2D Local Heart Motion Estimation Using Level Sets and Hierarchical B-Splines

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Abstract

Diagnosing complex heart malformations require the analysis of local heart motion. This paper presents a method for measuring local motion in a sequence of 2D echographic heart images. The heart cavities are segmented using an implicit geometric active contour robust to speckle. A combined rigid and non-rigid image registration method is then used to estimate the motion field. The cavity segmentation is done with our original level set method founded on the coefficient of variation. The curves obtained from two successive images are matched during the registration process to estimate their displacement. The registration process consists of three phases. First, we estimate a linear transform using the ICP algorithm to remove the linear difference between the cavities. The second phase consists of calculating an initial deformation embedding the B-spline transform in the ICP algorithm. Finally, we perform the hierarchical B-spline refinement in regions with unsatisfactory deviations. The result is a dense free form deformation field that is segmented to show the local heart motion. Experimental results using real ultrasound images are shown.

1. Introduction

The analysis of heart cavity motion provides an efficient method to detect some pathologies of the heart such as ischemia and infarction [1]. Several approaches have been proposed to quantify local heart motion from two-dimensional (2D) echocardiograms. Approaches that consists of segmenting heart cavity borders using active contours have been proposed in [2, 3]. The main problem of these methods is that the motion information is only obtained for cavity borders which are often poorly defined, due to low contrast and high level of speckle contamination of the ultrasound images.

The level sets method has been introduced by Osher and Sethian in [4]. Since its introduction, this technique has been used to solve various problems, such as image enhancement and noise removal [5], and contours detection [6]. But it is not tailored to handle speckle, a multiplicative locally correlated noise present in the ultrasonic images. In order to develop a more efficient edge detector in ultrasound images, the use of anisotropic diffusion based on the coefficient of variation (CV) is proposed in [7, 8]. In a previous work [9], we have developed an approach to robustly detect the heart cavities based on level sets and the CV.

Image registration is the procedure of finding a spatial deformation to match two images [10, 11]. The B-splines have been proposed as a continuous image representation and interpolation in [12]. In the problem of image deformation, several transform functions have been proposed in [13], the B-spline geometric transformation is proposed in [14]. In order to improve the accuracy of the geometric transformation, a hierarchical B-spline approach is proposed in [15, 16]. Recently, a hierarchical B-spline contour-based image registration approach was proposed in [17].

In this paper, we propose a novel method based on hierarchical B-splines and our original coefficient of variation-based level set to analyze the heart local motion. Prior to image deformation, we segment the cavities of two images with our robust active contour. The resulting pair of curves is used to find a free-form deformation. This transform is applied to deform the entire image. The process of estimating the free form deformation is adaptive. The initial estimated transform is locally refined building a hierarchical B-spline. The refinement is reapplied whenever the deformation is unsatisfactory.

The outline of this paper is as follows. Section 2 introduces our edge based registration method, and explains in detail each of its stages. Section 3 shows the results of our method on real ultrasound heart cavity images. Finally, section 4 provides some conclusions.

2. Proposed heart motion analysis

Our method to match heart cavity images is a non-linear edge-based image registration. It consists in three steps, first the edges of the cavities are robustly detected with an original active contour based on the coefficient of variation. After the detection of the contours, the transformation between the cavity contour of the test image and that of the reference image is estimated. The resulting transformation is applied to the entire test image in order to match corresponding cavity curves. In regions where the deviation is too large, a hierarchical B-spline refinement is applied. Our approach can be summarized as follows:

- Detection of the cavity contours C_t and C_r of the test image I_t and the reference image I_r, respectively. We perform this segmentation with our level set based on the CV.
- Estimation of a linear transform using the ICP algorithm to remove the linear difference between the cavity contour curves C_s and C_t.
- B-spline deformation is performed in the ICP algorithm in order to update the position of the control points iteratively and to match both contour curves until the results cannot be improved.
- In regions where unsatisfactory deviations persist, the control grid is refined with a hierarchical B-spline approach.

2.1. Robust contour detection of the heart cavities

The level set approach to image contour detection considers a closed curve $\delta(t)$ moving in the plane, where $\delta(0)$ is the initial curve. The main idea is to embed this propagating curve as the zero level set of a higher dimensional function $\Phi(\delta, t)$ [18]. The equation representing the motion of the surface $\Phi(\delta, t)$ in the normal direction of the propagating curve is:

$$\frac{\partial \Phi}{\partial t} + gF|\nabla \Phi| = 0. \tag{1}$$

where F is the propagation speed function and g is the term that stops the evolution of the curve at the edges.

The traditional edge stopping term g based on gradient has two main disadvantages. First, it is never exactly zero, allowing the moving curve to cross the boundaries of the object. Second, it is not adapted to speckle. In a recent work, we have proposed to overcome these problems by using a stopping term based on the coefficient of variation. To build our new stopping term we adapted the weight function of the Tukey's biweight error norm [19]. This function neglects the influence of outliers above a predefined threshold. The expressions of our new stopping criterion for the level set algorithm to segment ultrasound images is:

$$g(\gamma)_{i,j} = \begin{cases} \left[1 - \frac{\gamma_{i},_{j}^2}{\gamma_s^2}\right]^2 & \text{if} \quad \gamma_{i},_{j} \le \gamma_s \\ 0 & otherwise \end{cases} \tag{2}$$

where $\gamma_{i},_{j}$ is the local CV and γ_s is a scale parameter based on the global CV. Edges correspond to pixels where the values of the local CV is greater than the global CV. For details on our stopping criterion and the automatic estimation of γ_s see [9]. We use this method to find the heart cavity boundaries.

2.2. Rigid registration of the heart cavity contours

Elastic registration has two main problems. First, the results depends on the initial position of the points to register. Second, it is possible to generate a deformation that consider only the registered points. This causes nonuniform deformations in the entire image; in other words, with an elastic deformation, it is possible to obtain locally rough deformations in the vicinity of the points to register. In order to remedy this problems, our method starts with a rigid registration stage.

We eliminate the linear differences between the cavity contour curves by embedding a linear transformation inside of the Iterative Closest Points algorithm (ICP). This algorithm has been proposed in [20] as a method to match object edges in images by minimizing a generalized distance between them. We perform the ICP to match the curves iteratively.

2.3. Heart cavities edge based image registration

After the rigid registration phase of the test and the reference images, we perform a contour-based image registration. We consider two sets of points, the first one is composed by the points p_k of the cavity contour of the test image; the second set contains the corresponding points q_k of the edge cavity within reference image. The corresponding points are automatically determined with the ICP algorithm.

We adopt the B-spline geometric transformation due to its explicit form and its small compact support, yielding computationally efficient algorithms. The B-spline transform has the following form [17]:

$$q_k = \sum_{i=0}^{r} \sum_{j=0}^{s} b_{i,j} N_i^3(x_k) N_i^3(y_k) \tag{3}$$

where $b_{i,j}$ are the control points of the B-spline, x_k and y_k are the components of p_k; r and s are the number of control points in each direction. We control the distortions of the image deformation with a homogeneity restriction. If a B-spline surface s is used, the restriction minimizes $\delta s / \delta x \delta y$. A discrete form of this restriction is:

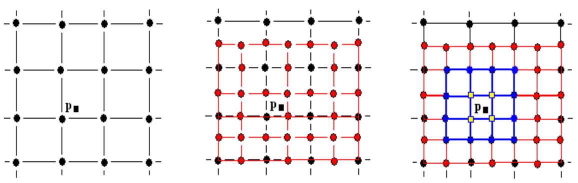
$$(b_{i+1,j+1} - b_{i+1,j}) - (b_{i,j+1} - b_{i,j}) = 0 \tag{4}$$

The overdetermined linear system composed by (3) and (4) is solved with least squares approximation. This leads to estimate an optimal image deformation.

2.4. Hierarchical B-splines

After the initial B-spline deformation, if a point p in the deformed image has an unsatisfactory deviation with respect to its corresponding reference point, we insert knots to locally refine the B-spline grid. The new position of point p is determined by 16 control points in its neighborhood. In the refined grid, the four neighboring control points of p are recomputed.

Figure 1 graphically presents the hierarchical refinement process previously described. Figure 1(a) shows the point p surrounded by a grid before the refinement; figure 1(b) depicts the knot insertion process; and figure 1(c) shows the new 16 control point neighborhood.



(a)Grid before the refinement. (b)Knot insertion. (c)New neighborhood.

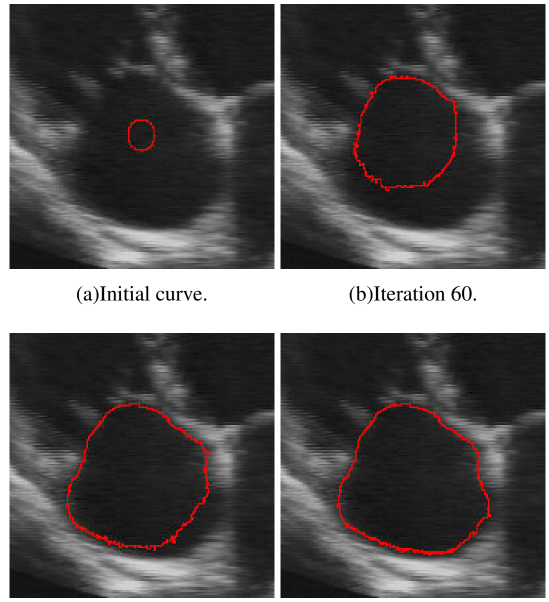
Figure 1. Hierarchical B-spline refinement.

3. Results

In order to validate our method, experiments using real ultrasound images have been conducted.

Figure 2 shows the detection of a heart cavity wall in an ultrasound image resulting from our robust active contour. The four images show the segmentation at different iterations. Figure 2(a) shows the initial position of the propagating front; figures 2(b)-(c) show the curve moving toward the wall cavity; and in figure 2(d) the curve precisely detects the cavity boundary. Our stopping term completely stops the moving curve on the edges of the cavity.

Figure 3 shows the registration results between two heart cavity images. Figure 3(a) is the test image; figure 3(c) is the deformed image; and figure 3(b) shows the reference image. Figure 3(d) presents the difference between the test image (green pixels) and reference image (red pixels) before the image registration; figure 3(e) shows the difference after the image registration, and figures 3(f)-(g) show the initial grid and the deformed grid on the test image and the deformed image, respectively. Figure 3(e) highlights the interesting performance of our registration method. The transformation superposes the deformed image on the reference image (the superposed pixels are shown in yellow color). It is possible to observe a good behavior of our method in the grid images. In figure 3(g) is shown the effect of the homogeneity restriction, obtaining a bidirectional and smooth deformation.



(a)Initial curve. (b)Iteration 60.

(c)Iteration 80. (d)Iteration 90, final curve.

Figure 2. Contour detection results.

4. Conclusion

This paper presented a novel approach to heart motion analysis problem. Our approach is an edge based image registration algorithm. The method combines the advantages of an active contour robust to speckle and a hierarchical B-spline refinement.

To segment the cavities we have adopted our active contour based on the coefficient of variation. This prevents the moving curve from crossing the boundary of the cavities. Our active contour segmentation of the wall cavities allows to overcome the problems of edge based registration approaches, as it goes beyond the poor definition of contours in ultrasound images.

Finally, the hierarchical B-spline approach has allowed to improve the registration process in complex zones.

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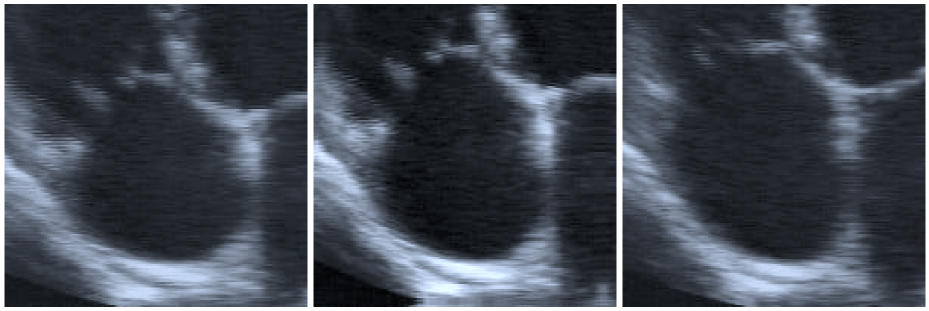
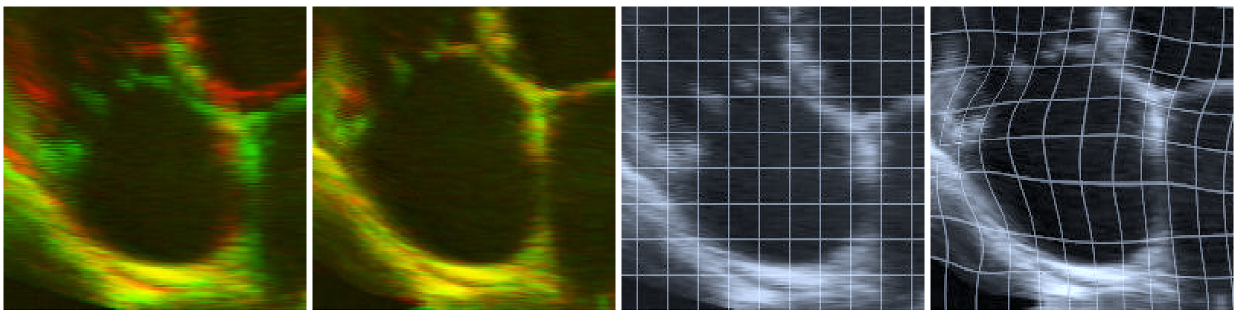


(a)Test image. (b)Deformed image. (c)Reference image.



(d)Initial difference (Color image). (e)Final difference (Color image). (f)Test image grid. (g)Deformed image grid.

Figure 3. Results of the registration process.

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