3-D Cardiac Motion Estimation By Point-Constrained Optical Flow Algorithm

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Abstract

In this paper we propose a technique for 3-D motion estimation of the left ventricle from image sequence of a beating human heart. Accurate motion estimation of cardiac wall has been shown to be very important in studying coronary diseases. The proposed technique requires initial 3-D segmentation of left ventricle area obtained for each time frame during cardiac cycle. Characteristic points at its surface are detected, and matched in two consecutive frames by matching shape properties. Optical flow is computed from the sequence of images using gradient-based Horn-Schunck method, additionally constrained with motion estimates for characteristic surface points.

Our work demonstrates application of Horn-Schunck optical flow algorithm for 3-D cardiac motion estimation, and proposes to improve the accuracy of estimation by introducing constraints obtained by shape-based matching method.

1. Introduction

This paper presents a method for estimation of 3-D left ventricle (LV) motion from the sequence of images of a beating human heart. The movement of the left ventricle can be represented as a very complex system of rotations and translations of points at its surface. Accurate estimation of the spatio-temporal trajectory for each point at cardiac wall gives valuable information for study of coronary diseases using finite-element modeling for finding regions with irregular behavior or increased strains in heart tissue [1].

Techniques that deal with this problem could be categorized into invasive and non-invasive. Invasive techniques track markers physically implanted on the surface of the ventricle wall [2]. Movement of the markers is tracked in sequence of cardiac images and estimation of LV motion is possible. Such techniques are not appropriate for wide application because of the need for surgical intervention Non-invasive techniques overcome this problem. There are three different main groups of approaches. The first group of approaches uses magnetic resonance tagging technique where magnetization of the tissue is altered such that grid of intersecting planes is produced [3][4]. Points of intersection are easily tracked as heart tissue moves, but motion of other points is not estimated. The second group of approaches analyzes shape of previously segmented cardiac wall, extracting motion information from the changes in the shape [5][6]. Such approaches are usually limited to several characteristic points extracted from the LV boundary. In the third group of approaches are optical flow techniques [7], which detect changes in brightness intensity of every pixel in an image, followed by estimation of movement from detected data. The optical flow approach shows some very good results in estimation of simple movements but for complex motion observed in cardiac images the algorithm need to be improved with additional constraints. Other approach uses optical flow results as input for further motion analysis [8]. In this paper we propose an optical flow algorithm enhanced by initial motion information obtained by shape-based matching method.

For initial segmentation of LV area we use a 2-D region growing technique applied to all image slices in one temporal frame, and for all temporal 3-D frames in one cardiac cycle [9]. Next, we find characteristic boundary points by investigating curvature distribution along extracted 3-D surface. Characteristic points found for two consecutive frames are matched using shape properties and motion estimation for those points is estimated. These estimates are used as point constraints in 3-D point-constrained optical flow algorithm that yields smooth and dense optical flow field of 3-D left ventricle motion.

The rest of the paper is organized as follows. Developed methods are described in the next section. In the following sections experimental results are presented and discussed. The conclusions are presented in the final section.

2. Methods

Initial segmentation of LV area is performed by means of contour-modified region growing algorithm proposed by Dai et al [10]. This method starts from a seed – a pixel belonging to target object, and iteratively expands set of pixels classified as members of the same region. After each iteration step, a contour is found, consisting of pixels adjacent to the region of interest. The similarity is tested by comparing the value of the boundary pixel with the mean value of the pixels already classified as part of the region. If the calculated difference is bellow certain threshold, the pixel is classified into the region, otherwise it is labeled as a boundary pixel. The process is repeated until no pixel is added to the region in single iteration. At the end of the process both region and its boundary are clearly detected. This technique is performed at original 2-D images of beating human heart. Contours extracted from the images representing different slices of the same temporal frame are combined to form 3-D contour of LV for further processing.

Shape-based matching is next step of the algorithm. We use it for finding exact displacement vectors for selected characteristic points at the LV surface. We propose to compare different shapes by comparing curvature at examined point.

Curvature at any point on a surface is defined by two parameters, mean curvature H and Gaussian curvature K [11]. They are defined by the following equations:

$$H = \frac{1}{2h^{3/2}} \begin{bmatrix} f_x^2 \left(f_{yy} + f_{zz} \right) - 2 f_y f_z f_{yz} + \\ f_y^2 \left(f_{xx} + f_{zz} \right) - 2 f_x f_z f_{xz} + \\ f_z^2 \left(f_{xx} + f_{yy} \right) - 2 f_x f_y f_{xy} \end{bmatrix}$$

$$K = \frac{1}{h^2} \begin{bmatrix} f_x^2 \left(f_{yy} f_{zz} - f_{yz}^2 \right) + 2 f_y f_z (f_{xz} f_{xy} - f_{xx} f_{yz}) + \\ f_y^2 \left(f_{xx} f_{zz} - f_{xz}^2 \right) + 2 f_x f_z (f_{yz} f_{xy} - f_{yy} f_{xz}) + \\ f_z^2 \left(f_{xx} f_{yy} - f_{xy}^2 \right) + 2 f_x f_y (f_{xz} f_{yz} - f_{zz} f_{xy}) \end{bmatrix}$$

$$h = f_x^2 + f_y^2 + f_z^2$$

$$f_x = \frac{\partial f}{\partial x} \qquad f_y = \frac{\partial f}{\partial y} \qquad f_z = \frac{\partial f}{\partial z}$$

$$f_{xx} = \frac{\partial^2 f}{\partial x^2} \qquad f_{yy} = \frac{\partial^2 f}{\partial y^2} \qquad f_{zz} = \frac{\partial^2 f}{\partial z^2}$$

$$f_{xy} = \frac{\partial^2 f}{\partial x \partial y} \qquad f_{xz} = \frac{\partial^2 f}{\partial x \partial z} \qquad f_{yz} = \frac{\partial^2 f}{\partial y \partial z}$$

where f is a function defining the surface. In our experiments we simply set f to zero at the boundary, to -1 for pixels belonging to the object, and to +1 for pixels outside the segmented area. Discretized versions of the partial derivatives in above equations are necessary for our implementation. Discrete partial derivatives are calculated using Sobel gradient operator.

The result of these operations is 3-D field of curvature vectors containing two features K and H. The algorithm continues by examining boundary pixels and finding if curvature values at the pixel location are local minimum or maximum in a small neighborhood area. The examined neighborhood is gradually expanded and same operation is repeated. Those pixels whose curvature values are detected as local extreme in the largest neighborhood area are selected as the most characteristic points at the surface of LV area. We can assign to each boundary pixel the value R equal to size of area in which its curvature value is found as local maximum or minimum.

In next step characteristic points in two consecutive time frames are matched such that for each point in the first frame algorithm finds a pair in following frame. In this process we find the best correlation between curvature values in a small 3-D window surrounding each of two points from two consecutive frames. The window is 3x3x3 pixels in size, and weighted, giving more weight to central point. When the pair of points with the best correlation is selected the displacement vector is calculated as distance between two paired points. It is assumed that maximal possible displacement is less than 3 pixels, thus characteristic points lying outside that perimeter are excluded from the matching process.

The estimated displacement vectors are introduced as constraints to point-constrained optical flow algorithm. Optical flow algorithms attempt to estimate the field of vectors representing spatial movements of every image point over time. We use a modified Horn-Schunck algorithm [12]. The algorithm calculates spatial and temporal derivatives for every position in the image and uses those for estimation of the optical flow vector field. A temporal sequence of 3-D frames is described by brightness function $I(x,y,z,t)$ where I is the image intensity at time t and at location (x,y,z). The assumption on brightness constancy is made that the total derivative of brightness function is zero.

$$\frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial z}\frac{dz}{dt} + \frac{\partial I}{\partial t} = 0$$

Horn and Schunck added additional smoothness constraint because brightness constancy equation is insufficient to compute all components of optical flow. Minimization of the weighted sum of smoothness term and brightness constraint term is performed:

$$\int_\Omega \left(I_x u + I_y v + I_z w + I_t \right)^2 + \lambda (\|\nabla u\|^2 + \|\nabla v\|^2 + \|\nabla w\|^2) dx$$

where u, v and w are components of optical flow in x , y and z directions, respectively. X-Y plane is parallel to plane of 2-D image slices, and Z axis is ortogonal to that plane. I_x, I_y, I_z, and I_t are partial derivatives of I with respect to x, y, z, and t (time) respectively, and λ is weighting parameter. Minimization and discretization of this term results in three equations for each image point where vector values u, v and w are optical flow variables to be determined. The resulting system of differential equations is solved using iterative Gauss-Seidel relaxation method.

On the basis of this algorithm the point-constrained optical flow technique is developed [13]. The technique uses displacement vectors previously estimated for several characteristic points at the object boundary, and it sets corresponding optical flow vectors to estimated values in order to influence computation of optical flow estimates in neighboring region. The introduced constraint values propagate to neighboring locations because the relaxation method uses information from neighboring points for calculation of new values in next iteration step. Influence of such constraints can be further enhanced by introduction of additional neighborhood constraints in the small area around every constrained point. Neighborhood constraints are derived from the original set of constraints. Influence of each original constraint is inversely proportional to the squared distance to the new constraint location and is given by the following expression:

$$u_{if} = \frac{\sum_{j\in F} \frac{u_j}{d(i,j)^2}}{\sum_{j\in F} \frac{1}{d(i,j)^2}}$$

where set F is original set of constraints, j is index of the constraint, and i is index of new constraint. $d(i,j)$ is a distance measure between corresponding constraints locations, and u_{if} is initial value of new constraint.

Our modified optical flow algorithm combines values of constraints u_{if} with vector estimates obtained by the computation of optical flow u_i after each step of iterative process, for each pixel location i. Weight factor α is used to balance influence of those constraints.

$$u_i^{'} = (1-\alpha_i)u_i + \alpha_i u_{if}$$

Similar equations are used to calculate other components of the vector field v and w. Weighting factor α_i at location i is function of distance d_i between that location and the location of the closest original constraint. It is also proportional to the sum of R-values of two matched points that represent the initial estimate for the constraint:

$$\alpha_i = (1-\frac{d_i}{d_{\max}})\cdot\frac{R_1+R_2}{2R_{\max}}$$

where d_{max} is size of neighborhood region in pixels, and R_{max} is maximum value of R. The above equation has value $\alpha = 1$ at the location of original constraints with highest R-values, allowing no modification of the vector value. It gradually decreases with distance, and $\alpha = 0$ for the pixels lying outside the neighborhood constraint region.

3. Experimental results

We have applied our technique to a set of magnetic resonance images acquired by means of ECG-gated magnetic resonance imaging using gradient echo cine technique. The resulting 3-D image set consists of sixteen 2-D image slices per temporal frame, and sixteen temporal 3-D frames per cardiac cycle. In this work we reduced the size of each image to 70x70 pixels, centered on area representing left ventricle.

Results of a segmentation of LV area are displayed in Figure 1. We displayed middle slices from several frames representing systolic contraction of heart tissue.

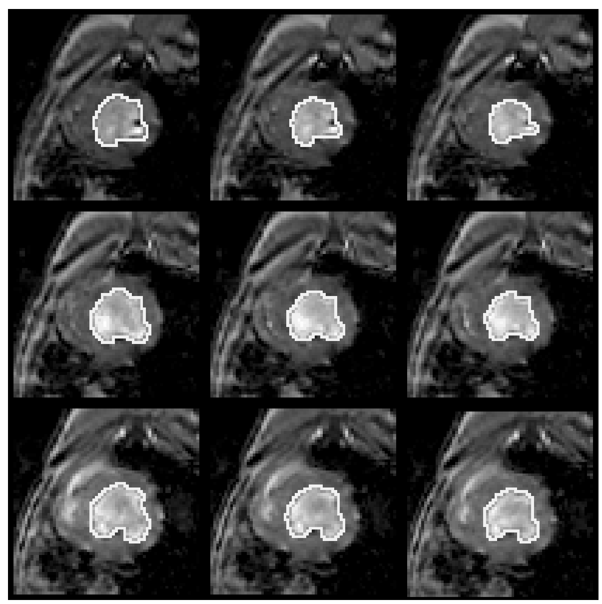

Figure 1. Segmented LV area for slices 4 to 6 (top to bottom), and time frames 3 to 5 (left to right)

Parameters of region growing segmentation, such as seed point and threshold were adjusted manually. Segmented boundaries were input data for shape based matching algorithm. Algorithm produced point constraints, which were introduced to optical flow algorithm. Resulting optical flow field for the images displayed in the first column in Figure 1 are presented in

Figure 2. In the first column vector projections to X-Y plane are displayed. The second column shows displacement in the third dimension. Vector component *w* of the same vectors is displayed using different gray levels. Lighter areas represent positive values of *w*, or vectors pointing down, while darker areas represent negative values, pointing in opposite direction.

Figure 2 shows that there are vector values that are significantly different than their neighbors, and therefore should be considered as noise. Such values could be additionally filtered to reduce error of estimated field.

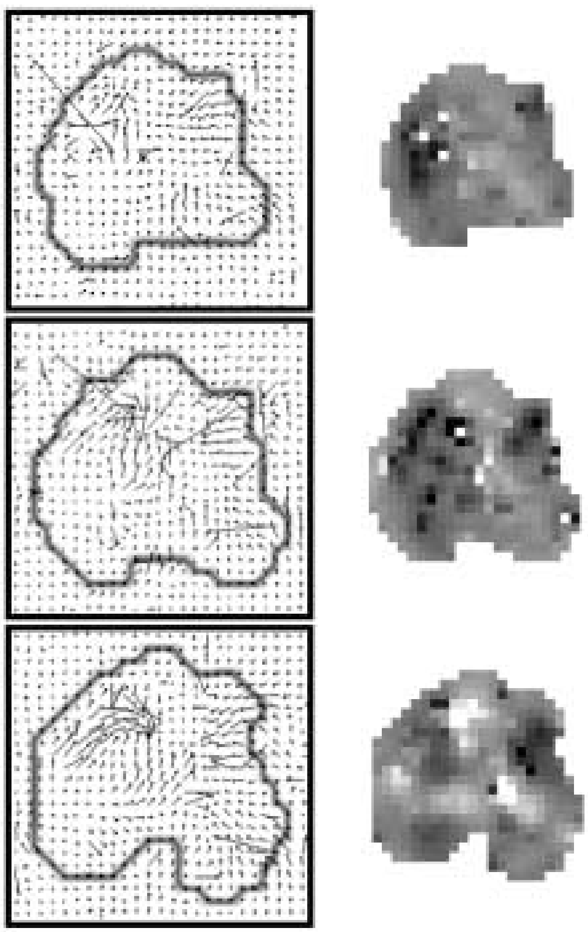

Figure 2. Estimated optical flow vectors for slices 4 to 6, for the third time frame. The first column shows projections to X-Y plane. The gray values in the second column represent the third component of the vector.

4. Discussion

Experimental results presented in the previous section are initial results obtained by proposed technique. The results demonstrate application of point constrained optical flow algorithm to estimation of motion in a set of MR images. Motion present in cardiac data is very complex, and application of standard optical flow techniques is not sufficient for estimation of accurate movement of left ventricle boundary. There are a lot of noise sources in MR cardiac data. Left ventricle area is not the only region where motion is present, other heart tissue and adjacent muscles moves as well. Further, blood flow and its turbulence are also registered at some images, which increases problem of accurate LV region segmentation during the initial steps of the technique. In this work we presented results for slices of the MR data where most of this problems are not present. The optical resolution of experimental data used in this work is another limiting factor. LV region is found in small area of approximately 30x30 pixels. Any observed deformation is therefore very small, and errors are consequently relatively large. This problem occurs especially in shape-matching algorithm, which can easily give significantly different estimates for two only slightly different segmented boundaries.

The optical flow algorithm is based on calculation of brightness gradient resulting with errors in estimation because of high frequencies present in brightness function describing the set of the cardiac images. Previously mentioned limitations lead the standard optical flow method to poor results in LV motion estimation. Estimated optical flow vector field in the region of interest is not smooth – orientation and magnitude of neighboring vectors is often very different. This is obviously in contradiction with physiology of the heart movement.

The proposed method deals with observed problems by applying point-constrained algorithm. Point-constrained algorithm additionally constrain optical flow algorithm with set of optical flow vectors extracted from shape of tracked object. The method heavily relies on accurate segmentation of LV area. In our work we assumed that contour-modified region growing method gives correct segmentation of LV area. Experiments proved that such assumption is not correct for all images in data set, and showed that segmentation algorithm needs to be improved. However, segmentation results were sufficient for evaluation of our point-constrained technique.

Shape matching algorithm based on finding best curvature correlates shows good and consistent estimates of displacement vectors that are physically acceptable, although medical expert opinion is necessary for evaluation of results. The experiments show that the optical flow field obtained with point-constrained algorithm, is smooth and more acceptable for modeling of LV boundary deformation than the field obtained without additional point constraints.

5. Conclusion

In this paper, we present a optical flow method for motion estimation of the LV of the heart from the image sequence. This method attempts to deal with the problems observed in application of standard optical flow technique, which does not provide accurate displacement estimates. An accurate segmentation of boundary and estimation of its deformation is used to improve motion estimation. Once segmentation of LV is performed, and its boundary is extracted, boundaries in consecutive frames are matched, and a set of displacement vectors is derived. Vectors are introduced to optical flow algorithm as point constraints to enhance final computation of optical flow field.

The experimental results demonstrate that our technique produces plausible results, but also pointed to problems to deal with in our future work. Improvement of initial segmentation algorithm is needed, which consequently enhance extraction of characteristic points and calculation of their displacements between two consecutive frames.

Compared to optical flow field obtained without additional constraints our results are smoother, and vectors orientation generally follows visually observed deformations of the LV boundary.

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