Spatial and Temporal Estimation of Left Ventricle Wall from Ultrasound Images using Optical Flow Algorithm

Antonio Bosnjak, Laybet Colmenares, Guillermo Montilla

Centro de Procesamiento de Imágenes, Universidad de Carabobo
Valencia. Venezuela

Abstract

This paper proposes a new technique for 3D motion estimation of the left ventricle from a sequence of a heartbeat. Accurate motion estimation of the movement of cardiac walls has been shown to be very important for studying the cardiovascular illnesses. This technique is based on a processing chain from the acquisition to the 3D segmentation of the left ventricle area obtained from each image during the cardiac cycle. With the purpose of estimating the movement of the Left Ventricle we calculate the optical flow starting from a sequence of images using the method proposed by Horn and Schunck [1]. Our work demonstrates the applicability of Horn and Schunck algorithms for optical flow to estimate the 3D cardiac motion, and proposes to improve the accuracy of estimation by introducing constraints obtained by matching method.

1. Introduction

This paper presents a new method for 3D motion estimation of left ventricle (LV) from a sequence of ultrasound images of the human heart. The movement of the left ventricle can be represented by a complex system of rotations and translations at each point of their surface. Accurate estimation of the spatio-temporal trajectory of each point of the heart's walls gives relevant important information for the study of cardiovascular diseases [2]. We can use a finite element modeling [3] to find irregular regions. The techniques related to this problem can be categorized as invasive or non-invasive. Invasive techniques use markers that are physically implanted on the ventricular wall surface [4]. The movement of these markers is followed during the sequence of cardiac images making it possible to calculate the motion of the LV. These techniques are not appropriate in most applications because they require a surgical intervention to place markers. Non-invasive techniques solve this problem, and we found three groups: The first group uses the technique of labeling with MRI, where the magnetization of tissue is altered just where it produces the intersection of planes [5]. The intersection points can be followed when the tissue is moving. The second group of techniques analyzes the shape of the heart wall previously segmented, extracting motion information from the changes on the shape [6]. These approaches are limited to extracting certain characteristic points of the edges of the LV. The third group of techniques uses optical flow to estimate the movement [7], which detects changes of the intensity of each pixel on the image. The optical flow method has shown excellent results on motion estimation of simple objects, but the movement observed in cardiac imaging is complex, consequently the algorithm needs to be improved with some additional constraints. For this reason, we proposed a new methodology based on a processing pipeline.

2. Methods

This project proposed a new pipeline of image processing (see Figure 1).

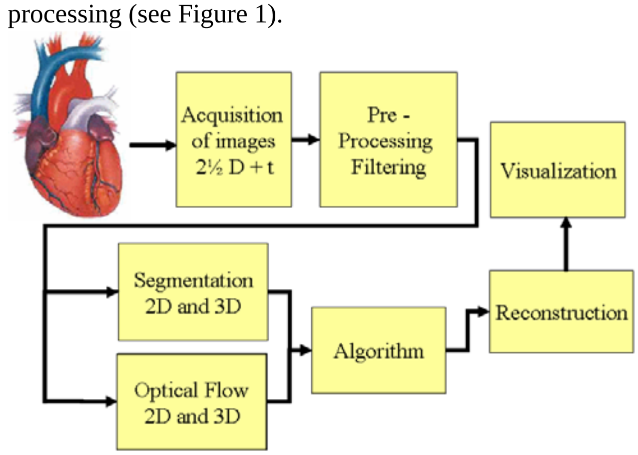

Figure 1. Methods for Ultrasound Image Processing.

This processing pipeline is divided into several modules from image acquisition to the 3D visualization of the heart. These modules are the following: Acquisition, Filtering, Segmentation, optical flow calculation, 3D Reconstruction and Visualization [8]. The novel contribution of this work is the combination of the

LV segmentation; with the velocity fields obtained using the optical flow method, which allows obtaining the motion vectors of the heart walls in three dimensions. Thus, while the optical flow estimates motion in the four-dimensional volume, the segmentation will validate the motion vectors most significant to characterize the dynamic behaviour of the heart.

The initial segmentation of the left ventricle area is performed using a front propagation algorithm (or Level Set) originally proposed by Sethian [9]. This method starts with a small circle or a sphere which belongs to the interior of the object to be segmented, and iteratively it is expanded to joint the set of pixels or voxels that belongs to the same region. The propagation front stops at the edge using a velocity function that depends on the gradient of the image [8]. After this process the region and its edge are clearly detected. This technique was tested with 2D images of the cardiac cycle. The contours extracted from the images of all 2D spatial sections of the same instant of time, are combined to materialize the 3D contour of the LV.

2.1. Mathematical bases – calculation of optical flow

The optical flow, displacement vector, or velocity vector is a vector field, which assigns to each pixel of an image: two components of displacement, using the intensity information of an image sequence. This vector field does not match the actual three-dimensional displacement, However it matches with the apparent motion on the image plane. In the case of medical imaging where the image is not a projection, it is a cut above a fixed plane; the optical flow quantitatively represents the displacement seen by an observer located perpendicular to the plane of image acquisition.

The main topic of this section is the mathematical derivation of the algorithm of Horn and Schunk [1] and its adaptation to our research. The objective of this algorithm is to interpret the changes in gray level as a movement.

Let (*x*, *y*) the coordinates of the pixels at time t, and let G(*x*, *y*, *t*) the function of gray level image. This function relates the position of the pixel, with the change of gray level in the case of motion of a pixel. Thus, the first step is to calculate the spatial and temporal partial derivatives of the input image: G_x, G_y, G_t.

If we related the position of the pixel with the pattern of the movement (the pixel under consideration is a part of the pattern), then the gray level does not change. We can describe the gray level as:

$$G(x,y,t) = G(x+\delta x, y+\delta y, t+\delta t) \tag{1}$$

Where δx, δy, y δt represent the spatial and temporal displacement of the pattern. When we applied the expansion on Taylor series of the right side of equation (1) we obtained:

$$G(x,y,t) = G(x,y,t) + \delta x \frac{\partial G}{\partial x} + \delta y \frac{\partial G}{\partial y} + \delta t \frac{\partial G}{\partial t} + R \tag{2}$$

Neglecting higher order terms *R* and dividing the above expression for δt, we obtain:

$$\frac{\delta x}{\delta t}\frac{\partial G}{\partial x} + \frac{\delta y}{\delta t}\frac{\partial G}{\partial y} + \frac{\partial G}{\partial t} = 0 \tag{3}$$

If δt is infinitesimally small, we obtain the equation describing the spatial and temporal changes of the gray levels.

$$\frac{\partial G}{\partial x}\frac{dx}{dt} + \frac{\partial G}{\partial y}\frac{dy}{dt} + \frac{\partial G}{\partial t} = 0 \tag{4}$$

In shorthand:

$$G_x u + G_y v + G_t = 0 \tag{5}$$

The partial derivatives of the gray levels (G_x, G_y, and G_t) can be obtained without any problem. However, to obtain the two unknown parameters ***u*** and ***v***, we needed more than a differential equation. Horn and Schunck [1] added smoothness conditions, since the condition of constant illumination is insufficient to calculate all components of optical flow. This condition is based on the fundamental idea that the image points do not move irregularly. In order to describe this idea Horn and Schunk [1] used the spatial changes of the components of movement. It describes two types of squared errors as following:

$$\varepsilon_c^2 = \left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2 \tag{6}$$

In practice, due to errors in measuring of the brightness of the image, the equation (5) has a component of errors ε_b^2, that we can presented as:

$$\varepsilon_b^2 = \left[G_x u + G_y v + G_t\right]^2 \tag{7}$$

Minimizing the weighted sum of the terms of smoothing and the term of the light conditions we obtain the following error equation:

$$\varepsilon^2 = \iint \left(\varepsilon_b^2 + \alpha^2 \varepsilon_c^2\right) dxdy \tag{8}$$

Thus, our goal is to minimize the error of equation (8). The parameter: α controls the ratio of influence of errors separately from the total error. The classic tool for solving this minimization problem is the calculus of variations. After making the procedure of calculus of variations, we obtain two Euler equations:

$$\frac{\partial F}{\partial u} - \frac{\partial}{\partial x}\left(\frac{\partial F}{\partial u_x}\right) - \frac{\partial}{\partial y}\left(\frac{\partial F}{\partial u_y}\right) = 0 \tag{9}$$

$$\frac{\partial F}{\partial v}-\frac{\partial}{\partial x}\left(\frac{\partial F}{\partial v_x}\right)-\frac{\partial}{\partial y}\left(\frac{\partial F}{\partial v_y}\right)=0 \tag{10}$$

Calculating all the partial derivatives of the function $F=\left(\varepsilon_b^2+\alpha^2\varepsilon_c^2\right)$ for the first and second Euler equation; we obtained:

$$2\left(G_x^2u+G_xG_yv+G_xG_t\right)-2\alpha^2u_{xx}-2\alpha^2u_{yy}=0 \tag{11}$$

$$2\left(G_y^2v+G_xG_yu+G_yG_t\right)-2\alpha^2v_{xx}-2\alpha^2v_{yy}=0 \tag{12}$$

Where $\nabla^2u=u_{xx}+u_{yy}$ and $\nabla^2v=v_{xx}+v_{yy}$ correspond to the Laplacians of $u(x,y)$, and $v(x,y)$ respectively. Additionally for computing of the Laplacians, we used the following approximation: $\nabla^2u\approx\overline{u}-u$. Thus, the equations (11) and (12) are become:

$$G_x^2u+G_xG_yv+G_xG_t-\alpha^2\overline{u}+\alpha^2u=0 \tag{13}$$

$$G_y^2v+G_xG_yu+G_yG_t-\alpha^2\overline{v}+\alpha^2v=0 \tag{14}$$

The values of $\overline{u}(x,y)$ and $\overline{v}(x,y)$ correspond to the average of projections of the velocity vector in the neighborhood of the point (*x*, *y*). It is a complex task to solve this equations system using any standard method. Therefore, we use an iterative method of analysis, specifically the Gauss-Seidel method. With this method we calculate a set of displacements $u(x,y)^{n+1}$ and $v(x,y)^{n+1}$ from estimates of the derivatives and the average value of displacements previously calculated $u(x,y)^n$ and $v(x,y)^n$. Finally we obtain the following equations.

$$u^{(n+1)}=\overline{u}^{(n)}-\frac{G_x\left(G_x\overline{u}^{(n)}+G_y\overline{v}^{(n)}+G_t\right)}{\alpha^2+G_x^2+G_y^2} \tag{15}$$

$$v^{(n+1)}=\overline{v}^{(n)}-\frac{G_y\left(G_x\overline{u}^{(n)}+G_y\overline{v}^{(n)}+G_t\right)}{\alpha^2+G_x^2+G_y^2} \tag{16}$$

This formulation saves computing time since long terms of these equations are identical.

The correspondence of shapes is the next step for this algorithm. Therefore, we find exactly the displacement vectors at the selected characteristic points on the surface of LV. Thus, we propose to compare different ways, comparing the curvature at the point we wish to examine. The curvature and any point of the surface is defined by two parameters, mean curvature κ_M, and Gaussian curvature κ_G [10].

The next step is matching the characteristics points between two consecutive images. Thus, the algorithm finds for each point of the first image its corresponding pair in the second image. In this process we find the best correlation between the values of the curvature in a small window around each pair of points in two consecutive images. The window size is 3*x*3*x*3 pixels. When selecting a pair of points, the best correlation is calculated. The displacement vector is calculated as the distance between these two points matched. It is assumed that the maximum possible offset is 3 pixels. Thus, the characteristic points fall outside the perimeter are excluded from the correlation process.

3. Results

Based on the optical flow algorithm we developed a new technique. This technique uses the motion vectors previously estimated to obtain some features of the points belonging to the edge of the object. These conditions introduced spread the values to the neighbor locations.

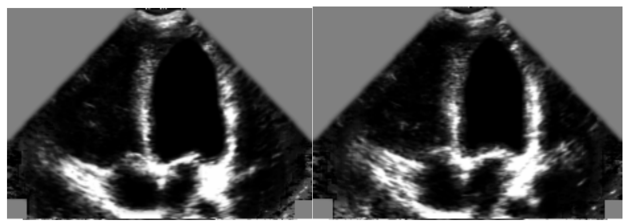

Figure 2. (a) Echocardiographic image. Time: t_01, first radial slice. (b) Echocardiographic image. Time: t_02, first radial slice.

To process the optical flow and obtain the images of vector field we reduced the resolution of the original image (see Figure 2) at the middle. Thus, the original images of 232 *x* 160 *x* 30 voxels are reduced to 116 *x* 80 *x* 30.

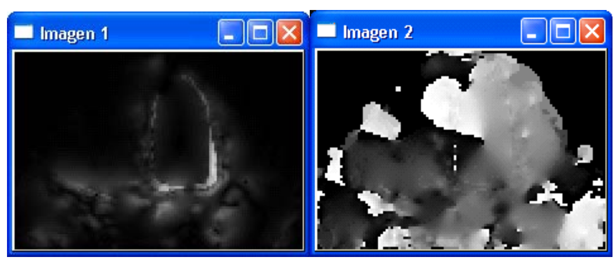

Figure 3. (a) Modulus of the optical flow obtained from the time instants t_01 and t_02. (b) Representation of the angle of the velocity field during LV contraction.

Figure 3 depicts the modulus of the velocity field on (a) and their respective angle (b). However, their interpretation is complex therefore we obtained the vector field's graph of Figure 4. Each vector in this figure is represented by a needle wherein the head of needle represents the origin of the vector and the needle tip represents the end of the vector. Thus, if all the needle tips are close to the center, it means the ventricle is contracting.

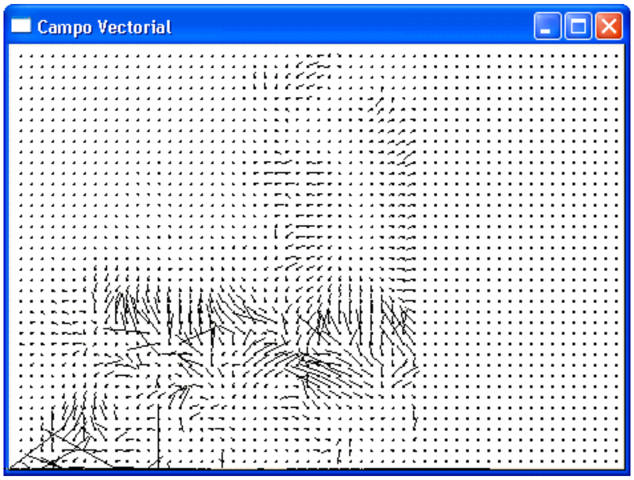

Figure 4. Vector field obtained only with the optical flow method.

Figure 4 depicts the results of optical flow. However, this method detected the movement throughout the image and considered points that not belong to LV. For this reason, we make a previous segmentation of the image in order to determine which motion vectors belongs to LV. Thus, in Figure 5 we have discriminated the vector field that belongs to LV (red) from ultrasound images.

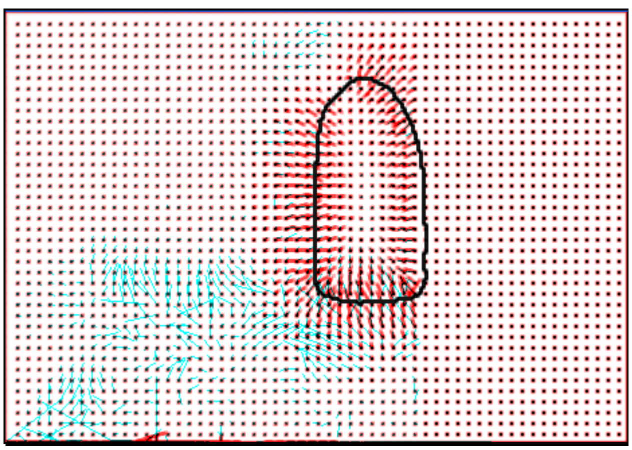

Figure 5. Overlay of velocity fields segmented contour together with the velocity fields of the image without segmenting

4. Conclusions

This paper presented the optical flow method for estimating the motion of the LV from a sequence of cardiac images. This method solves some problems encountered in the application of standard optical flow method, which does not provide sufficient accuracy to estimate the displacement. An accurate contour segmentation and estimation of the deformations of the walls is important to improve the motion estimation. Once segmented LV, and extracted their contour, we can follow the successive contours, and it is possible to calculate the displacement vectors. Experimental results show that our technique produces feasible results. Finally, we observe that the vectors of the velocity field obtained with our method are much smoother, and the orientation of the vectors pointing generally toward the deformations observed on the walls of the LV.

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Address for correspondence.

Name: Antonio BOSNJAK SEMINARIO
Address: Centro de Procesamiento de Imágenes. Universidad de Carabobo. Final Av. Universidad, Bárbula.
Ciudad: Valencia. Edo. Carabobo. Venezuela
E-mail: antoniobosnjak@yahoo.fr