A Framework for Real-Time Left Ventricular Tracking in 3D+T Echocardiography, Using Nonlinear Deformable Contours and Kalman Filter Based Tracking

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Abstract

This paper presents a new framework for automatic real-time left ventricular (LV) tracking in 3D+T echocardiography. The framework enables usage of existing biomechanical deformation models for the heart, with nonlinear modes of deformation, combined with edge models for the endocardial boundary.

Tracking is performed in a sequential state estimation fashion, using an extended Kalman filter to recursively predict and update contour deformations in real-time. Contours are detected using normal-displacement measurements from points on the predicted contour, and are processed efficiently using an information-filter formulation of the Kalman filter.

Promising results are shown for LV-tracking using a truncated ellipsoid contour model, with deformation parameters for translation, orientation, scaling and bending in all three dimensions. The tracking framework automatically detects LV position initially, even in situations where it is partially outside the volume. It also successfully tracks the dominant motion and shape changes throughout the heart cycle in real-time. A collection of 21 3D echocardiography recordings of good quality demonstrates that the framework is capable of automatically identifying and tracking the left ventricle in 90% of the recordings without any user input.

1. Introduction

There is a clinical need for real-time monitoring of cardiac function during invasive procedures and intensive care. Real-time tracking of the left ventricle (LV) would hence be beneficial in such situations. The last few years, 3D echocardiography has been introduced. However, no method for real-time tracking or segmentation of such data is currently available.

Most tracking approaches in 2D echocardiography have been based on traditional deformable models as introduced by Kass [1], which facilitate free-form deformation. However, these methods tend to be too slow for real-time applications and also have to be initialized close to the LV boundaries. The problem can, however, be made tractable by restricting the allowable deformations to certain predefined modes. This both regularizes the problem to make tracking more robust, and allows for real-time implementations based on sequential state estimation.

This state estimation approach was first presented by Blake et al. in [2], [3] and [4], which used a Kalman filter to track B-spline models deformed by linear transforms within a model subspace referred to as *shape space*. Later, the framework was applied for real-time left ventricular tracking in long-axis 2D-echocardiography by Jacob et al. in [5], [6] and [7]. All these papers were using a B-spline representation, deformed by a trained linear principal component analysis (PCA) deformation model. The papers also discuss the possibility of extending the framework to 3D echocardiography, which is what has been done in this paper. The proposed framework also allows for nonlinear modes of deformations.

2. Methods

Contour model

The tracking framework is based on a contour deformation model. This model is a function $\mathcal{D}(...)$ that transforms points on a contour template $\mathbf{p_0}$ into deformed points $\mathbf{p}$ using a state vector $\mathbf{x}$ as parameter:

$$\mathbf{p} = \mathcal{D}(\mathbf{p_0}, \mathbf{x})$$

This parameterization puts very few restrictions on the allowable deformation, so virtually "any" deformation model can be used, including biomechanical models. One must, however, be able to derive all partial derivatives of the position as a function of the deformation parameters. Deformation of contour normals also requires calculation of the spatial derivatives [8]. This approach differs from the linear *shape space* deformations used by Blake and Jacob [2],[3],[4],[5], [6] and [7], where all deformations had to be linear in the state vector.

Pursuing the approach by Park et al. [9] we use a truncated ellipsoid as contour template in this paper, and allow for the following deformation parameters:

- Translation (t_x, t_y, t_z).
- Scaling (s_x, s_y, s_z).
- Rotation/orientation (r_x, r_y).
- Bending/curving (c_x, c_y).

In total, these parameters form the state vector below.

$$\mathbf{x} = \begin{bmatrix} t_x & t_y & t_z & s_x & s_y & s_z & r_x & r_y & c_x & c_y \end{bmatrix}^T$$

Kinematic model

To enable modeling of motion in addition to position, the state vector is augmented to contain the last two successive state estimates [3]. The kinematic model for the predicted state $\bar{\mathbf{x}}$ at timestep $k+1$ then becomes:

$$\bar{\mathbf{x}}_{\mathbf{k+1}} = \mathbf{A_1}\hat{\mathbf{x}}_{\mathbf{k}} + \mathbf{A_2}\hat{\mathbf{x}}_{\mathbf{k-1}} + \mathbf{B_0}\mathbf{w_k}$$

Tuning of kinematic properties like damping, regularization and prediction uncertainty for all deformation parameters can now be accomplished by adjusting the coefficients in matrices $\mathbf{A_1}$, $\mathbf{A_2}$ and $\mathbf{B_0}$.

Edge measurements

Edge measurements are used to guide the contour towards the object being tracked. This is performed by measuring the distance between contour points and measured edges in normal direction, called *normal displacement* [4], for points along a predicted contour inferred from the measurement model.

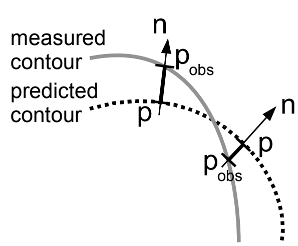

Figure 1. Normal displacement measurements along normal vectors of a predicted contour.

The normal displacement between a predicted contour point $\mathbf{p}$ with associated normal vector $\mathbf{n}$ and a measured edge point $\mathbf{p_{obs}}$ is:

$$v = \mathbf{n^T}(\mathbf{p_{obs}} - \mathbf{p})$$

This inner-product form is dimensionally invariant, thus function just as good for measurements in 3D-data as 2D. The associated measurement noise r can either be constant for all edges, or dependent on edge-strength or other measure of uncertainty.

Edge model

The high levels of noise and speckle in ultrasound recordings makes edge detection difficult. Robust edge detectors that minimize the chance of detecting spurious edges in noisy areas are therefore desired.

An edge-model that exhibits robust characteristics is the *step model* [10]. This model assumes edges to form a transition in image intensity, for one plateau to another, and calculates the edge position that minimizes the sum of squared errors between the model and the data.

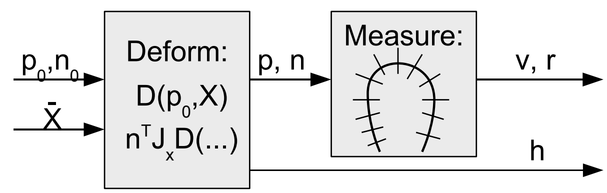

Figure 2. Overview over the contour deformation and edge measurement process. The figure shows how points on the initial contour $\mathbf{p_0}$, $\mathbf{n_0}$ are first deformed using a predicted state $\bar{\mathbf{x}}$, yielding a deformed contour $\mathbf{p}$, $\mathbf{n}$ and measurement vector $\mathbf{h}$. Edges are then measured relative to the predicted contour, resulting in normal displacements v with associated measurement error variances r.

Measurement linearization

Normal displacement measurements can be used as measurement model in a *Kalman filter* model for the tracking problem. This is possible by linearizing the nonlinear deformation model around the predicted deformation state and using an *extended Kalman filter* [11] implementation. Altogether, this results in a measurement vector $\mathbf{h}$ that is based on the state-space Jacobian of the measurement model, meaning all partial derivatives of contour position with regard to all state dimensions, evaluated at the predicted state.

The linearized measurement vector then becomes the normal vector projection of the Jacobian matrix:

$$\mathbf{h^T} \equiv \mathbf{n^T}\frac{\partial \mathcal{D}(\mathbf{p_0}, \mathbf{x})}{\partial \mathbf{x}}$$

Measurement processing

Assumption of independent measurements allows measurements to be summed together efficiently in *information space* [11], since independent measurements lead to diagonal measurement covariance matrices. All measurement information can then be summed into an information

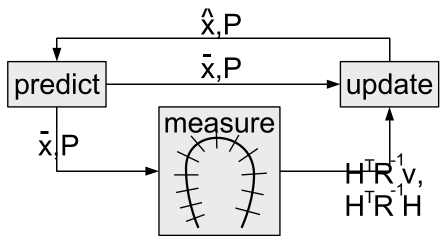

Figure 3. Overall framework structure.

vector and matrix of dimensions invariant to the number of measurements:

$$\mathbf{H^T R^{-1} v} = \sum_i \mathbf{h_i} r_i^{-1} v_i$$
$$\mathbf{H^T R^{-1} H} = \sum_i \mathbf{h_i} r_i^{-1} \mathbf{h_i^T}$$

This is the same form as was used in [4].

Measurement update equations

Contour tracking forms a special problem structure, since the number of measurement typically far exceed the number of state dimensions. Ordinary Kalman gain calculation will then be computationally intractable, since they involve inverting matrices with dimensions equal to the number of measurements. An alternative approach, presented by Blake and Isard in [4], avoids this problem by altering the measurement update step in the Kalman filter. This is accomplished by utilizing that the Kalman gain $\mathbf{K_k} \equiv \mathbf{\hat{P}_k H^T R^{-1}}$, and reformulating to account for measurements on information filter [11] form. The updated state estimate $\hat{\mathbf{x}}$ for timestep k then becomes:

$$\mathbf{\hat{x}_k} = \mathbf{\bar{x}_k} + \mathbf{K_k v_k}$$
$$\mathbf{\hat{x}_k} = \mathbf{\bar{x}_k} + \mathbf{\hat{P}_k}(\mathbf{H^T R^{-1} v_k})$$

Measurement innovations are here efficiently summed into a measurement vector with dimension equal to the state dimension.

The error covariance update equations can similarly be performed in information space to avoid inverting large matrices:

$$\mathbf{\hat{P}_k^{-1}} = \mathbf{\bar{P}_k^{-1}} + \mathbf{H^T R^{-1} H}$$

This form only requires inversion of matrices with dimensions equal to the state dimension.

3. Results

A collection of 21 apical 3D-echocardiography recordings served as independent validation of the method. The same configuration were used for all recordings, with an initial LV contour automatically placed at a depth of approximately 80mm in the first frame as shown in figure 4. The tracking was then run for a couple of heartbeats to give the contour enough time to lock on to the LV.

The experiments were performed using an LV-contour consisting of 426 contour points. Edge detection was performed in the normal direction of each of these points, using 20 samples spaced 1mm apart. Real-time tracking in 25fps 3D echocardiography datasets yielded a modest CPU load of approximately 18%[1].

The results are summarized in table 1. One can see that the tracking was performed with subjectively *good* or *adequate* quality in 90% of the 21 recordings present in the dataset. Figure 5 and 6 shows examples of *good* tracking in an ordinary recording, and a recording with apex outside the volume. Figure 4 shows the initial contour used in all recordings, as well as the contour after tracking for a couple of heartbeats.

Quality	Count	Description
Good	16	Tracking performed well.
Adequate	3	Tracking with reduced accuracy.
Fair	1	Tracking with low accuracy.
Poor	1	Unable to automatically track

Table 1. Overall performance of the automatic tracking. Subjectively scored by the author.

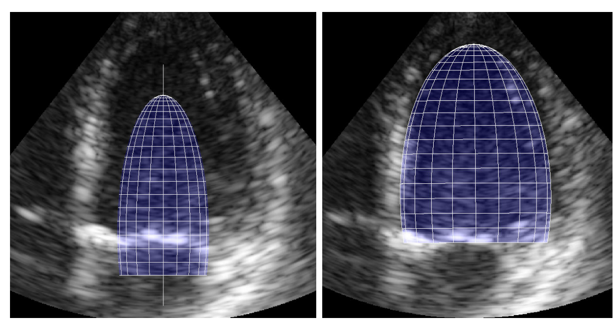

Figure 4. Azimuth view of the initial contour (left), and tracking results after the contour has locked on the LV after a couple of heartbeats (right).

4. Discussion and conclusions

A novel framework for real-time contour tracking in 3D echocardiography using sequential state estimation has been proposed. The framework builds upon previous work by Blake et al. [4], and enables tracking of of deformable contours with nonlinear modes of deformation. The feasibility of the framework has been demonstrated by automatic tracking in several recordings using a truncated el-

[1] The tracking were then performed using a C++ implementation on a 3GHz Intel Pentium 4 processor. Visualization were disabled for CPU benchmarking.

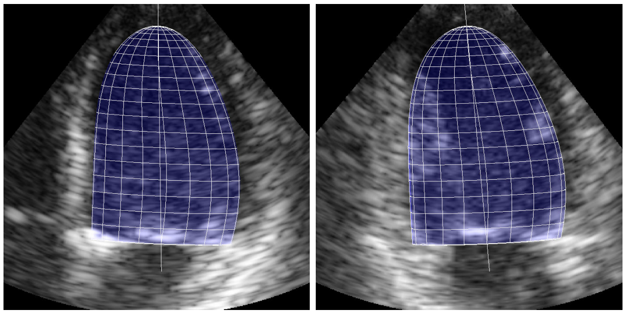

Figure 5. Azimuth and elevation view of a recording with *good* tracking.

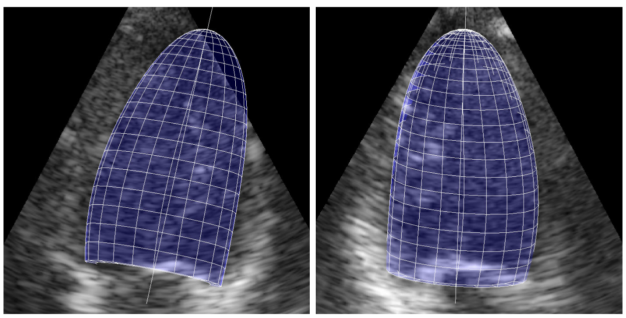

Figure 6. Azimuth and elevation view of tracking when LV is partially outside the volume.

lipsoid model. The tracking framework was found to automatically detect LV position initially, even in situations where the LV is partially outside the acquired volume.

It can be argued that the evaluation procedure performed is too subjective and should have been performed by a medical clinician. However, the principal objective was not to get an accurate segmentation of the LV suitable for clinical diagnosis, but merely to demonstrate the ability to track the dominant motion and shape changes throughout the heart cycle. Further research will focus on perfecting the method, and striving towards tracking that is both robust and accurate.

Traditional free-form deformation models are not capable of operating in real-time in volumetric data. The proposed framework instead sacrifices accuracy for the capability of automatic real-time tracking within a limited shape space. This limited shape space also serves to regularize the problem, thus making tracking more robust.

The general deformation formulation also places few restrictions on the modes of deformations allowed. It is therefore believed that the truncated ellipsoid model can be replaced with a more realistic biomechanical model for the LV. This is likely to yield better model fitting to the data, and hence improve tracking accuracy.

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References

[1] Kass M, Witkin A, Terzopoulos D. Snakes: Active contour models. International Journal of Computer Vision 1988; 1(4):321–331.

[2] Blake A, Curwen R, Zisserman A. A framework for spatiotemporal control in the tracking of visual contours. International Journal of Computer Vision 1993;11(2):127–145.

[3] Blake A, Isard M, Reynard D. Learning to track the visual motion of contours. Artificial Intelligence 1995;78(1-2):179–212.

[4] Blake A, Isard M. Active Contours. Secaucus, NJ, USA: Springer-Verlag New York, Inc., 1998. ISBN 3540762175.

[5] Jacob G, Noble JA, Mulet-Parada M, Blake A. Evaluating a robust contour tracker on echocardiographic sequences. Medical Image Analysis 1999;3(1):63–75.

[6] Jacob G, Noble JA, Kelion AD, Banning AP. Quantitative regional analysis of myocardial wall motion. Ultrasound in Medicine Biology 2001;27(6):773–784.

[7] Jacob G, Noble JA, Behrenbruch CP, Kelion AD, Banning AP. A shape-space based approach to tracking myocardial borders and quantifying regional left ventricular function applied in echocardiography. IEEE Transactions on Medical Imaging 2002;21(3):226–238.

[8] Barr AH. Global and local deformations of solid primitives. In SIGGRAPH '84: Proceedings of the 11th annual conference on Computer graphics and interactive techniques. New York, NY, USA: ACM Press, 1984; 21–30.

[9] Park J, Metaxas D, Young A, Axel L. Deformable models with parameter functions for cardiac motion analysis from tagged mri data. IEEE Transactions on Medical Imaging June 1996;15(3):290–298.

[10] Rabben SI, Torp AH, Støylen A, Slørdahl S, Bjørnstad K, Haugen BO, Angelsen B. Semiautomatic contour detection in ultrasound M-mode images. Ultrasound in Medicine Biology 2000;26(2):287–296.

[11] Bar-Shalom Y, Kirubarajan T, Li XR. Estimation with Applications to Tracking and Navigation. New York, NY, USA: John Wiley & Sons, Inc., 2002. ISBN 0471221279.

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