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# TRACKING OF THE MITRAL VALVE LEAFLET IN ECHOCARDIOGRAPHY IMAGES

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## ABSTRACT

This paper presents a semi-automatic method for the segmentation and the tracking of the mitral valve leaflet in transesophageal echocardiography. We use two connected active contours in order to track efficiently the mitral leaflet. Segmentation of very fast and non rigid motions involved are realized in two steps. In the first step we use transformation fitting to provide a rough segmentation that will be refined in a second step using snakes with Dynamic Programming minimization. The method successfully tracks the inner cardiac muscle and the mitral valve leaflet axis.

Keywords : Medical Image Analysis, Tracking and Motion, Active Contour, Ultrasound Imaging.

## 1. INTRODUCTION

The mitral valve is one of the four valves of the heart, whose function is to keep the blood flow in the physiological direction when the heart contracts. Transesophageal echocardiography is the classical imaging for the mitral valve (Figure 1) but there is no satisfactory method allowing an automated segmentation of the leaflet. This would be a potentially useful tool in the new field of CAS<sup>1</sup> particularly in a context of beating heart surgery where real-time conditions are required. The tracking of features in the echographic sequence is a very complex problem due to the speckle noise and to the artefacts. The use of low-level image-processing techniques does not provide efficient solutions. A large literature use Active Contour Model (ACM) or snakes to track cardiac ultrasound features [1]. These methods are efficient tools particularly for tracking non rigid motion. Their main problem is that they can diverge easily because they do not incorporate global information about the shape. Other methods use Active Shape Model (ASM) which incorporates global prior on the shape. In these models a mean shape defined by a set of point is allowed to deform into a subspace defined by a transformation. These models can be build by a statistical analysis (point distribution model) or hand-craft (using a mean shape and a pre-defined transformation). The main problem of these methods is that they cannot segment efficiently an object if the model

does not include all object variability ; a refinement can be necessary [2].

Other works use temporal prior to tracking more efficiently features in the echographic sequence. This can be done introducing a kalman filter into a snake based approach or into a ASM based approach

Another way is to use Markov random field. These methods provide robust solutions in very noisy data, but they are very computationally expensive and do not provide solutions for real time or near real time implementations.

In this paper, we present a semi-automatic method (a manual initialization on the first image of the sequence is required) to segment the axis of the mitral valve leaflet in transesophageal ultrasound images. The proposed approach uses 2 active contours to achieve the segmentation of the mitral valve leaflet. The method was designed to be fast in order to segment mitral leaflet in near real-time.

## 2. MATERIAL AND METHOD

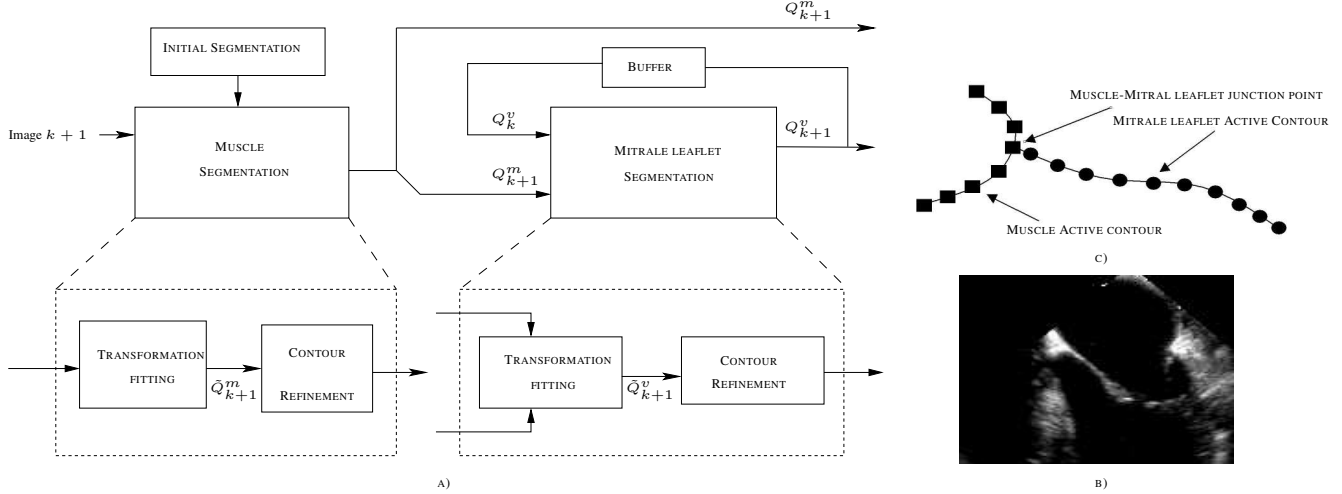
### 2.1. Context

The mitral valve is a left-sided valve located between the left atrium and the left ventricle, made up of two fibrous membranes which are attached to the left ventricle muscle through the mitral annulus. The analysis of the motion of the mitral valve in echocardiography shows two major kinds of movements (Figure 1) : *i) the leaflet movement (the main component), which is non-rigid but relatively close to a rotation around a point located on the muscle-leaflet junction area (which we call the "junction point")*, *ii) the muscle movement (the secondary component), which is approximately a rigid transformation with essentially translational components and a small rotational component.*

### 2.2. Method

The proposed method relies on the use of two active contours to track the leaflet efficiently : one tracks the cardiac muscle and the other tracks the mitral valve leaflet. In fact, in the echographic sequence, the mitral valve leaflet is always 'connected' to the cardiac muscle by a junction point in the

<sup>1</sup>CAS stands for Computer Aided Surgery



**Fig. 1.** a) Synoptics of the proposed method - b) The two contours - c) Echographic image of the mitral leaflet

image corresponding to the intersection of the echographic plane with the mitral annulus. The tracking method can be divided in 2 steps : in a first step we track the *cardiac muscle*, in a second step we track the *mitral valve leaflet*.

In order to provide an efficient segmentation we both use snake based algorithm and curve fitting. A first step consists in computing a rough segmentation using curve transformations, that is refined by the use of a snake. For the muscle curve a rigid transformation of the initial segmentation is estimated at each step. For the mitral curve a transformation of the previous segmentation is computed at each step. This transformation is defined using the new estimated position of the junction point in order to approximate the mitral motion which is close to a rotation around the junction point. For the two contours we use feature point detections on normals of the curve to calculate the transformation.

This paper describes the method in a non-chronological way. The section 3 describes the method used to build a rough segmentation. The section 4 presents the method developed to refine rough segmentations and to determine correctly the junction point. The figure 1 presents the pipeline of our method, and sets up briefly the connection between the presented parts.

### 3. ROUGH SEGMENTATIONS

In this section, the method proposed to provide a rough segmentation of contours is explained.

#### 3.1. Transformation fitting

In this section we present the method to estimate the parameters of a transformation which minimizes the distance between two curves. Making the assumption that the curves are defined by some control points stored in vectors :  $Q = [x(s), y(s)]$ , then the regularized estimation can be written, as

follows :

$$\hat{X} = \arg \min_X [\alpha(X - \bar{X})^T \bar{S}(X - \bar{X}) + \|W \cdot X + Q_c - Q_t\|^2] \quad (1)$$

where  $X$  is the transformation vector,  $Q_t$  is the target curve (the one we want to be close to),  $Q_c$  is the current curve (i.e. the initial contour),  $\bar{S}$  is a positive semi-definite weight matrix,  $\bar{X}$  is the mean transformation vector and ( $\| \cdot \|$ ) is a particular norm defined by feature point detection along the normal to the curve and which allows us to measure distance between curves. It is defined by :

$$\|Q_c - Q_t\|_n^2 = \frac{1}{N} \sum_{k=1}^N [(Q_c(k) - Q_t(k)) \cdot \vec{n}(k)] \quad (2)$$

where  $\vec{n}(k)$  is the normal vector to the curve  $Q_c$  at point  $(x_k, y_k)$ .

Solving Eq 1 is equivalent to a classical curve fitting problem which was solved by Blake and Isard using a recursive algorithm given in [2].

#### 3.2. Cardiac Muscle Transformation Estimation

The motion of the cardiac muscle, to which the leaflet is attached, is supposed to be close to a rigid motion. Therefore, the rough contour position of the cardiac muscle is estimated from the initial template by translating it. We use measures on normals to the curve to estimate the transformation. Feature point detection on normals is performed by a 1D Canny edge detector which is approximated by the derivative of a Gaussian kernel ( $\sigma = 1.4$ ).

#### 3.3. Mitral Valve Leaflet Transformation Estimation

In the case of the mitral leaflet, the movement is supposed to be mainly rotational and centered on the junction point.

Let  $s_{junc}$  be the abscissa of the junction point on the muscle curve in image  $k$ . The point located at the abscissa  $s_{junc}$  on the curve resulting of the muscle segmentation process in image  $k + 1$  (after the two steps processing : rough segmentation, refinement) is a rough estimate of the junction point. The rough segmentation of leaflet is processed as follows : First the previous segmentation of the leaflet (in image  $k$ ) is translated in order to adjust it on the new rough estimate of the junction point; then curve fitting enables rough segmentation. The transformation involved must approximate the mitral leaflet motion between two successive frames: we use an affine transformation without translations components ; its parameters are mapped to a coordinate system translated to the junction point. In this way the junction point is an invariant to any transformations previously defined. The presence of the mitral valve leaflet is characterized by a local maximum (ridge) in the gray-level profile along the normal direction. This is detected by using a maximum detector on the gray-level profile which is smoothed by a Gaussian lowpass filter ( $\sigma = 2$ ).

## 4. REFINEMENTS BY ACTIVE CONTOUR

### 4.1. Need for a refinement

The rough curves and the junction point are close to reality but a refinement must be performed. Snakes [1] are parametric curves which can evolve very freely only constrained by a smoothness constraint. These methods can easily diverge if they are too far from the solution; it results that they are efficient to refine rough segmentation as provided by our curve fitting algorithm. Snakes are parametric contours which evolve by the minimization of an energy function composed of one external energy term (imposing constraint like continuity or curvature) and one internal energy term (which attracts the snake in feature area like edge or ridge).

### 4.2. Cardiac Muscle Snake Energy Definition

The energy of the 'cardiac muscle' snake is composed of 2 terms related to the internal energy and one term related to the external energy.

The 1<sup>st</sup> internal energy term is related to the length of the curve. It verifies that the distance between to successive snaxels is close to a distance  $d_m$  which is computed at the beginning of the algorithm. This 1<sup>st</sup> energy term  $E_{Int1}^m(s_i)$  is proportional to  $(\|s_{i-1} - s_i\| - d_m)^2$  with a weighting parameter  $\alpha_1^m$ .

The 2<sup>nd</sup> internal energy term  $E_{Int2}^m(s_i)$  is an approximation of the 2<sup>nd</sup> derivative of the curve. It is computed from snaxels of the 'cardiac muscle' by using the finite differences and it is proportional to  $\|s(i-1) - 2s(i) + s(i+1)\|$  with a weighting parameter  $\alpha_2^m$

The external energy ( $E_{Ext}^m(s_i)$ ) term is related to the modulus

of the gradient image. It enforces the contour to move toward the cardiac muscle which appears as an edge in the image. This energy term is given by  $E_{Ext}^m(s_i) = \|\Delta_\sigma I(s_i)\|^2$ . The final energy snake is the sum of all internal and external energy terms with their respective weighting parameter. The choice of the weighting parameter is discussed in section 5.

### 4.3. Mitral Valve Leaflet Snake Energy Definition

As regards the mitral valve leaflet, the internal energy is also composed of two terms. The first one is related to the tension of the curve and it is defined using first order derivative :  $E_{Int1}^v(s_i) = \|s(i) - s(i-1)\|$ . Its weighting parameter ( $\alpha_1^v$ ) could change dynamically according to the length of the curve in order to keep it in an acceptable range. Let  $L_0$  be the initial valve length. When valve length is longer than  $1.3L_0$ ,  $\alpha_1^v$  is set to  $-a$ , else if its length is smaller than  $0.8L_0$ ,  $\alpha_1^v$  is set to  $a$  in other cases  $\alpha_1^v = 0$ . Where  $a$  is a constant which must be tuned at the beginning of the algorithm. The 2<sup>nd</sup> term is also related to the curvature of the snake and it is defined in a same manner as describe for the muscle snake.

A close look to the gray-level profile of the leaflet reveals that it corresponds to a local maximum of intensity in the direction of the largest image curvature. At these particular points called ridge, one of the principal curvature is high and the other one is close to zero. We proposed to build a robust external energy term based on the highest principal curvature  $E_{ext} = K+$ . These ones are computed by finding the eigenvalues of the Hessian matrix and second order derivatives are computed using derivatives of a Gaussian kernel. In order to characterize correctly the ridge leaflet we need setting correctly  $\sigma$  (standard deviation of the Gaussian kernel) in order to take account of the ridge width. We experimentally set sigma to 0.8.

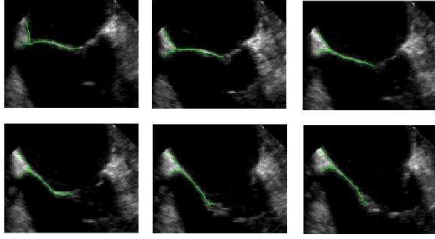
### 4.4. Dynamic programming minimization (DP)

The problem of energy snake minimization is solved using dynamic programming. Amini proposed this method [3] in order to overcome limitations of classical variational methods like instability or non optimality and makes possible the use of stronger constraints without falling into a local minima. The algorithm is iteratively applied to the contour. At each iteration, a pixel can move to a previously defined neighborhood (search area). The energy of snakes can be written as :

$$E_{snake} = \sum_{i=1}^{N-2} E_i(s_{i-1}, s_i, s_{i+1}) \quad (3)$$

In this case minimization can be obtained using Dynamic programming as described in [3].

In our method DP allows us to correctly minimize snake's energy function and provides a way to determine the junction point. The search-area for each snaxel of the muscle curve is



**Fig. 2.** Process of a sequence. Segmentation of the biggest leaflet

defined by the 8-neighborhood around the snaxel. We defined the same neighborhood for the leaflet snaxels except for the first (junction point) which is connected to muscle curve. For this point we defined a search area which is composed of the 8 pixels belonging to the muscle curve and around the actual estimate of the junction point. We do not defined external energy term for this point. In this way, the snaxel will be only driven by its internal energy term depending on the two next snaxels and will be correctly adjusted to the muscle curve by continuity of the leaflet curve.

## 5. RESULTS AND CONCLUSION

### 5.1. Results and discussion

The described method has been implemented using Matlab<sup>®</sup> (and in Matlab language). The algorithm is initialized by the manual segmentation of both the muscle and the mitral valve leaflet and by the specification of the junction point. It requires the tuning of the following parameters :  $\alpha_1^m, \alpha_2^m, \beta^m, \alpha_1^v, \alpha_2^v, \beta^v, S^m, S^v$  which is probably the main drawback of the method. However optimal parameters do not change much from one sequence to another as we observed on several test data sets. We can image compute the mean parameters from several sequences and use it as an estimate of optimal parameters of a new sequence. We processed 3 sequences of 250 to 300 images which result was validated as successful by expert for 90% of them. In the remaining 10%, although the segmentation is "bad" (and not absolutely false !), it naturally re-converges to a quite good contour in the next 3-to-6 images. The mean processing time is about 1.8 seconds with 10 iterations for both snakes.

### 5.2. Conclusion

In this paper, we presented a method to segment the mitral valve leaflet in echocardiography in a fast manner. The power of this method is to use two active contours connected by a junction point in order to capture the muscle motion and track efficiently the valve. Methods have been proposed in the literature to track the valve using only one snake [4]. However in these methods snake segmented both the contour of the valve

and the contour of the muscle. Due to the fact that the motions of the valve and the motions of the muscle are quite different, this should limit the efficient of such methods. The segmentation in two steps allows the algorithm to succeed in tracking mitral leaflet although its motion is very fast and non rigid. In a first step we compute rough segmentations based on curve fitting then we refine these segmentations using snakes. Dynamic programming provides a efficient minimization and a way to estimate the junction point.

The method does not require any prior knowledge on the mitral valve nor complex modeling of its movement.

The method has still some drawbacks. First the tuning of parameters need few experiments at each new sequence to obtain a correct tracking; then the algorithm can fail when motion of the muscle is very fast from an image to the following one (more than 10 pixels); we think an optical flow estimation could solve this issue. As mentioned in section 1, the monitoring of CAS procedures with the ultrasound imaging requires real-time or near real-time image processing. We are very confident in the near real-time possibilities of this algorithm. From our experience, converting algorithms from Matlab language to 'C' language should divide the processing time by a factor of 10. Other 'coding' optimization such the dynamical selection of a ROI to process (instead of processing the whole image) should speed up the image processing and thus allow a near real-time mitral valve leaflet detection. The tuning of parameters is the main drawback of the method, however the objective of our algorithm is not to directly provide the segmentation used during the surgical act because the algorithm is not enough robust. The presented work is intended to be the 'preprocessing' step of the surgical scenario and should only provide semi-automatic segmentation of several cardiac cycles in order to construct a pre operative segmentation data base. A second step which is under development will use this database in order to find, for each new image, the segmentation which best corresponds to that image. Temporal information would enable to narrow the searching window.

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