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Review of Myocardial Motion Estimation Methods from Optical Flow Tracking on Ultrasound Data

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***Abstract*- Quantitative analysis of cardiac motion is of great clinical interest in assessment of ventricular function. Ultrasound imaging, especially matrix transducers acquiring real-time three dimensional data, provide valuable information, from which quantitative measures of cardiac function can be extracted via optical flow computation. Such analysis requires tracking of the image brightness patterns with underlying assumptions of visual persistency. We present a review of myocardial motion analysis on cardiac ultrasound, based on optical-flow computation, with phantom and clinical evaluations for segmental wall assessment and motion features quantification.**

***Keywords*- echocardiography, three-dimensional ultrasound, optical flow, cardiac motion analysis, cardiac imaging, myocardial wall motion.**

I. INTRODUCTION

Two-dimensional echocardiography (2DE) is the current clinical standard imaging modality to evaluate myocardial motion. Fine motion analysis is currently performed using Tissue Doppler Imaging (TDI) that precisely estimate the 1D motion of cardiac tissue in the direction of the transducer.

Optical flow (OF) computational methods aim at assessing and quantifying myocardial motion from ultrasound image data., taking into account imaging artifacts such as speckle noise and signal dropout. From the motion field estimated via OF computation, myocardial wall motion and contractility can be assessed for the detection of abnormalities induced in several cardiac pathologies. In current clinical settings, wall motion analysis is commonly assessed qualitatively by visual examination of motion and thickening patterns on 2DE data. The American Heart Association (AHA) recently proposed a standardization of the sub-division of the LV myocardial wall into 17 segments with different coronarial supplies, for regional wall assessment [1].

Recent three-dimensional echocardiographic (3DE) transducers enable access to all myocardial motion components, eliminating planar measurement errors induced by out of plane translations and rotations. This article presents results on the very active research field of quantitative myocardial motion analysis with a focus on 3DE.

II. Myocardial Motion via Optical Flow Computation

Optical flow computation can be used for quantitative evaluation of myocardial tissue motion via estimation of a field of motion vectors from the ultrasound image data.

OF computation can be divided into two general methods: **block matching methods** based on image similarities, and **variational methods** based on image intensity preservation assumptions, expressed with partial derivative equations.

Four methods used for OF computation and applied to ultrasound data are presented in this review.

A. Block Matching

Block matching compares two dataset frames $I(\mathbf{x},t)$ and $I(\mathbf{x},t+\Delta t)$, by evaluating the displacement vector $\Delta\mathbf{x}$ in a small neighborhood, around a pixel x via maximization of a similarity measure (e.g. cross-correlation coefficient).

Advantages of this general family of OF computation methods include ease of implementation and straightforward extension to multiple dimensions. OF computation is typically performed on some pixels in the ultrasound image data, having specific features leading to local motion estimation and non-dense and non-uniforms motion vector fields that have then to be interpolated. This set of method is called **speckle tracking** and is currently tested in clinical environment [2-4].

In [5], Duan *et al* applied this framework on real-time 3D echocardiographic data to estimate the displacement of selected voxels on the endocardial surface.

B. Gradient Based Methods (Horn and Shunck)

The general differential formulation of the OF computation consists in assuming that the intensity $I\left(\vec{x},t\right)$ of a particular point in a moving pattern does not change with time [6]. This constant intensity assumption is written as:

$$\vec{\nabla} I\left(\vec{x},t\right)\bullet\vec{s}\left(\vec{x},t\right)+I_t\left(\vec{x},t\right)=0 \quad (1)$$

where $\vec{s}\left(\vec{x},t\right)$ is the speed of the motion field to estimate.

When the dimension of this speed vectors is 2 or above, this single equation is not sufficient to solve the estimation problem. Horn and Shunck [6] proposed to introduce a regularization term on the speed function in the following minimization problem:

$$\int_{\Omega}\left(\vec{\nabla} I(\vec{x},t)\bullet\vec{s}(\vec{x},t)+I_t(\vec{x},t)\right)^2+\alpha^2\sum_{i=1}^{N}\left\|\vec{\nabla} s_i\right\|^2 d\Omega \qquad (2)$$

where $\vec{s}=[s_1,s_2,...]$ is defined on the image domain $\Omega\subset\mathbb{R}^N$ and α is a real parameter.

This method was applied to phantom ultrasound images in [7].

C. *Locally constant motion (Lucas-Kanade)*

As an alternative to overcome the sub-dimensionality of the OF formulation in Equation (1), Lucas-Kanade [8] proposed to solve the problem on small local windows where the motion field is assumed to be constant.

This method was applied to phantom ultrasound images in [7]. Lamberti *et al.* [9, 10] used this framework to compute OF on the endocardial surface. They then select only a subset of "reliable" vector motion estimation, on local sliding windows $W(\vec{x})$, emphasizing values at the center. Reliability of the estimation was measured via the following test:

$$\lambda_{\min}\left[\int_{W(\vec{x})}\vec{\nabla} I\bullet\vec{\nabla} I^T d\vec{x}\right]<\tau \qquad (3)$$

where I is the image data, $\lambda_{\min}$ is the minimum eigen value of overall system matrix and τ is a pre-selected threshold. The authors then diffused the scattered motion vector field, from the reliable points to the entire field of view, to get a continuous version of the myocardial wall.

D. *Locally Affine Model (Suhling-Unser)*

In a recent paper, Suhling et al. [11] proposed a novel optical-flow algorithm, tuned for the analysis of ventricular wall motion from dynamic B-mode echocardiograms. Derived from the Lucas-Kanade approach, the method uses a local sliding window, into which affine motion models and linear temporal constraints are applied. This spatio-temporal affine model is defined in 2D for the speed term $\vec{s}=[s_1\ s_2]$ and the position vector $\vec{x}=[x\ y]$ as:

$$\begin{bmatrix} s_1(\vec{x},t) \\ s_2(\vec{x},t)\end{bmatrix}=\begin{bmatrix} s_1^0 \\ s_2^0\end{bmatrix}+\begin{bmatrix} s_{1x} & s_{1t} & s_{1t} \\ s_{2x} & s_{2y} & s_{2t}\end{bmatrix}\begin{bmatrix} x-x^0 \\ y-y^0 \\ t-t^0\end{bmatrix} \qquad (4)$$

In this model, the speed term is modeled with respect to a center point $\vec{x}^0=\left[x^0\ y^0\right]$ at a center time t^0. The matrix of speed derivatives is assumed constant in the local window of interest, allowing to decompose it into the sum of a rotation matrix R and a deformation matrix D.

The speed vector is estimated via a least-square (LS) minimization of the constant intensity constraint of Equation (1) with 8 unknowns ($\vec{s},\vec{\nabla} s_1,\vec{\nabla} s_2,\vec{s}_t$). The method is refined with spatially variant weights inside the LS minimization, the use of a multiresolution moment computation approach to incorporate image data, and a coarse to fine strategy.

III. Feature Extraction

Affine motion models allow the description of the myocardial motion into four components: rotation, contraction, expansion, and shear. Motion models with temporal linear components also provide estimation of the myocardium acceleration.

A. *Surface vs. dense motion field estimation*

In general OF is performed on the overall ultrasound image data. However, since myocardial motion characteristics vary greatly from the endocardial to the epicardial surface, local flexibility should be allowed. Taking this factor into account, the authors in [5], compared motion field interpolation methods inside the myocardium, after tracking only the endocardial and epicardial surfaces, from manually traced surfaces at end-diastole.

B. *Dense motion field features*

Direct extraction of **rotation and deformation matrices** and translation vectors in a 3D space was proposed by Lamberti et al [12], based on Umeyama's [13] approach on least-squares estimation of transformation parameters between two point patterns. The outputs of this method are the translation vector and the rotation matrix that characterize motion between two time frames. The authors extracted the following motion parameters: principal axes of deformation, deformation modules, rotation angles, percentage volume variation

Topological features of the 3D optical flow were analyzed in [9]; to evaluate the global behavior of the motion field and derive **cardiac function indexes** via computation of the Jacobian matrix, representing the variation of the motion field around a given point. For example, computing the eigenvalues and eigenvectors of the vector field at critical points (i.e. identified points where the components of the vector field vanish and where its neighborhood is well approximated by first order Taylor expansion), they obtain the following global motion information:

- **Eigenvectors directions:** principal axis of deformation and rotation axis.
- **Eigenvalues**: deformation and rotation magnitudes, relative variation of volume and twisting.

Based on the values of the eigenvalues, they classify the critical points as nodes, saddle nodes, spiral or spiral saddles, with attracting of repelling behaviors. Further decomposing the Jacobian tensor, they characterize the 3 principal strain values and directions via the eigen decomposition of the symmetric part and the rotation axis of the twist with the eigen vector of the antisymmetric part.

In [5], the authors present results for computation of myocardial flow field (Figure 1), decomposed into:

- **radial displacement** (Figure 2),
- **thickening**,
- **twist,**
- **strain, strain rate.**

In [11], the authors reported **averaged peak radial velocities** inside the myocardium.

C. *The Centroid problem*

The use of a floating centroid can be necessary to correct for important global translation. As underlined in [11], the choice of a fixed or floating centroid to extract temporal motion parameters depends on the imaging and the patients conditions.

IV. Evaluation of OF Motion Estimation

Evaluation of OF-based myocardial motion is typically performed on phantom and clinical data.

A. *Phantom studies with motion ground-truth*

The use of **synthetic phantoms** is important to evaluate the accuracy and precision of the estimation of a motion vector fields. As pointed out in [11], such evaluation is even more important for ultrasound data as two types of errors can be introduced: (1) intrinsic errors from the OF algorithm via computation of temporal and spatial derivatives, (2) errors related to the constant brightness assumption that is violated on ultrasound data due to speckle noise and acquisition artifacts. To distinguish between these two sources of errors, one, as in [11], can generate two types of phantoms, applying a known motion field: (1) to the intensity distribution, simulating **brightness-preserving motion** or (2) to the continuous distribution of point scatterers, simulating **real-tissue motion**.

Phantom images for myocardial studies typically represent an homogeneous annulus on a background, with a strong reflective interface. The applied motion field typically simulates isotropic radial expansion of an incompressible material and a temporal sequence is generated simulating a cardiac cycle.

When evaluating the accuracy of the OF-based motion computation, typical **motion error estimates** include:

- **Mean angular error** between estimated and exact velocity fields;
- **Mean absolute magnitude error**;
- **Mean relative magnitude error**.

In [7], results showed that both the Horn-Shunck and Lucas-Kanade methods produced accurate results on the “constant brightness” phantoms, with accuracy of angular estimates between 0.05° and 0.1°, depending on the density of the motion field, and magnitude accuracy between 10% and 18%, corresponding to an average error of 0.5 pixels. For the “real-motion” phantoms, the results showed that both methods only produced accurate results at tissue interfaces, where coherent scattering prevails, with accuracy of angular estimates between 0.6° and 1.0°, depending on the density of motion field, and magnitude accuracy between 42% and 54%, corresponding to an average error of 1.5 pixels. Both methods tended to under-estimate the velocity magnitude on the two types of phantoms.

In [9], the authors evaluated the identification of critical points on compression and rotation motion fields on spherical surfaces, thus using OF to track surfaces

In [11], the authors first evaluated their method on simulated 2D ultrasound B-mode images, with Rayleigh distributions, computed as the modulus of complex RF signals. Motion was simulated on a short-axis like slices, with area-preserving radial displacements and a global translation. The overall velocity was set to a maximum of 2 pixels. Results showed accuracy of angular estimates between 2.5° and 5°, depending on the image SNR, and magnitude accuracy between 7% and 10%.

More sophisticated phantom studies include the use of real phantom objects such as a rotating cylinder-shaped tissue-mimicking gelatin, placed inside a tank of water [11]. Results in [11] showed an underestimation of the radial velocity of 9% but a good correlation of the linear increase in radial velocity along circular contours inside the phantom (made of incompressible material). In [14], a tracking method using information in both spatial and spectral domains was used to estimate motion of an excised rat heart rotated in laboratory settings. The proposed method was able to correctly assess the rotation.

B. *Clinical Evaluation*

In [11], the authors tested their OF algorithm on six dog data sets, with induced LAD occlusion and divided the LV wall into 16 segments according to the AHA protocol [1], for segmentational wall motion analysis. Open-chest data was acquired before and after infarction. Their results showed that dyskinesia in the apical to mid anteroseptal segments was correctly captured by the estimated motion field, with correct outward/inward motion during systole/diastole. Average peak radial velocities in diskinetic segments were 1.99±0.92 cm/s versus 0.18±0.15 cm/s before infarction, with significant statistical differences.

Longitudinal velocities, strain and strain rate parameters as estimated from speckle tracking method were compared in 2 patient populations in [4]. The measured parameters were found to be significantly lower in the infracted segments.

Regarding twisting motion components, results in [15] correlated rotation measurements of the LV with tagged MRI (and TDI) on 15 patients. In systole the LV apex exhibited counterclockwise rotation whereas the base rotated clockwise. Correlation in both peak and speed of rotation was excellent between the two methods.

In [5], the authors evaluated their OF algorithm on a real-time 3D ultrasound volume from a heart-transplanted patient. Most of the radial displacement components showed inward motion of the ventricular wall during systole, except on the septal side, where reduced amplitude and outward motion was observed. These findings were in agreement with clinical observations on the dataset and typical findings after heart-transplant surgery. The gradient of radial displacement, or thickening, yielded positive thickening at the endocardial surface except for the septal wall where zero or small thinning at the epicardium border were observed. Such pattern agrees with experimental findings [16].

V. Conclusion

Quantification of myocardium motion is a very active research fields that should bring new clinical parameters to the physician, specifically using 3D echocardiography. Current works include validation against TDI [17], which only provides one-dimensional information on tissue motion velocities in the direction of the transducer, while remaining the current state of the art screening method for clinical motion estimation.

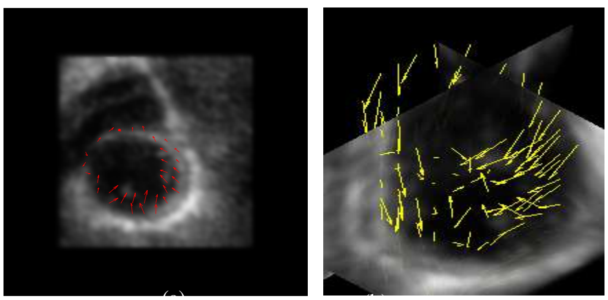

Figure 1. OF motion vector field: (a) Single short-axis slice; (b) 3D rendering.

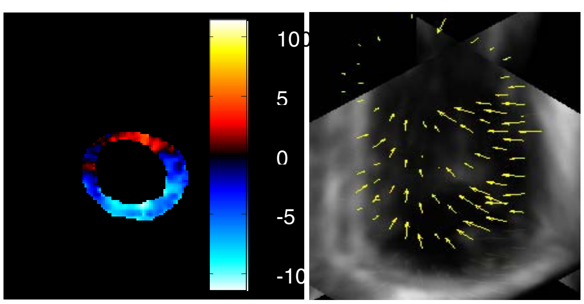

Figure 2. Radial displacement: (a) Single short-axis slice (blue: inward); (b) 3D rendering.

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