FAST AND FULLY AUTOMATIC 3D ECHOCARDIOGRAPHIC SEGMENTATION USING B-SPLINE EXPLICIT ACTIVE SURFACES

D. Barbosa [a,b] *T. Dietenbeck* [b] *B. Heyde* [a] *H. Houle* [c] *D. Friboulet* [b] *J. D'hooge* [a] *O. Bernard* [b]

[a] Lab on Cardiovascular Imaging & Dynamics, Katholieke Universiteit Leuven, Belgium
[b]Université de Lyon, CREATIS; CNRS UMR5220; INSERM U630;
Université Lyon 1; INSA-LYON, France
[c]Siemens Ultrasound, Mountain View, California, USA

ABSTRACT

We have recently introduced a novel framework to efficiently deal with 3D segmentation of challenging inhomogeneous data in real-time. However, the existing framework still relied on manual initialization, which prevented taking full advantage of the computational speed of the method. In the present manuscript we propose an automatic initialization scheme adapted to 3D echocardiographic data and we couple it with the existing segmentation framework. Moreover, a novel segmentation functional, which explicitly takes the darker appearance of the blood into account, is also proposed in the present manuscript. We show that fully automatic segmentation of the left ventricle using the proposed method provides an efficient, fast and accurate solution for quantification of the main cardiac indices used in routine clinical practice.

Index Terms— Active contours, variational method, image segmentation, B-splines, 3D echocardiography.

1. INTRODUCTION

Several studies have recently shown the potential of real-time 3D echocardiography (RT3DE) for accurate volumetric assessment of left ventricular (LV) dimensions and global function [1]. Despite these efforts, 3D LV segmentation typically remains a time consuming task and heavily relies on user interaction to accurately measure LV volumes. Indeed, a recent study using a state-of-the-art commercial software package shows that although fully automated LV volume measurements are feasible, optimal LV volumetric assessment still requires a significant amount of manual correction [2]. This results in doubling the analysis time [2] and also introduces a user-dependent bias. Thus, there is still a significant need for tools allowing automatic real-time 3D LV segmentation.

We recently proposed a framework for real-time segmentation of challenging inhomogeneous 3D data [3]. This method uses B-spline explicit active surfaces (BEAS) to recover objects from volumetric data, allowing to use both global or local region-based segmentation energies to evolve the contour. We have recently developed a pipeline to segment RT3DE data using BEAS. In spite of obtaining promising results, the existing semi-automated algorithm relies on manual input (6 clicks per 3D volume) to fit an ellipsoid used to initialize the segmentation algorithm [4]. This fact intrinsically introduces user-dependent bias. Moreover, manual initialization accounts for the vast majority ($\sim$95%) of the total analysis time. Thus, a fast and automatic initialization method would be of great clinical value. This would overcome any variability introduced by the manual initialization, while taking full advantage of the real-time ability of BEAS.

Several attempts have recently been made to tackle the initialization dependence of energy-based image segmentation strategies. For example, Tauber *et al.* have proposed the concept of centers of divergence to solve the initialization dependence of active contours [5]. Regarding cardiac segmentation problems, van Stralen *et al.* have proposed a method for automatic estimation of both LV orientation and mitral valve detection [6]. While being an elegant method, it heavily relies on the initial gradient-based edge detection step. Given the challenging characteristics of ultrasound images, gradient-based edge detection is not ideal to properly detect the myocardial boundaries in echocardiographic data. Furthermore, this method has a computational burden around 8s per initialized frame, in a C++ implementation.

The originality of the proposed method is twofold: first, we modify the algorithm proposed by van Stralen *et al.* with the inclusion of a robust, phase-based edge detector and we propose a novel, fast ellipsoid fitting algorithm which allows to keep the computational burden of the initialization method under 4s, in a MATLAB implementation. Secondly, we introduce a new segmentation energy which takes explicitly into account the darker appearance of the blood pool, contributing to a more robust and accurate segmentation. The fully automatic segmentation method is then validated using clinical volumetric ultrasound data.

This work was partially funded by the region Rhône-Alpes, Tournesol French-Flemish cooperation programme and by the Portuguese Science Foundation (PhD grant SFRH/BD/62230/2009).

2. AUTOMATIC INITIALIZATION ALGORITHM

2.1. Image Pre-Processing

The first step for the automatic initialization of a 3D ultrasound volume is to detect the myocardial boundaries using edge operators in several C-planes (*i.e.* planes parallel to the transducer surface), perpendicular to the acquisition axis. Given that ultrasound images possess low contrast between the blood pool and the myocardial tissue, we propose to include a robust, phase-based edge detector, due to its intrinsic invariance to intensity. The local phase extracted using monogenic signal was recently applied to ultrasonic data by Rajpoot *et al.* and has a remarkable performance in the detection of the myocardial boundaries in noisy data, even in low contrast areas [7]. This edge detector is applied to each of the 2D C-planes taken 5mm apart.

Since the endocardium is approximately a circle in these 2D C-planes, low level computer vision methods can be employed to robustly find the most likely position for the center of the LV cavity. To this end, the Hough transform for circles (HTc) is employed. This transform will return the probability of a given position (x, y) in the 2D C-plane image being the center of a circle of radius r. In order to keep r in a physiologically relevant range, $[r_{min}, r_{max}]$ was set to $[15, 35]$mm.

2.2. Long Axis Detection

By concatenating the output of the HTc, a 4D (x, y, z, r) circle center probability matrix, P_c, can be generated. This matrix carries valuable information regarding the positions which are the most likely centers of the LV cavity at each z-depth. Since at this point the radius information is not yet totally relevant, P_c is transformed into a 3D matrix, P_{max}, by taking the maximum value along the r direction. Subsequently, multi-dimensional dynamic programming (MDP) is used to find the optimal path that maximizes the center probabilities along the Z direction. This path will correspond to a set of positions on each of the 2D C-planes that have high probability of being a center of a circle. Through these positions, a straight line is fit in order to determine the left ventricular long axis (LAX). A demonstrative example of P_{max} and the optimal path found with MPD are shown in Figure 1 (b).

2.3. Base Detection

After LAX detection, a perpendicular square plane of size r_{max} was slided along the LAX. For each position an average gray level was taken by averaging over this square plane. Given that the base plane corresponds both to an area of brighter appearance and to a dark-to-bright transition, a simple merit function, whose maximum corresponds to the base position, was built as:

$$g(z) = I_{LAX}(z) + (I_{LAX}(z) - I_{LAX}(z - \zeta)) \quad (1)$$

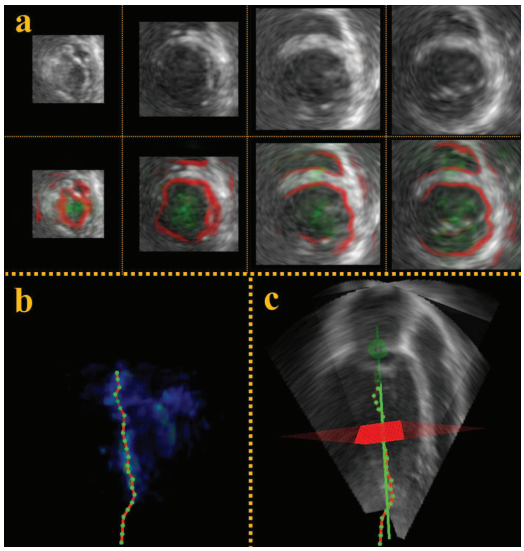


Fig. 1. LAX and base detection: (a) Image pre-processing (red- edge indicator, green- circle center probability); (b) Maximum probability path, displayed over P_{max}; (c) Base detection (red - sliding averaging plane, green ball- detected base position).

where $I_{LAX}(z)$ corresponds to the average gray level of the square plane perpendicular to the LAX at the depth z and ζ is a distance parameter used to assess the expected dark-to-bright transition. ζ was set to 0.5cm in all the experiments. Note that the first term in (1) accounts for the brighter appearance of the valve plane and the second term accounts for the variation in the gray level intensity due to the blood-valve plane transition.

2.4. Ellipsoid Fitting

After base detection, P_c is sampled along the estimated LAX resulting in a 2D feature map, $FM(z, r)$ which will correspond to the probability of the estimated LAX positions being the center of a circle of radius r, as given by the Hough transform for circles computed previously. This feature map provides valuable information on the cardiac boundaries, since it estimates at each depth which are the most likely radii of the endocardial interface. Next, this feature map needs to be converted to a true 3D model that can be used to initialize the segmentation algorithm. To this end, we propose to formulate the ellipsoid fitting problem using its parametric equation defined in a cylindrical coordinate system. It should also be noted that all the required data was already computed in the long axis detection step, being thus a very computationally efficient solution. Taking the ellipsoid parametric equation:

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} + \frac{z^2}{c^2} = 1. \quad (2)$$

Assuming that $a = b$, *i.e.* that the ellipsoid is actually a spheroid, it can be easily shown that $x^2 + y^2$ is actually the

radius of the circle that results from the intersection of the ellipsoid and a plane perpendicular to the Z axis. Thus, we can express the radius of each z-cut of the ellipsoid as:

$$r = f(z) = a\sqrt{1 - \frac{z^2}{c^2}} \tag{3}$$

At this point, we simply fix the apex position at 2 cm away from the probe in order to provide a rough estimate of the longitudinal measure for the LV ellipsoid fitting process. From all the plausible curves f(z) ($a \in [r_{min}, r_{max}]$ and $c \leq d_{LAX}$, where $d_{LAX} = base_Z - 2cm$), we select the one maximizing sum of the radius probability along the LAX, as shown in Figure 2 (a).

3. 3D LV SEGMENTATION USING BEAS

Once an automatically fitted ellipsoid is available, it will be used as initialization of the segmentation algorithm. The segmentation framework (BEAS) used in the present work has been recently proposed by the authors in order to allow real-time segmentation of challenging inhomogeneous 3D data [3]. The segmentation energy used in the present work is a modified version of the localized Yezzi energy, as proposed in [8]. Since the blood pool is usually darker than the myocardial tissue, we have introduced a small change in the original function in order to take this into account. Indeed, we propose to minimize the following segmentation energy:

$$E_{LY} = \int_{\Gamma} (u_x - v_x) \tag{4}$$

where u_x and v_x are the local means inside and outside the interface Γ, computed along the normal direction as suggested in [3]. Note that whenever $u_x > v_x$, we will have a local positive energy value, which is penalized in our minimization strategy. This energy can be directly minimized wrt. the B-spline coefficients using the following evolution equations:

$$c[\mathbf{k}]^{(t+1)} = c[\mathbf{k}]^{(t)} - \lambda \frac{\partial E_{LY}}{\partial c[\mathbf{k}]^{(t)}}, \tag{5}$$

$$\frac{\partial E_{LY}}{\partial c[\mathbf{k_i}]} = \int_{\Gamma} \Big(\frac{\big(\bar{I}(\mathbf{x}^*) - u_x\big)}{A_u} - \frac{\big(\bar{I}(\mathbf{x}^*) - v_x\big)}{A_v} \Big) \beta^d \left(\frac{\mathbf{x}^*}{h} - \mathbf{k}_i \right) \, \mathrm{d}\mathbf{x}^*. \tag{6}$$

where A_u and A_v are the areas inside and outside the interface used to estimate the local means u_x and v_x, respectively. Further details on the BEAS framework can be found in [3].

4. RESULTS AND DISCUSSION

The proposed framework was tested using 24 real-time 3D echocardiography exams which were acquired with a Siemens Acuson SC2000 (Siemens Ultrasound, Mountain View, CA), using a 4Z1c matrix transducer. The dataset comprised a mixture of both healthy individuals and patients with a multitude of pathologies including myocardial infarction and dilated cardiomyopathy with severely distorted LV geometry. Volume sequences were acquired from an apical window and the sonographer aimed at the inclusion of the entire LV within the pyramidal field of view. Each sequence was manually segmented by 3 clinical experts. The reference LV volumetric parameters (end-diastolic volume (EDV), end-systolic volume (ESV), stroke volume (SV) and ejection fraction (EF)) were estimated as the average of the values estimated by the experts.

In order to assess the added value of taking the darker appearance of the blood explicitly into account in the segmentation energy, we have compared the proposed functional with the local-based Yezzi energy suggested in [8]. At this point, a semi-automated version of the proposed method was used, where an ellipsoid is automatically fitted to the points provided by the user (6 points per 3D volume) and it is used to initialize the segmentation algorithm. To validate the proposed automatic initialization algorithm, we have also compared the results of the proposed fully automatic framework with the aforementioned semi-automated approaches.

The overview of the results for the comparison between the LV volumetric indices extracted using the semi-automated (manual initialization) and the proposed fully automatic approach can be found in Table 1. Note that for the manual initialization, we clearly show the increased segmentation performance with the proposed functional. In fact, some cases have shown severe errors when using the local Yezzi energy, specially when the contour was initialized near the mid-myocardium. In these cases, the interface occasionally evolved towards the outer boundary (for instance at the septal wall) instead of the correct endocardial border.

The proposed framework for automatic LV volumetric assessment shows a very strong correlation with the reference values (R= 0.973, 0.962, 0.916 and 0.894 for EDV, ESV, SV and EF respectively). Bland-Altman analysis revealed small bias and none of these was statistically significant for the fully automatic approach, while the bias for the EDV, SV and EF were statistically significant for the semi-automated framework using the proposed segmentation energy (paired t-test, $p<0.05$). Thus, it is clear that the proposed initialization scheme provides an appropriate ellipsoid to initialize the segmentation algorithm, since there is no reduction on the performance when compared to the semi-automated approach. Furthermore, bypassing the manual initialization avoids the introduction of user-dependent variability and allows to significantly reduce the time of analysis required to extract the desired cardiac indices. Indeed, it may be observed that the average total analysis time was in the order of 30s (manual initialization time $\sim$29s) for the 2 semi-automated approaches, whereas it was around 5s (automatic initialization time $\sim$4s) for the proposed automatic analysis framework.

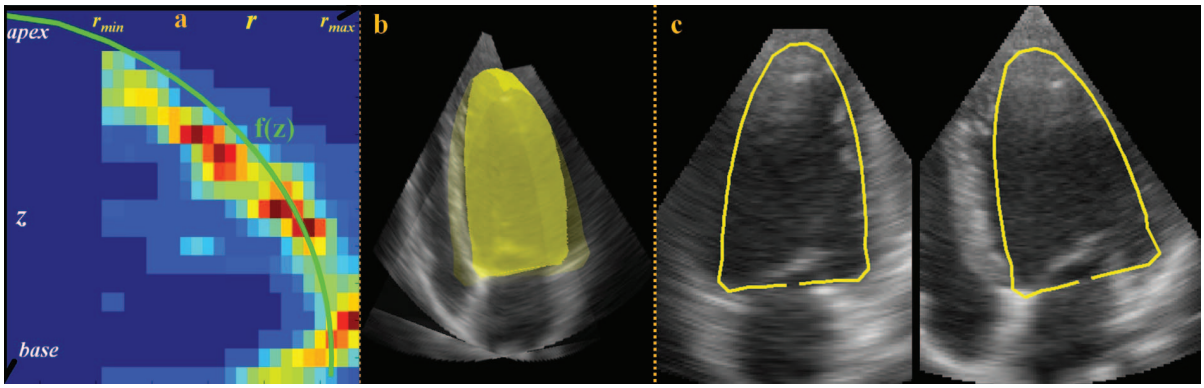


Fig. 2. Ellipsoid Fitting: (a) Feature map and optimal ellipsoid fit in cylindrical coordinates (green); (b,c) Initial surface for the 3D image segmentation step.

Table 1. Comparison between LV volumetric indexes using manual or automatic initialization of the 3D segmentation algorithm

Initialization/ Segmentation	**Semi-Automated Analysis 1** (Manual/Local Yezzi [8])				**Semi-Automated Analysis 2** (Manual/Proposed Energy)				**Automatic Analysis** (Automatic/Proposed Energy)			
	EDV (ml)	ESV (ml)	SV (ml)	EF (%)	EDV (ml)	ESV (ml)	SV (ml)	EF (%)	EDV (ml)	ESV (ml)	SV (ml)	EF (%)
Correlation Coefficient (R)	0.934	0.887	0.720	0.800	0.954	0.951	0.932	0.843	0.973	0.962	0.916	0.894
Bias (μ)	-3.91	-18.4*	-14.5*	11.63*	7.35*	0.77	6.58*	3.12*	3.50	0.84	2.66	1.18
LOA ($\mu \pm 1.96\sigma$)	[-39.1, 31.3]	[-63.9, 27.1]	[-35.0, 64.0]	[-13.7, 36.9]	[-22.4, 37.5]	[-21.3, 22.9]	[-13.6, 26.7]	[-9.72, 16.0]	[-19.2, 26.2]	[-18.8, 20.5]	[-18.6, 23.9]	[-9.25, 11.6]
Total Analysis Time (s)	30.7±7.5				30.7±7.5				4.6±0.39			

5. CONCLUSION

We proposed in the present work an algorithm to automatically estimate an ellipsoid corresponding to an approximation of the LV endocardial interface in RT3DE data. This ellipsoid is used to initialize our segmentation framework (BEAS), allowing fully automatic segmentation of the left ventricle. We also introduce a novel segmentation energy which takes the darker appearance of the blood into account. We have found that this energy leads to more accurate and robust 3D LV segmentation results. Our results support the feasibility of accurate and fully automatic volumetric assessment of LV shape, size and global function in a time-window close to real-time.

6. REFERENCES

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