Automatic 3D Reconstruction of the Beating Left Ventricle Using Transthorasic Echographic Images

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Abstract

In this paper we present an algorithm for 3D reconstruction of the beating left ventricule from echocardiographic image sequences. We especially stress on the automatic tracking process of the ventricular wall. Our algorithm is based on a combination of active shape modelling (snakes) and methods for computing the ventricular wall motion between two frames. We also investigate anisotropic diffusion filtering methods to improve the ventricule detection. Results are presented which prove the efficiency of our method.

1 Introduction

There has been increasing interest in analysing left ventricular function using cardiac imaging technology. The clinical demand is for real time analysis as most pathologies manisfest themselves by abnormalities in heart dynamics. That is the reason why we have developped a fast echographic system for 4D acquisition using a transthoracic approach [6]. The systeme consists in a probe rotating around its axis. The probe is controlled by an electronic device triggered by the ECG signal taken directly from the patient. For each rotation of the probe, an entire heart contraction is recorded at a 25 frames/sec rate.

In this paper we present a computationnal approach which allows us to automatically reconstruct and visualize the beating left ventricle from the data acquired. As the geometry of our acquisition system is known, dynamic 3D reconstruction of the LV amounts to track the ventricular inner border in the images for each probe angle.

Within the computer vision community, considerable attention has been given to tracking and understanding object motion. Unfortunately, there are significant problems with many of the approaches already proposed. The primary objection is the inability to estimate point wise motion and track speicific points on the wall over time. Therefore curve based tracker have been developped to overcome this problem. They often use a model to guide the LV detection [3]. A training stage is therefore needed to capture the natural variability within a class of patients. However, as the variability within a class can be large, model based approaches can be unefficient. That is the reason why we attempt to measure motion directly on the grey level images.

Our original contour tracking algorithm is based on a combination of active shape modelling (snakes [4]) and methods for computing the ventricular wall motion between two frames. Owing to the regular contraction of the heart during a cycle, we assume that the ventricular motion can be approximately modelled with a similarity (product of a rotation, a scaling and a translation). Thus, computing a rough estimation of the wall motion between two frames amounts to compute four parameters. From this initialization, the snake process converges towards the ventricle contour.

Unfortunately, snakes can be attracted by high gradients which do not belong to the ventricular wall. Therefore, images must be enhanced before tracking: we then use non linear diffusion filters [7, 5] because they lead to an image simplification which enhances semantically important information such as edges. We prove in this paper that the use of diffusion filtering on echographic images greatly improves the tracking stage as noisy structures are removed from the images. As a result, starting from the contour of the left ventricle outlined by the physician in the first frame of the patient dataset, the wall ventricle is automatically tracked in the echo-cardiographic image sequence.

The outline of the paper is as follows. In section 2 we review the key ideas behind the tracking algorithm. Section 3 presents results of applying anisotropic diffusion to improve tracking performance. Further dynamic reconstruction results are also given in this section. We conclude on section 4 with a discussion of directions of future works.

2 Tracking the ventricular wall

Detecting and tracking curved contours is an arduous task because the extraction of corresponding contours between two frames is difficult. That is the reason why a global method like *active contour models* [4] can be of great benefit since it makes it possible to simultaneously solve both the segmentation and the tracking problem. Once the snake is initialized in the first frame, it will automatically track the contour from frame to frame. However, owing to the excessive flexibility of the snakes, this approach is restricted to the case where the movement and deformation of the contour is small between two frames.

To overcome this problem, we consider a two stage tracking process: the prediction stage allows us to compute a rough estimation of the motion field. From this initialization, the snake generally converges towards the corresponding contour. Because of the warping capabilities of the snakes, an approximate modeling of the 2D motion field is only needed. We therefore use a 2D similarity (scale+rotation+translation) which proves to be well suited to describe the heart contraction.

2.1 Motion computation

Our algorithm is based on the iterative computation of the 2D motion field . Our aim is to find the best 2D similarity $\mathcal{S}$ such that the intensity profile on the contour to be tracked $\mathcal{C}$ and $\mathcal{S}(\mathcal{C})$ are roughly the same. Because of the aperture problem, constraints on the motion must be added to solve for both components of the velocity. Our method is therefore based on the normal optical flow which can be recovered with sufficient accuracy [2].

Let $(M_i)_{0\leq i<N}$ be the discretization of $\mathcal{C}$, $f_0^{\perp}(M_i)$ be the normal optical flow at point (M_i) and let n_i be the unit normal to $\mathcal{C}$ at point M_i. Let I_1 and I_2 be two consecutive frames. The 2D similarity $\mathcal{S}_0$ minimizing

$$\sum_{0\leq i<N} |(\vec{M_i}\mathcal{D}_0(M_i).n_i)n_i - f_0^{\perp}(M_i)|^2 \qquad (1)$$

gives a first rough approximation of the similarity. Then this estimation is refined by computing the normal optical flow $f_1^{\perp}$ on $\mathcal{S}_0(\mathcal{C})$ between the registrated image $I_1(\mathcal{S}_0^{-1}(x,y))$ and I_2 and so on . . . .

Successive infinitesimal displacements $\mathcal{S}_0, ..., \mathcal{S}_j, ...\mathcal{S}_p$ can then be computed. They move the curve $C_j = \mathcal{S}_p...\mathcal{S}_0(C)$ progressively closer to the corresponding curve in I_2. On a technical point of view, $\mathcal{S}_j$ can be approximated with

$$\mathcal{S}_j \left\{ \begin{array}{l} a_j x - b_j y + t_j^x \\ b_j x + a_j y + t_j^y \end{array} \right.$$

and is computed using a least squares approach.

The use of an explicit global model of the 2D motion field permits us to override the divergence trend at erroneous flow points. Moreover, the use of the similarity modeling allows the heart dynamics to be handled properly.

2.2 Snake process

Once a rough estimation of the 2D motion field has been computed, it still remains to detect the ventricule boundary. Modeling the heart dynamic with a similarity proved to be well suited and the ventricule presiction is then close to the real one. A snake based approach can therefore be used: startin form the predicted curve C, the curve u minimizing

$$-\int |\nabla I(u(s))|^2 + \int \alpha |u'(s)|^2 + \beta |u''(s)|^2 ds$$

allows us to to determine the most regular contour in the neighborhood of the initial curve C.

Fig. 1 illustrates our two stage process: the prediction computed with the similarity model is near the actual ventricule boundary (Fig. 1.a) and the ventricule is reached successfully after the snake process.

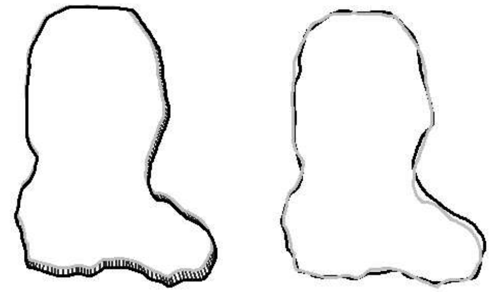

Figure 1: Tracking the ventricule: (a) prediction after motion computation (b) result after snake process

However, this tracking process can fail in some particular cases. Indeed, the prediction stage is sensitive to a low signal-to-noise ratio. Other problems can originate in the snake process as the snake can be attracted by high gradients which do not belong to the searched contour.

3 Improving the tracking process with anisotropic diffusion

In this section we turn our attention to improving the tracking process. A way to improve the tracking process is to use a preprocessing stage to reduce the noise due to the acquisition process as well as to the backscattering of the echo signal.

Classical preprocessing stages are gaussian or median filtering. Unfortunately they induce blurring or delocalization of the edges. On the contrary, non linear diffusion filters lead to an image simplication which preserves semantically important information (edges, lines, . . .). The historically first non linear diffusion filter has been proposed by Perona and Malik [7]. The basic idea was to reduce smoothing at edges in order to preserve their contrast and location in a better way than gaussian scale space. If we embed the original image in a family of derived images $u(x,y,t)$ obtained by convolving the original image $I_0(x,y)$ with a gaussian kernel $G(x,y,t)$ of variance t $u(x,y,t) = I_0 * G(x,y,t)$, Koenderink pointed out that

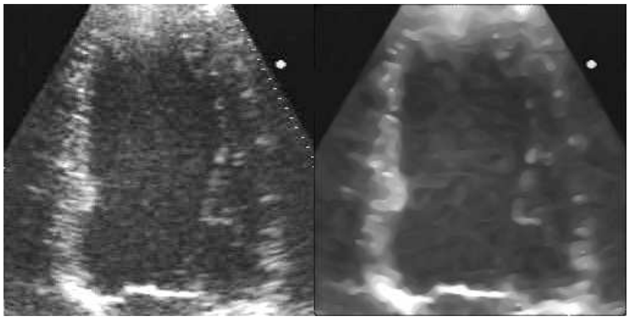

Figure 2: Smothing with anisotropic diffusion

u can be viewed as the solution of the heat equation

$$\begin{cases} \frac{\partial u}{\partial t} = div(c\nabla u) \\ u(x,y,0) = I_0(x,y) \\ c(x,y,t) = 1 \end{cases}$$

In the non linear diffusion proposed in [7] and used in [1], c is not constant but choosen to be a decreasing function of the gradient ($c(x,y,t) = \frac{1}{1+|\nabla u(x,y,t)|^2}$). This way, they encourage smoothing within a region in preference to smoothing across the boundaries. Improvements of these ideas were proposed in [5] to overcome the ill-posedness of the perona-malik filter: the intuitive idea of edges is that they are generally piecewise smooth. Therefore it seems natural to use a directional smoothing kernel such that it diffuses more in the direction parallel to the edges and less in the perpendicular one. This leads to the following scheme:

$$\begin{cases} u_t = c|\nabla u| div(\frac{\nabla u}{|\nabla u|}) = cu_{\xi\xi} \\ u(x,y,0) = I_0(x,y) \end{cases}$$

where ξ is the perpendicular direction to the gradient ∇u. Such non linear diffusion filters prove to be useful for improving the tracking task: First, they reduce speckle noise in the images and produce rather homogeneous regions. This improves the prediction step as well as the snake process because the snake is no longer attracted by high gradient due to noise. Moreover, as smoothing is performed in the direction parallel to the edges, the edges are accurately located even for large smoothing. Fig. 3 shows the results of the tracking algorithm without preprocessing (first line) and with anisotropic diffusion (second line). Observe that the curves are more regular for the algorithm which uses anisotropic diffusion. Moreover, we can somehow quantify the degree of improvement because we have some kind of ground truth.Indeed, a physician has drawn the epicardium on the images for some patient (black points on the images). One can observe that the results are closer to the contours drawn by the physician with the algorithm which uses anisotropic diffusion.

The beating ventricule built from these results during the systolic period is shown in Fig.4.

4 Conclusion

In this paper we have presented our algorithm for 3D reconstruction of the beating ventricule. Unlike other approaches, it does not require preliminary learning of ventricular deformation. Currently, the user has only to outline the ventricular boundary in the first image of each sequence. Tracking in the subsequent frame is then achieved automatically. Our results are very encouraging and we want to test our algorithm on a large set of patients. We now plan to investigate how to solve problems due to drop outs in the images. A first solution would be to introduce regularity constraints when the gradient information is too weak. Finally regularization must be performed on the reconstructed ventricule in order to cope with unavoidable error tracking.

References

[1] M. helbing and R. Orglmeister. Anisotropic Filtering for Detecting Left Ventricular Borders in Echocardiographic Images. In *Computers in Cardiology, 1993*, pages 197–200, September 1993.

[2] B. Horn and B. Schunck. Determining Optical Flow. *Artificial Intelligence*, 17:185–203, 1981.

[3] G. Jacob, A. Noble, and A. Blake. Robust Contour Tracking in Echographic Sequences. In *Proceedings of 6th International Conference on Computer Vision, Bombay (India)*, pages 408–413, January 1998.

[4] M. Kass, A. Witkin, and D. Terzopoulos. Snakes: Active Contour Models. *International Journal of Computer Vision*, 1:321–331, 1988.

[5] L.alvarez, P.L. Lions, and J.M. Morel. Image Selective Smoothing and Edge Detection by non Linear Diffusion. *SIAM Journal on Numerical Analysis*, 29(3):845–866, 1992.

[6] J.-P. Lethor, G. Winterfeldt, M.-O. Berger, M. Handschuhmacher, and I. Marcon. A Fast automated System for Four Dimensional Reconstruction of the left Ventricle Using Transthorasic Echographic Images. In *Computers in Cardiology*, September 1997.

[7] P. Perona and J. Malik. Scale Space and Edge Detection Using Anisotropic Diffusion. *IEEE Transactions on PAMI*, 12(7):629–639, July 1990.

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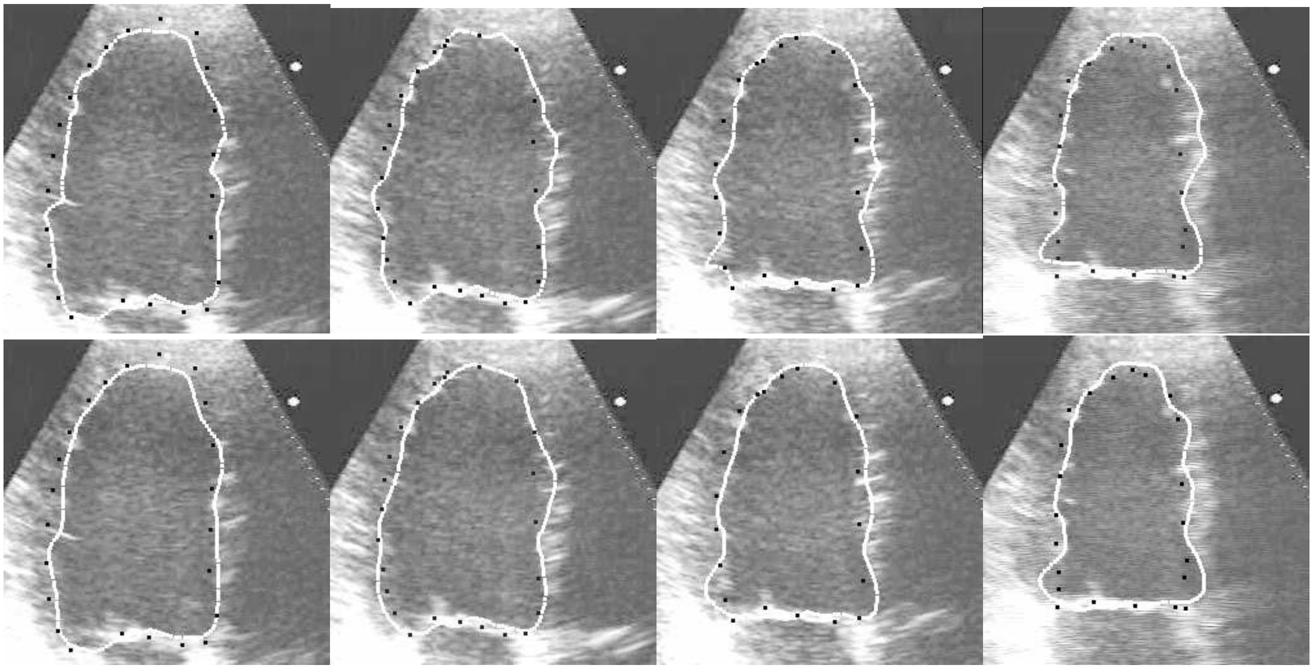

Figure 3: Result of the tracking algorithm (a) without preprocessing (first line)(b) with anisotropic diffusion (second line). The ventricule boundary drawn by the physician is shown with black points.

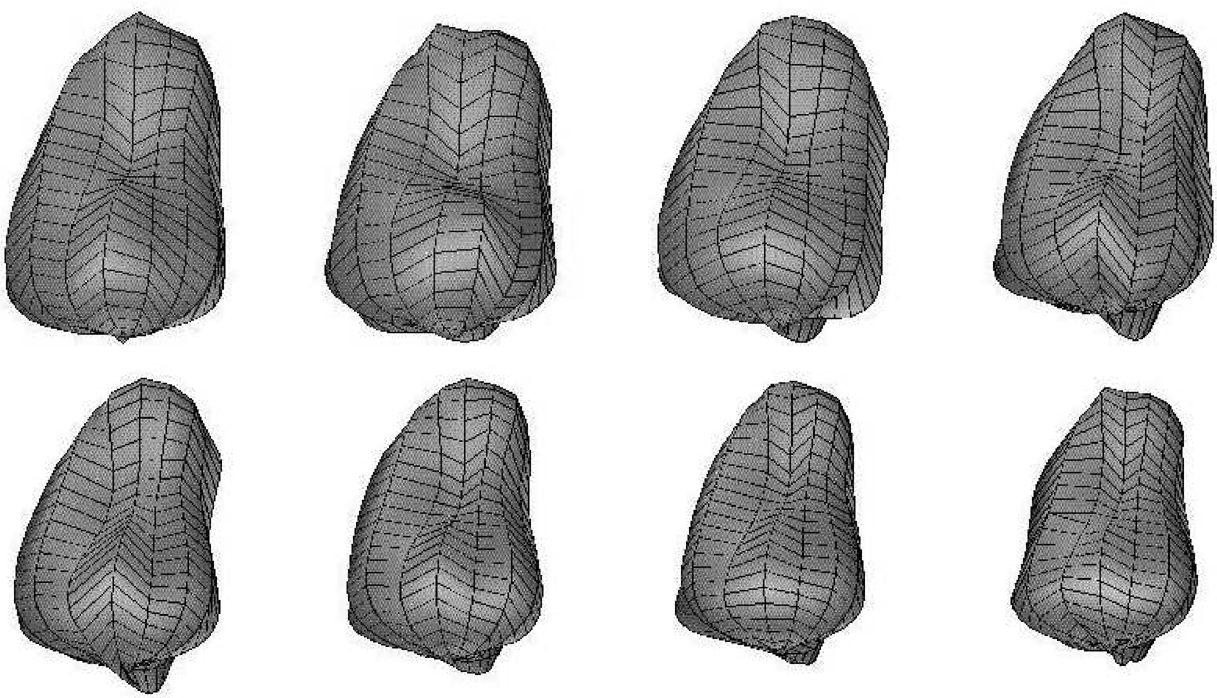

Figure 4: Automatic 3D reconstruction of the beating heart.