledge-based anisotropic diffusion** (KBAD) algorithm [4]. This algorithm smooths the image intensity while preserving sharp edges. It uses the heat diffusion equation with a tensor conductance term which is an explicit function of the the position, intensity and gradient, and can also incorporate a priori and a posteriori information of the geometric and dynamic characteristics of the image, for instance, a probabilistic measure of the image intensity distribution [3].

Multi-scale fuzzy clustering:

The KBAD scheme used for generating the scale-space gets feedback from the clustering in progress. The fuzzy classification of the image domain provides a measure of the a **posteriori probability** that neighbouring pixels belong to the same tissue type, and is therefore incorporated into the diffusion process by means of the conductance function, penalizing or encouraging diffusion between pixels depending on the probability of them to belong to the same cluster.

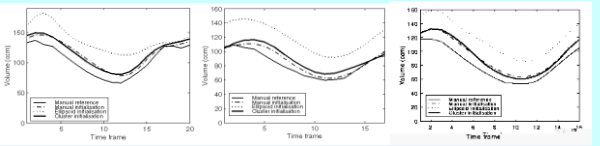


Fitting and tracking

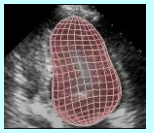
Both, the LV cluster and the phase-based feature points obtained for each of the **2D+T images are reconstructed to 3D**. The surface of the 3D LV cavity cluster at end diastole is used as initialisation for the surface fitter, and then deformed to match the phase-based boundaries at all time frames. A 3D matching is initialised with the result obtained at the previous time frame. Each of these matching steps is processed using a variant of the method described in [5], where the **initial surface** is **deformed to the boundary points** using B-spline tensor products. The control points of the 3D B-spline tensor products that define the deformations at each time frame are interpolated over time using a periodic temporal B-spline. The final deformation of the surface over time is therefore a continuous 4D (3D+T) tensor product of B-splines from which valuable dynamic information can be computed.

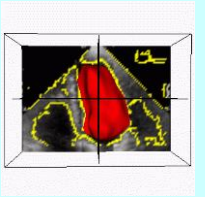
LV function results

We investigated the effect of using sparse acquisitions (60, 30, 12 and 6 image planes) and decided 12 is a good compromise between resolution and practicality [1]. The experiments have been conducted on three healthy human subjects. Left ventricular cavity volume curves are **compared** when computed with **four tracking processes** on each of the three data sets: **a) Manual segmentation** performed by an expert for the complete 3D sequence; **b)** automatic tracking using manual segmentation of the end-diastolic surface as initialisation; **c)** automatic tracking using as an initial surface an ellipsoid manually placed by an expert with the help of a 3D graphic interface; and **d)** the **fully automatic method**, i.e. initialised using clustering. The plots below show the volume curves obtained with these four methods on the three data sets. If the initialisation is not sufficiently close to the target LV cavity (method (c)), the tracking fails and the volumes are meaningless. On the other hand, the trackings (b) and (d) give similar results, showing that clustering based automatic initialisation gives as good results as initialisation from manual segmentation.



Method	Ejection Fraction (%)		
	Patient (1)	Patient (2)	Patient (3)
Manual segmentation	51	45	54
Manual initialisation	46	43	52
Ellipsoid initialisation	38	37	46
Cluster initialisation	46	41	54

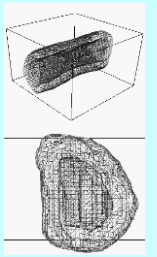




Discussion and future work

The main reason for the volume overestimation is that endocardial boundaries are not clearly defined in some regions of the lateral wall, often shadowed by the rib cage. In these regions the tracker followed spurious edges located far, outside the cavity. However, the computed **ejection fractions** are, in the case of the fully automatic method, less than **5%** over the value obtained from the manual segmentation (see table above). At present we validate results on clinical case study.

Filtering: Using the LV cluster we can derive two surfaces within which the endocardium is likely to be. We are currently using these as a confidence measure to discard the phase-based boundary detection outliers (see preliminary results of filtering surfaces on the right).



References

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[5] J. Declerck, J. Feldmar, M.L. Goris, and F. Betting. Automatic registration and alignment on a template of cardiac stress and rest reoriented SPECT images. *IEEE Trans. on Medical Imaging*, 16(1):1--11, 1997.

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