Endocardial Tracking in Contrast Echocardiography Using Optical Flow

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Abstract. Myocardial Contrast Echocardiography (MCE) is a recent technique that allows to measure regional perfusion in the cardiac wall. Segmentation of MCE sequences would allow simultaneous evaluation of perfusion and wall motion. This paper deals with the application of partial differential equations (PDE) for tracking the endocardial wall. We use a variational optical flow method which we solve numerically with a multigrid approach adapted to the MCE modality. The data sequence are first smoothed and a hierarchical-iterative procedure is implemented to correctly estimate the flow field magnitude. The method is tested on several sequences showing promising results for automatic wall tracking.

1 Introduction

The analysis of the motion of the heart wall is a standard technique for studying myocardial viability [1]. The measurement of cardiac perfusion using ultrasound imaging has recently become available with contrast agents. Contrast agents provide information about the degree of perfusion and the speed of reperfusion of the myocardium. Tracking of the myocardium would allow simultaneous quantification of wall motion and perfusion. Caiani [3] et al. proposed an interactive tracking method that segmented each frame independently.

In this work, we consider a new optical flow algorithm proposed recently in [4] where real time performances are reported when test sequences of synthetic images are considered. Our aim is to evaluate the effectiveness of the Combined Local-Global approach (CLG) for endocardial tracking where noisy corrupted image sequences are analysed. The algorithm combines local and global regularization of the flow field. A hierarchical implementation has been designed that allows to capture large inter-frame motion present in clinical sequences acquired with low frame rate. To filter the high degree of speckle present in the image, we evaluate two different smoothing schemes.

This paper is organized as follows: Section 2 introduce to the basic material and definitions. The algorithms used in the model cases are detailed, the reconstruction steps and the numerical implementation are presented. In Section 3

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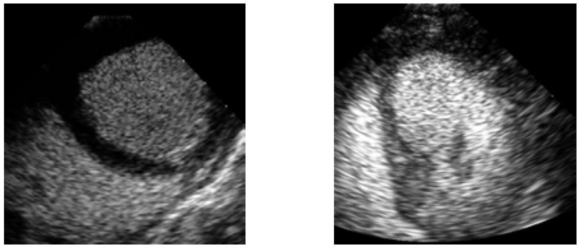

Fig. 1. Frames of two myocardial contrast echocardiography sequences. Short axis view (left) and apical four-chamber view (right)

we show the results we have obtained with different pre-processing steps as well as a parametric study relating the optical flow problem and the segmentation paradigm. Section 4 is devoted to the discussion and future work.

2 Material and Methods

The use of PDE's is becoming a standard tool in digital images processing and reconstruction [8]. On the other hand multigrid methods represent a new computational paradigm which can outperform the typical gradient descent method.

2.1 Preprocessing

Before applying an optical flow algorithm a pre-processing smoothing step is necessary ([2]), specially when dense flow fields and noisy images are analised. Otherwise a mismatch in the direction field appears. This step, usually, amounts to a convolution of the original sequences with a Gaussian kernel of standard deviation σ. As a result we get a smoothed new sequence of images which can be considered as the initial data of the CLG algorithm. This filtered version can suffer from several drawbacks when tracking is performed. In fact the resulting convolved images have a blur in the boundary of the cardiac wall and this can complicate its tracking. As an alternative, we have also pre-processed the original sequence with a Total Variation scheme because of its well known properties ([8]) as regards to edge preservation.

2.2 CLG Approach for Optical Flow

In this section, following Bruhn et al. ([4]), we shall introduce the basic notation and equations. Let $g(x, y, t)$ be the original image sequence where $(x, y) \in \Omega$ denotes the pixel location, $\Omega \subset \mathbb{R}^2$ is a bounded image domain and t denotes time. Let $f(x, y, t)$ be its smoothed version which represents the initial data of the CLG algorithm.

The optical flow field $(u(x, y), v(x, y), t)^T$ at some time t is then computed as the minimum of the energy functional

$$E(u, v) = \int_{\Omega} \left(\omega^T J_\rho(\nabla_3 f)\omega + \alpha(|\nabla u|^2 + |\nabla v|^2)\right) dxdy$$

where the vector field $\omega(x, y) = (u(x, y), v(x, y), 1)^T$ is the displacement, $\nabla u = (u_x, u_y)^T$ and $\nabla_3 f = (f_x, f_y, f_t)^T$. The matrix $J_\rho(\nabla_3 f)$ is given by $K_\rho * (\nabla_3 f \nabla_3 f^T)$ where $*$ denotes convolution, K_ρ is a gaussian kernel with standard deviation ρ and $\alpha > 0$ is a regularization parameter. More details of CLG method can be found in [7]. As usual in the variational approach the minimum of the energy $E(u, v)$ corresponds to a solution of the Euler-Lagrange equations

$$\alpha \Delta u - [J_{11}(\nabla_3 f)u + J_{12}(\nabla_3 f)v + J_{13}(\nabla_3 f)] = 0 \quad (1)$$

$$\alpha \Delta v - [J_{12}(\nabla_3 f)u + J_{22}(\nabla_3 f)v + J_{23}(\nabla_3 f)] = 0 \quad (2)$$

where Δ denotes the laplacian operator. This elliptic system is complemented with homogeneous Neumann boundary conditions.

As reported in Bruhn et al. [7] this approach speeds up the computation when compared with the clasical gradient descent method and we shall follow his indication here.

Discretisation. Optical flow seeks to find the unknown functions $u(x, y, t)$ and $v(x, y, t)$ on a rectangular pixel grid of cell size h_xxh_y. We denote by u_{ij} and v_{ij} the velocity components of the optical flow at pixel (i, j). The spatial derivates of the images have been approximated using central differences and temporal derivatives are approximated with a simple two-point stencil.

The finite difference approximation to the Euler-Lagrange equations (1) and (2) is given by

$$0 = \frac{\alpha}{h_x^2}(u_{i,j-1} - 2u_{ij} + u_{i,j+1}) + \frac{\alpha}{h_y^2}(u_{i-1,j} - 2u_{ij} + u_{i+1,j}) - \quad (3)$$

$$-(J_{11,ij}u_{ij} + J_{12,ij}v_{ij} + J_{13,ij})$$

$$0 = \frac{\alpha}{h_x^2}(v_{i,j-1} - 2v_{ij} + v_{i,j+1}) + \frac{\alpha}{h_y^2}(v_{i-1,j} - 2v_{ij} + v_{i+1,j}) - \quad (4)$$

$$-(J_{21,ij}u_{ij} + J_{22,ij}v_{ij} + J_{23,ij})$$

where J_{nm}, ij is the component (n, m) of the structure tensor $J\rho(\nabla_3 f)$ in the pixel (i, j).

2.3 Numerical Implementation

The system of equations 3 and 4 has a sparse system matrix and may be solved iteratively with a Gauss-Seidel scheme [5].

System Resolution. Iterative solvers of equation systems, such as Gauss-Seidel, have an great initial convergence, however, after the initial iterations the convergence slows down significatly. Multigrid algorithms, take this idea and combine it with a hierarchy model of equations systems that come from differents levels of detail in the problem discretisation. The main idea of multigrid methods is to first aproximate one solution in a level of discretisation, then calculate the error of the solution from a coarser level and correct the aproximate solution with the error.

Suppose that the system $Ax = b$ has arisen from the above discretization. We can obtain a approximate solution, $\tilde{x}$, with a few iterations of an iterative method, say the Gauss-Seidel method. It is posible to calculate the error e of the solution and correct the solution: $x = \tilde{x} + e$. We calculate e from the residual error

$$r = b - A\tilde{x}$$

As A is a linear operator, we can find e solving the equation system

$$Ae = r$$

Solving this equation requires the same complexity as solving $Ax = b$, but we can solve $Ae = r$ at a coarser discretisation level, where the problem is much smaller and will be easier to solve [6]. Once we have e at he coarser level, we calculate $\hat{e}$ interpolating e from the coarser level to the finest level and suddenly we do the correction $x = \tilde{x} + \hat{e}$.

The multigrid method takes this idea of approximate-correction and yields it to several levels of discretisation. The detailed algorithm is: (the superscripts h_1, $h_2 ... h_n$ indicates the level of discretisation: h_1 the finest level and h_n the coarsest level)

- We start at the finest level (h_1). With a few iterations of Gauss-Seidel method we aproximate a solution $\tilde{x}^{h_1}$ of the system

  $$A^{h_1} x^{h_1} = b^{h_1}$$

  We calculate the residual error r^{h_1}

  $$r^{h_1} = b^{h_1} - A^{h_1} \tilde{x}^{h_1}$$

- In this step we solve the equation $Ae = r$ in the next coarser level of discretisation:

  $$A^{h_2} e^{h_2} = r^{h_2}$$

  Restrict r^{h_1} to r^{h_2}, A^{h_1} to A^{h_2}. Now, we recall e^{h_2} such as x^{h_2}, and r^{h_2} such as b^{h_2}. The equation is now

  $$A^{h_2} x^{h_2} = b^{h_2}$$

  At level h_2, we aproximate a solution $\tilde{x}^{h_2}$ with a few iterations, and repeat the process throw levels until reach the level h_n.
- At level h_n, the equation $A^{h_n} x^{h_n} = b^{h_n}$ is exactly solved. Be $\tilde{x}^{h_n}$ to the exact solution in this level.

Now we start the correction of the solutions calculated at the levels.

- Interpolate $\tilde{x}^{h_n}$ to level h_{n-1} and add to $\tilde{x}^{h_{n-1}}$ to obtain $\hat{x}^{h_{n-1}}$

- Starting from $\hat{x}^{h_{n-1}}$, run a few iterations of Gauss-Seidel over

$$A^{h_{n-1}}x = b^{h_{n-1}}$$

- Interpolate the new calculated aproximation $\tilde{x}^{h_{n-1}}$ to the level h_{n-2} and repeat the process throw levels until the level h_1 is reached.
- The solution obtained in the h_1 is the solution of the original system.

Two operators are needed to move between levels in the multigrid. The restrictor operator used is a arithmetic mean and the interpotalion operator is a constant interpolation.

Large Displacements: Hierarchical Approach. The CLG method, as all variational methods, assumes that the movement of the objects in two consecutive images is small. This is necessary because CLG is based on the a linearisation of the grey value constancy assumption and the movements must be small for holds the linearisation. However, this is not in MCE imaging where acquisition frame rate can be small and heart motion can be non-linear.

This limitation can be overcome by calculating optical flows in coarser scales, where the displacements are smaller. To calculate the optical flow of two consecutive images $I1$ and $I2$, we scale the two images into several levels, L_1 to L_n, obtaining $I1_1, I1_2, .., I1_n$ and $I2_1, I2_2, .., I2_n$, where $L1$ is the finest level (the original images), Ln is the coarsest level and $I1_i$ $I2_i$ correspond to the scaled images. The detailed process is:

- Compute the optical flow, u_n and v_n, at the level L_n between the images $I1_n$ and $I2_n$.
- Interpolate the optical flow to the next level L_{n-1}. Compute a new image $I1^w_{n-1}$ warping I_{n-1} with the interpolated optical flow, then compute a new optical flow among $I1^w_{n-1}$ and $I2_{n-1}$. Correct the interpolated optical flow with the new optical flow adding the two fields.
- Repeat the process until level $L1$. The final optical flow is the corrected optical flow at level $L1$.

Improving the Optical Flow: Iterative Hierarchical Approach. In the ultrasound test sequences we noticed that the algorithm computes a correct field direction but it subestimates the magnitude of the displacement. To overcome this handicap we repeat the computation of the optical flow, warp the initial image and calculate a new optical flow. This process is repeated iteratively until the highest displacement is less than $\| h_x, h_y \|$. The final optical flow is the sum of all previously obtained optical flow values. This iterative process is applied only at scale levels L_2 to L_n.

3 Results

Algorithms were evaluated using images provided by Gregorio Marañón Hospital in Madrid. The algorithm has been tested on two type of sequences, to take

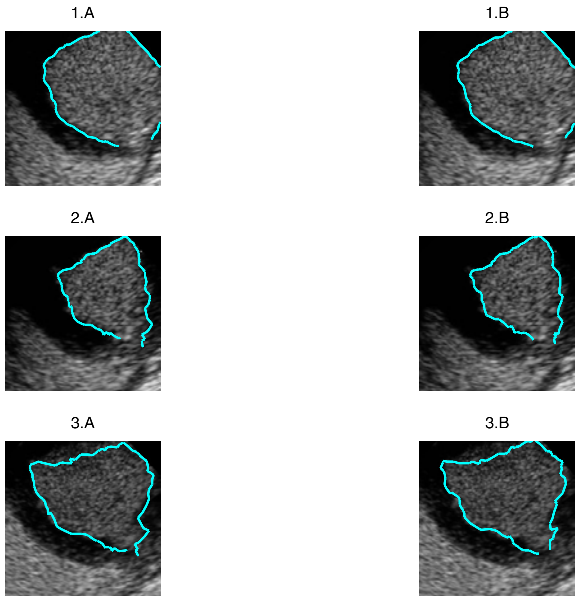

Fig. 2. Results of endocardial tracking with different preprocessing methods. Figures 1.A, 2.A, 3.A have been obtained with TV filtering while figures 1.B, 2.B and 3.B have been obtained with a gaussian ($\sigma = 3$)

into account different signal to noise ratios and different acquisition views. The first are short-axis views obtained during experimental surgery. The second are clinical images obtained from patients in a four-chamber view.

A first set of experiments was carried out to evaluate the two different presmoothing filters. The role of the smoothing process is to improve the results of the tracking. Therefore, the evaluation was carried out by comparing the result of the tracking with both filters on the same sequences. Fig. 2 shows the result on three frames with both filters. We did not appreciate any substantial improvement using the TV filter. As the gaussian filter is computationally more efficient, all further tracking results are obtained using this filter. To evaluate the optical flow algorithm the endocardial wall was manually segmented in the first frame of the sequence and the wall was automatically tracked in the remaining frames using the CLG algorithm with $\alpha = 200$ and $\rho = 3$. Fig. 2 shows examples of automatic tracking on short axis views. Fig. 3 shows the results on several frames of a four-chamber view sequence. Notice the different degrees of perfusion of the heart wall.

4 Discussion and Future Work

The results obtained in our study indicate that the CLG algorithm can be succesfully applied to myocardial contrast echocardiography sequences. We have designed an iterative-hierarchical approach that allows to capture large displace-

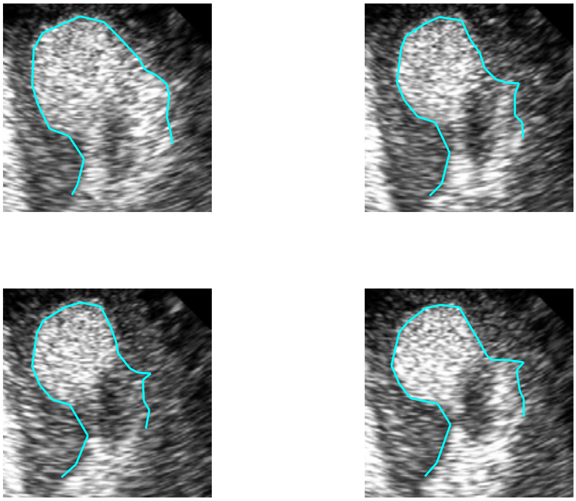

Fig. 3. Results of automatic tracking on several frames of a clinical sequence

ments accurately. The cardiac wall is tracked using only the information provided by the dense optical-flow. Post-processing of the curve to include curvature or smoothness assumptions would improve the current results. Also notice that the model does not assume any hypothesis about the specific noise of this specific imaging modality. Future work will consist in evaluating a denoising step combined with nonlinear regularization as preprocessing.

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