

Motion Estimation along The Myocardial Boundary using Boundary Extraction and Optical Flow

Adhi Harmoko Saputro, Mohd. Marzuki Mustafa, Aini Hussain, Oteh Maskon, Ika Faizura Mohd Noh

Abstract— Myocardial motion can be helpful in diagnosing the heart abnormalities because it relates to cardiac vascular supply. Analyzing the motion of all segments of the myocardial is a difficult task because of the random noise of echocardiographic images. Noise in the echocardiographic images that is produced by the image acquisition is not consistent in each frame. It causes error in motion computation especially in optical flow computation that relies on brightness constancy. To increase the accuracy of motion estimation along the myocardial boundary, we proposed a method that combines boundary detection and optical flow to compute myocardial motion at the myocardial boundary. In this method, computation of optical flow from 2 consecutive images is done after myocardial boundary is detected in each frame. The result shows that the motion estimation algorithm along the myocardial boundary yields better result compared to without using boundary extraction methods.

Index Terms—Boundary estimation, Optical Flow, Myocardial, Echocardiographic.

I. INTRODUCTION

Analysis of 2D echocardiographic images for the assessment of regional function of Left Ventricle (LV) is usually investigated by motion and/or shape analysis of contour sequences. Certain clinical parameters can be evaluated after the investigation and detection of the left ventricle motion and boundary during the end-diastole and end-systole in order to assist the cardiologists in the diagnosis of cardiac diseases.

Several methods have been proposed to detect left ventricle boundary detection. Jierong [1] has proposed boundary detection using directional gradient vector flow. This is a new type of dynamic external force for snakes. Reis [2] has proposed two semi-automatic methods for the detection of the left ventricular border in two-dimensional short axis echocardiographic images. Zwirn [3] has presented a novel algorithm, aimed at automatic endocardial boundary (inner boundary) detection in myocardial opacification scenarios.

In motion estimation, there are many methods that have been proposed such as block matching or optical flow. Several methods of motion estimation have been proposed to increase accuracy of motion computation in

echocardiographic images. Tavakoli [4] has proposed a new algorithm based on a variation technique that combines the efficiencies of optical flow methods and affine registration in combination with multi-resolution spatiotemporal spline moments. Suhling [5] proposed a new method to estimate heart motion from echocardiographic sequence which uses a spatio-temporal affine model for the velocity within a local window.

Myocardial motion can be helpful in diagnosing the heart abnormalities because it is related to cardiac vascular supply. Analyzing the motion of all segments of myocardial is a difficult task caused by random speckle noise in each frame of echocardiographic images. However, in cardiac motion analysis, motion vectors along specific area are usually better indicators of wall motion abnormality. In this study, we propose a method for optical flow estimation along boundary of myocardial. The method consists of two main steps; the first step is boundary detection and then followed by optical flow computation utilizing this estimated boundary. A morphological technique was applied to cardiac electrocardiograph 2D image to detect myocardial boundary automatically. The result was then subjected to optical flow computation to find motion vectors along the boundary of myocardial. The proposed method was tested using Long-Axis view of cardiac electrocardiographic 2D image.

II. BOUNDARY DETECTION

A. Preprocessing

The echocardiographic data is acquired from several healthy volunteers using Acuson Squoia C512 Ultrasound Machine at Cardiac Care Unit UKM Medical Centre. These echocardiographic images have a width and height of 384×287 pixels. Figure 1(a) shows an example of such images.

The preprocessing of ultrasound images plays a key role for the accurate boundary delineation of myocardial images because of the noisy characteristics and bad contrast of ultrasound images. The first step of the preprocessing of ultrasound image consists of the rejection of speckle noise. To reduce the influence of speckle noise, the original image is filtered by an averaging mask.

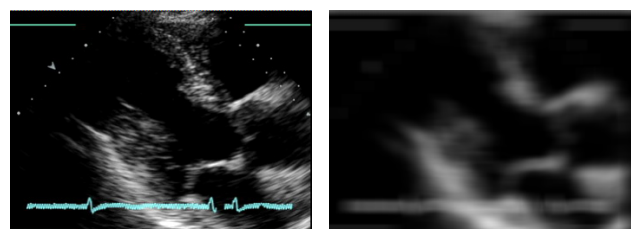


Figure 1. (a) Original image at end-diastole and (b) filtered image

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Figure 2. (a) The binary image before morphological closing (b) after morphological closing

The value at each pixel location is the result of the average value of 15×15 pixels in the neighborhood of the pixel. Figure 1(b) shows the result of applying the filtering process to the echocardiographic images shown in Figure 1(a).

B. Binary Image Processing

After the speckle noise is removed by smoothing, the resulting image is then converted to a binary image using the threshold τ as a demarcation criterion.

In the resulting binary image, there may be several small holes in the middle of posterior segment of left ventricle, generated by speckle noise or artifacts that are not previously eliminated by smoothing. To remove these holes, the binary image is then filled by the following morphological operation. The binary image (Figure 2(a)) is first subjected to a morphological closing with structuring element of 5×5 to reduce unwanted or noisy segments. The morphological closing consists of a gray-scale dilation, followed by erosion of the binary image.

Let the erosion of a binary image P by structuring element Q be denoted by $P \ominus Q$, and the dilation of a binary image P by structuring element Q , be denoted by $P \oplus Q$. The closing morphological is then denoted in terms of the primitive operations of dilation and erosion as [6]

$$X^{cl} = (P \oplus Q) \ominus Q \quad (1)$$

As a result of the operation, most of the small holes are removed, while the cardiac segment in the image is still the same.

C. Boundary Detection

The final myocardial boundary (Figure 3) was identified as the inside of the binary image. This procedure is done by the Canny edge detector [7] that tries to assemble the individual edge candidate pixels into contours. These contours are formed by applying a hysteresis threshold to the pixels. If a pixel has a gradient larger than the upper threshold, then it is accepted as an edge pixel; if a pixel is below the lower threshold, it is rejected. If the pixel's gradient is between the thresholds, then it will be accepted only if it is connected to a pixel that is above the high threshold. Canny recommended a ratio of high:low threshold between 2:1 and 3:1.

The myocardial boundary detection process extracts from each echocardiographic frame a set of border pixels representing the edge of the myocardial. This result will then be used in the optical flow computation to find the vectors motion of the left ventricle.

In the next step, this boundary will also be used as a mask for selecting the optical flow vectors field along the

myocardial boundary. This process will reject unwanted vector motion field that is located outside of the myocardial boundary.

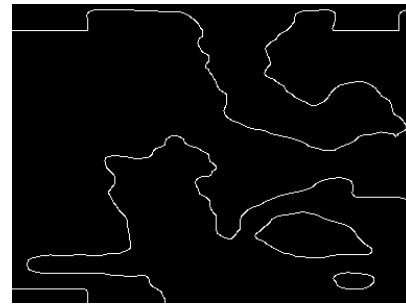


Figure 3. The result of Canny edge detector that shows a set of boundary of myocardial

III. OPTICAL FLOW COMPUTATION

Optical flow (OF) tracking refers to the computation of the displacement field of objects in an image, based on the assumption that the intensity of the object remains constant. There are several optical flow computation techniques available such as the differential techniques [8-10] that calculate velocity from spatio-temporal derivatives of pixel intensities and region-based matching techniques [11], which compute the OF via identification of local displacements corresponding to optimal correlation of two consecutive image frames.

In this study, technique based on Horn and Schunck [8] was selected to compute motion vectors from 2 consecutive cardiac ultrasound images. Let the intensity at time frame t of the point (x, y) in the image is $I(x, y, t)$, with $u(x, y)$ and $v(x, y)$ being the corresponding x and y components of the optical flow vector at that point, it is assumed that the image intensity will remain constant at point $(x+dx, y+dy)$ at time $t+dt$, where $dx = udt$ and $dy = vdt$ are the actual motion of the point during time period dt , leading to the following equation:

$$I(x + dx, y + dy, t + dt) = I(x, y) \quad (2)$$

If the image intensity is smooth with respect to x, y , and t , the left-hand side of equation (2) can be expanded into a Taylor series. By ignoring the higher order terms and taking limits as $dt \rightarrow 0$, lead to the following equation:

$$I_x u + I_y v + I_t = 0 \quad (3)$$

using the notations:

$$u = \frac{dx}{dt}, v = \frac{dy}{dt}, I_x = \frac{\partial I}{\partial x}, I_y = \frac{\partial I}{\partial y}, I_t = \frac{\partial I}{\partial t} \quad (4)$$

Equation (3) is called the optical flow constraint equation, as it expresses a constraint on the components u and v of the optical flow.

The Horn and Schunck method was one of the first to make use of the brightness constancy assumption and to derive the basic brightness constancy equations. The solution of these equations devised by Horn and Schunck was obtained by imposing a smoothness constraint on the velocities u and v . This constraint was introduced by minimizing the regularized Laplacian of the optical flow velocity components:

$$\begin{aligned} \frac{\partial}{\partial x} \frac{\partial u}{\partial x} - \frac{1}{\alpha} I_x(I_x u + I_y v + I_t) &= 0 \\ \frac{\partial}{\partial y} \frac{\partial v}{\partial y} - \frac{1}{\alpha} I_y(I_x u + I_y v + I_t) &= 0 \end{aligned} \quad (4)$$

Here α is a constant weighting coefficient known as the regularization constant. Larger value of α leads to smoother vectors of motion flow. This is a relatively simple constraint for enforcing smoothness, and its effect is to penalize regions in which the flow is rapidly changing in magnitude.

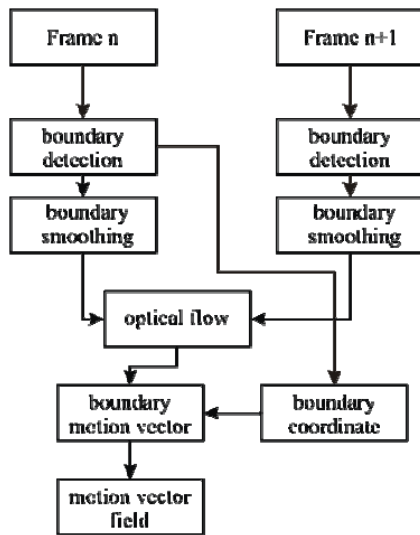


Figure 4. Flow chart of the computation of motion vector along the myocardial boundary

A. Implementation

The detail of the method of the motion vector computation along the myocardial boundary is shown in Figure 4. The first step extracts the myocardial boundary using the technique that has been described previously. The result is the contour image that represents a set of border of myocardial. This image is then smoothed by the filter that performs an average of neighborhood pixels. The output of this process is a grayscale image that has a gradient intensity perpendicular with the myocardial boundary.

Figure 5 shows an example of two consecutive smooth boundary images that are produced by the filter. These images are then used by the optical flow algorithm to generate the u and v velocities.



Figure 5. Two consecutive images as input of optical flow computation

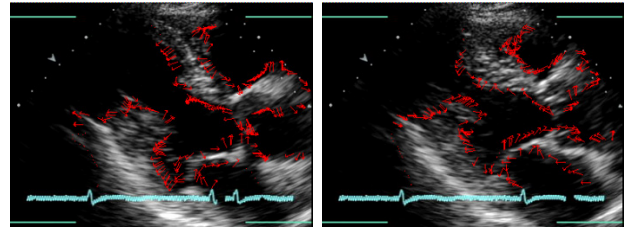


Figure 6. Echocardiograms with superimposed motion information at end-diastole (a) and end-systole (b)

The image of myocardial boundary is also used as input in finding a set boundary coordinates. The boundary coordinates are extracted using contour finding on the set of myocardial boundary. The coordinates are used to select the appropriate u and v velocities along the myocardial boundary. This process is termed as the masking process. The u and v velocity vectors are masked by the boundary image. The result of this masking process is a set of motion vector field along the myocardial boundary. The set of motion vector field is then drawn as needles diagram and combined with appropriate image as shown in Figure 6.

The needles diagram is the final image of all processes. The directions of the myocardial are shown by the direction of the needles and the speeds of myocardial are indicated by the length of the needles. The longer the length of the needle, the higher is the speed of myocardial.

B. Computation Parameters

The values of the pixels of the image are the result of the average value of 15×15 neighborhood pixels. The size of the neighborhood used for the averaging mask will determine the gradient or sharpness of the boundary. For optical flow computation, we used a regulation constant α of 150 as in [12] and iterated up to 100 steps maximum iteration. The result of this experiment demonstrated that the performance of the selected parameter in the case of analyzing of vector motion is appropriate with the myocardial boundary image.

For measuring the value of the motion vectors along the left ventricle boundary, we used a large averaging mask of size 5×5 . It is computationally more expensive but we expect that larger neighborhood contains more information on movement in the region and consequently produces better estimation of the motion vector field.

C. Evaluation

The proposed method was tested on several ultrasound sequences containing long axis view images of the left ventricle. As example, two frames at end-diastole and at end-systole are shown in Figure 6(a) and 6(b). The corresponding motion estimation results are superimposed in the form of a red needle diagram. The red needle is drawn by computing the hypotenuse of the optical flow velocities u and v . A typical ventricular contraction and expansion of a normal beating heart during systole and diastole can be clearly captured and represented by the motion vector along the boundary.

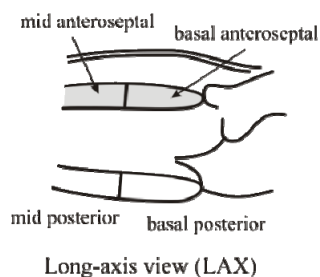


Figure 7. Standard definition of left ventricular segments (long-axis view) for 2-D echocardiography.

To evaluate the performance of the proposed method, we used visual interpretation based on medical knowledge in myocardial motion. Figure 6 shows a standardized division of the left ventricle into 16 segments according to the American Heart Association [13]. Based on this standard the myocardial motion is evaluated segment by segment.

Anatomically, the motion of myocardial in long-axis view is rotated to left and downward. The basal anteroseptal rotate to left and move upward and the mid anteroseptal move downward. As shown in Figure 8(a), the bottom of boundary basal anteroseptal moves left and upward as shown by the red needle.

The red needles that are shown in figure 8(a) are more accurate than the red needles in Figure 8(b). Both motion estimations are computed using same optical flow algorithm and parameters. The difference between these two motion estimations is in the image input of optical flow algorithm. The first image is produced by the smoothing boundary image and the other is produced by computing the optical flow directly from the original image. The result shows that the motion estimation algorithm along the myocardial boundary that combines boundary detection and optical flow gives better result compared to the other method.

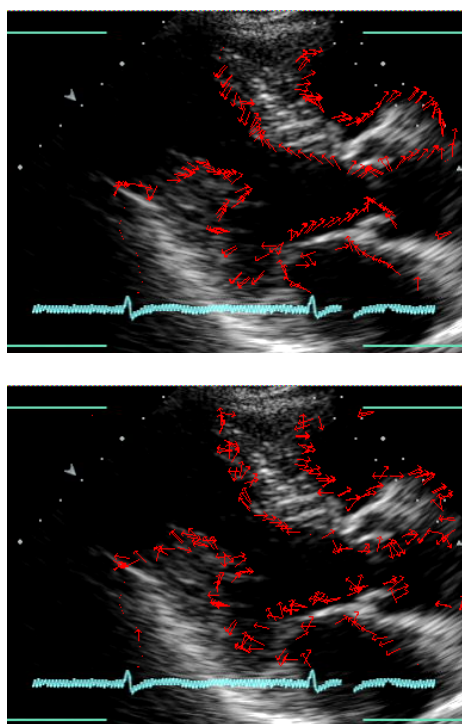


Figure 8. Optical flow vector motion along the boundary of myocardial that shown by red needles. (a) Using the boundary extraction and (b) without boundary extraction

IV. CONCLUSION

A method of motion estimation by integrating boundary detection and optical flow is proposed to find motion vectors along the boundary of myocardial of left ventricle. The detection of myocardial boundary does not require human intervention. This method is based on the morphological operation, and could detect the boundary automatically. The boundary image that is smoothed using information from neighboring pixels is used as input to the optical flow algorithm. The result shows that the motion estimation algorithm along the myocardial boundary yields better result compared to without using boundary extraction methods.

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