Dynamic Speckle Tracking Based on B-spline Model

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***Abstract*—We developed an elastic registration approach to compute cardiac motion by analysis of 3D ultrasound image sequences. The main principles applied here were the modeling of the unknown spatial deformations between two successive views by B-splines, and the minimization of a cost function derived by a maximum likelihood technique applied to the log-speckle noise. Numerical results matched quite well the patient specific geometric models of the mitral valve annulus generated by splines based on 3D image tagging by cardiologists.**

***Index Terms*—speckle tracking, B-spline, image registration**

I. Introduction

Clinical diagnosis and therapy planning are increasingly often supported by 3D imaging modalities, such as MRS (Magnetic Resonance Spectroscopy), PET (Positron Emission Tomography), SPECT (Single Photon Emission Computed Tomography) for functional information, and CT (Computed Tomography), MRI (Magnetic Resonance Imaging), Ultrasound Echography , X-ray, for anatomical visualization[1]-[3].

Thus clinicians and medical researchers become natural users for 3D image registration providing voxel to voxel matching of two 3D images of the same anatomical object obtained by different imaging modalities, at different times, or from different perspectives. The search for a good voxel to voxel correspondence between reference and target images Jr and Jt, is guided by one or several matching quality criteria.

Image registration methods [4]-[6] were initially designed for 2D images, for instance to align tomographic slices of different recordings, but in the last decade, 3D image registration based on volumetric data sets has become the main technical challenge, and involves much heavier computing resources.

We apply speckle tracking techniques to numerically construct the dynamic deformations between multiple 3D snapshots of the human mitral valve annulus in the mitral valve apparatus. Our starting point is a patient's specific set of static models of the mitral valve apparatus. These models were generated by image analysis of live 3D echocardiographic movies at specific heart cycle instants. Each 3D movie includes roughly twenty 3D frames per heartbeat cycle, acquired by ultrasound technology, and represents a high volume of image data corrupted by "speckle" noise.

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II. Speckle Tracking

A. Mitral Valve

The mitral valve is a dual-flap valve in the heart that lies between the left atrium (LA) and the left ventricle (LV) [7]. The mitral valve and the tricuspid valve are known collectively as the atrioventricular valves because they lie between the atria and the ventricles of the heart and control the flow of blood. A normally functioning mitral valve opens secondary to increased pressure from the left atrium as it fills with blood. As the pressure increases above that of the left ventricle, the valve opens allowing blood to flow into the left ventricle during diastole (early rapid filling and atrial contraction), and closes at the end of atrial contraction to prevent blood flowing back.

B. B-Splines

For a spline of degree n, each one of these basic polynomials has degree n, which would suggest that we need n+1coefficients to describe each piece. However, there is an additional smoothness constraint that imposes the continuity of the spline and its derivatives up to order n-1 at the knots, so that, effectively, there is only one degree of freedom per basic polynomial. Here, we will only consider splines with uniform knots and unit spacing. The remarkable result, due to Schoenberg [8-9], is that these splines are uniquely characterized in terms of a B-spline expansion

$$s(x) = \sum_{k \in Z} c(k) \beta^n (x - k) \tag{1}$$

which involves the integer shifts of the central B-plines of degree n denoted by $\beta^n(x)$; the parameters of the model are the B-spline coefficients c(k). B-splines, defined below, are symmetric, bell-shaped functions constructed

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from the (n+1)fold convolution of a rectangular pulse $\beta^0(x)$

$$\beta^0(x)=\begin{cases}1, & -1/2<x<1/2\\ 1/2, & |x|=1/2\\ 0, & otherwise\end{cases} \tag{2}$$

$$\beta^n(x)=\underbrace{\beta^0(x)*\beta^0(x)*\cdots\beta^0(x)}_{(n+1)times} \tag{3}$$

The family of B-splines of degree 3 (cubic B-splines) is shown in Fig. 1. Since the B-spline model is linear, studying the properties of the basic atoms can tell us a lot about splines in general. Thanks to this representation, each spline is unambiguously characterized by its sequence of B-spline coefficients c(k), which has the convenient structure of a discrete signal, even though the underlying model is continuous.

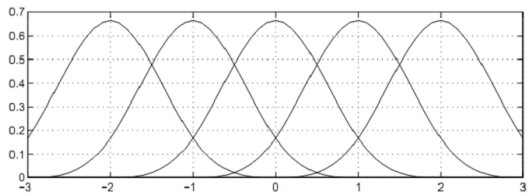

Figure 1. The centered spline of degree 3: cubic B-splines

C. B-Spline Model for the Displacement Vector Field

Consider a Lattice of Knots:

$$L=\{\boldsymbol{k}=(k_1,k_2,k_3)\,|\,1\le k_i\le L_i\}$$

where the knots k are placed on a regular sub grid of the pixel grid G. Denote by $N_1=224, N_2=208, N_3=208$ the dimensions of the grid G and define the knot spacing $h=(h_1,h_2,h_3)$ where $h_i=N_i/L_i$.

Here we put the knots within the image grid only, therefore the deformation is zero for voxels that are at least 2h outside the image grid.

The unknown displacement field u is a 3D non-linear transformation which is modeled by a linear combination of cubic B-splines associated to the knots of the lattice L. The unknown vector c of coefficients $c_k=(c_k^1,c_k^2,c_k^3)$ of this linear combination completely defines the displacement field u by the explicit formula:

$$u(x)=\sum_{k\in L}c_k B_3(x,h,k) \tag{4}$$

where

$$B_3(x,h,k)=\prod_{i=1,2,3}\beta(x_i/h_i-k_i+1/2) \tag{5}$$

During the warping process, we need a continuous version of the discrete image Jt. Using also cubic B-splines, we interpolate the discrete image Jt to extend it form the pixel grid G to a continuous function still denoted Jt:

$$J_t(x)=\sum_{y\in G}b_y B_3(x-y) \tag{6}$$

where $B_3(x-y)=\prod_{i=1,2,3}\beta(x_i-y_i)$ and b_y is a set of interpolation coefficients, which can be computed prior to the search for u by solving a linear system.

D. Image Model

The displayed ICE image intensity $J(\boldsymbol{x})$ at pixel x is modeled as the sum of an unknown uncorrupted B-mode image $I(\boldsymbol{x})$ and a log-speckle noise

$$S(\boldsymbol{x})=\ln(N(\boldsymbol{x}))/\alpha \tag{7}$$

where α is an unknown scaling coefficient, and the random noise $N(x)$ has a standard Rayleigh distribution. We allow α varying across different image regions.

Fix two ICE image frames J_r and J_t acquired at times r and t, we assume J_r is our reference image. We have $J_r(x)=I_r(x)+S_r(x)$ and $J_t(x)=I_t(x)+S_t(x)$ for all voxels x. Let f=x+u: G→G the unknown spatial deformation of the pixel grid G capturing the deformation (between times r and t) of the planar heart section displayed by image I_r.

We then assume that $I_t(f(x))=I_r(x)$ for all pixels x. Hence after warping by the unknown true deformation f, the residual intensity disparities verify

$$\begin{aligned}d(x)&=S_t(f(x))-S_r(x)\\&=\ln(N_t(f(x))/N_r(x))/\alpha\end{aligned} \tag{8}$$

The maximum likelihood principle indicates that a good estimator of the unknown true deformation f should maximize in f the conditional joint probability distribution of the disparities given the image data. We thus introduce a natural disparity cost functional:

$$K(u)=\frac{1}{|M|}\sum_{x\in M}g(d(x)) \tag{9}$$

where M is the region of interest, and

$$g(z)=\ln(e^{2z}+1)-z\,,\ \forall z\in R^+ \tag{10}$$

E. Multi-Resolution Optimization of Cost Functionals

To compute the unknown spatial displacement field u matching images Jt and Jr, we need to minimize the cost functional K(u). To minimize K(u) we implement a multi-resolution gradient descent in u at coarse to fine

successive resolutions. Multi-resolution is used for both the image model and the deformation model.

First, we build an image pyramid composed of gradually coarser versions of the original image by regularly spaced down-sampling. Starting from an initial ICE image of size 224x208x208, we create, by successive dichotomic decimations of pixels, a sequence of increasingly coarser images. Second, we use multi-resolution also for the B-spline deformation model of u. We start with a coarse B-spline model of u defined by a lattice of knots L_1 with a large initial distance h^1 between knots. We fix an increasing sequence of knots lattices L_i with corresponding knots spacing $\{h^i\}_{i=1,\cdots,q}$, where $h^{i+1} = 2h^i$.

F. Gradient Descent at Fixed Resolution

To minimize the cost functional K(u) we implement a multi-resolution gradient descent in u at coarse to fine successive pairs of resolutions RS(m), both for the image model and for the B-spline model. For each fixed pair of resolutions RS(m), the current lattice of B-spline knots L is fixed, and hence u is approximated by its corresponding B-spline expansion, which is defined by an unknown vector of coefficients $c_k^i, (i = 1,2,3; k \in L)$. After adequate restriction to the current image model, the cost functional to minimize becomes an explicit function K(c). To minimize K(c) we implement a gradient descent in c, with the following update rule

$$\Delta \boldsymbol{c} = -\mu \nabla K(\boldsymbol{c}) \tag{11}$$

III. Numerical Performance

Our experiment is based on a patient's specific finite set of static models of the mitral valve apparatus. These models were generated by image analysis of live 3D echocardiographic movies at specific heart cycle instants. Each 3D movie includes roughly twenty 3D frames per heartbeat cycle, acquired by ultrasound technology, and represents a high volume of image data corrupted by “speckle” noise. The mitral valve models are based on NURBS (non uniform rational B-splines), and were obtained by combining optical flow extraction algorithms with sparse tagging by medical experts.

The mitral valve apparatus involves the annulus (a closed thin deformable ring) and two deformable surfaces with boundaries, namely the anterior and posterior leaflets. These mitral leaflets are flexibly linked to the annulus by a sub segment of their boundaries. When the valve is closed, the exterior parts of the leaflets have a common boundary called the coaptation line. The mitral valve apparatus can be viewed as a composite deformable object built from several smooth deformable shapes (see Fig. 2), namely a closed curve MA (the mitral annulus), a curve segment COA (the coaptation line), two surfaces AL and PL (the mitral leaflets) with boundaries.

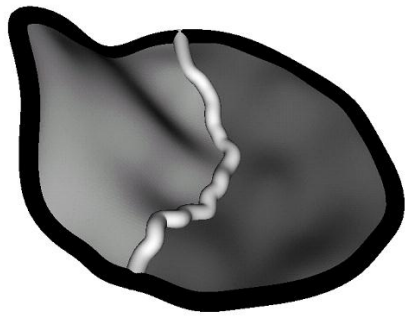

Figure 2. Mitral valve structure (the black curve denotes the annulus)

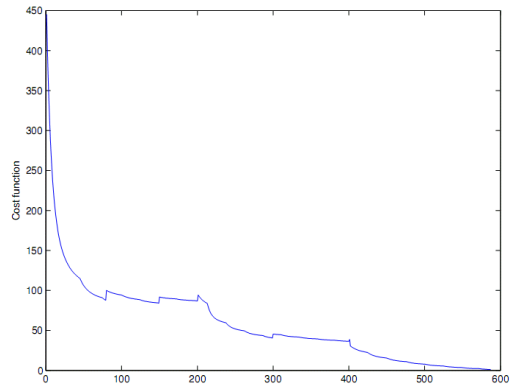

Figure 3. Evolution of cost functional

We use the annulus model in the first frame to generate the mask for optimization, and validate our registration method at every time frame against the annulus models generated from the doctors' tagging at other frames in the 3D image sequences. Fig. 3 shows the evolution of cost function in the optimization process. At the end of optimization, the value of cost function is very close to the theoretical value 1.The mean and std of the distances between the reference and the target annulus generated from spline models are 11.08 and 3.53 respectively. After optimization, the results show good agreement between deformed annulus and target annulus with mean 2.05 and std 1.16.

IV. Conclusion

We apply speckle tracking techniques to numerically construct the dynamic deformations between multiple 3D snapshots of the human mitral valve annulus in the mitral valve apparatus. Within a framework of parametric elastic registration, the deformation was estimated by optimizing the energy function computed by applying the maximum likelihood approach to the speckle noise model. Our computing results matched quite well the patient specific geometric models of the mitral valve annulus generated by splines based on 3D image tagging by cardiologists.

REFERENCES

[1] J. Ren, D. Schwartzman, D. Callans, S. Brode, C. Gottlieb, and F. Marchlinski, "Intracardiac echocardiography (9 mhz) in humans: Methods, imaging views and clinical utility," *Ultrosound Med. Biol.*, vol. 25, pp. 1077-1086, 1999.

[2] F. Roithinger, P. Steiner, *et al.*, "Low-power radiofrequency application and intracardiac echocardiography for creation of continuous left atrial linear lesions," *J. Cardiovasc. Electrophysiol*, vol. 10, pp. 680-691, 1999.

[3] N. Marrouche, D. Martin, *et al.*, "Phased-Array intracardiac echocardiography monitoring during pulmonary vein isolation in patients with atrial brillation: Impact on outcome and complications," *Circulation*, vol. 107, pp. 2710-2706, 2003.

[4] M. Ledesma-Carbayo, J. Kybic, M. Desco, A. Santos, M. Suhling, P. Hunziker, and M. Unser, "Spatio-temporal nonrigid registration for ultrasound cardiac motion estimation," *IEEE Transactions on Signal Processing Medical Imaging*, vol. 24, pp. 1113-1126, 2005.

[5] J. Barron, D. Fleet, and S. Beauchemin, "Performance of optical flow techniques," *Int. J. Comp. Vis.*, vol. 12, pp. 43-47, 1994.

[6] P. Baraldi, A. Sarti, C. Lamberti, A. Prandini, and F. Sgallari, "Evaluation of differential optical flow techniques on synthesizedecho images," *IEEE Transactions on Biomedical Engineering*, vol. 43, pp. 259-272, 1996.

[7] R. Anderson and M. Kanani, "Mitral valve repair: critical analysis of the anatomy discussed," *Multimedia Manual of Cardiotheractic Surgery*, vol. 2007, no. 0102, 2006.

[8] I. J. Schoenberg, "Contribution to the problem of approximation of equidistant data by analytic functions," *Quart. Appl. Math.*, vol. 4, pp. 45-99, 112-141, 1946.

[9] I. J. Schoenberg, "Cardinal spline interpolation," *Society of Industrial and Applied Mathematics*, Philadelphia, PA, 1973.

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