DENSE MYOCARDIAL MOTION FROM 4D ULTRASOUND: COMPARATIVE PERFORMANCE EVALUATION

R. Mukherjee[1], A. Pinheiro[2], J. Gammie[5], D. Yuh[6], T. Abraham[2], E. McVeigh[3], and P. Burlina[1,4]

Johns Hopkins University, [1]Applied Physics Laboratory, [2]Division of Cardiology,
[3]Dept. of Biomedical Engineering, [4]Dept. of Computer Science
[5]University of Maryland Medical Center, Division of Cardiothoracic Surgery
[6]Yale School of Medicine, Section of Cardiac Surgery

ABSTRACT

This paper is an extension of our ISBI 2011 work, where we proposed a novel variational approach to estimate dense myocardial velocity fields from 4D ultrasound (4DUS). In this paper, we present a thorough performance evaluation of our method by comparing it with the primary method of record, which relies on cross-correlation. Our comparative performance evaluation uses several data sources, including (a) real intraoperative 4D transesophageal sequences, (b) synthetic sequences, and (c) phantom sequences. Results from qualitative and quantitative evaluations show an improvement in error for the variational over the cross-correlation motion estimation method.

Index Terms— 4D ultrasound , 4D transesophageal echocardiography, motion estimation, 3D optical flow

1. INTRODUCTION

In 2006, an estimated 26% of all deaths were caused by cardiovascular disease (CVD) [1], making CVD one of the leading causes of death. Fortunately, many of these conditions can be treated or prevented if doctors have the right tools at their disposal and are able to diagnose CVD early. Myocardial motion estimation can play a crucial role in the diagnosis of CVD [2, 3], as well as in elucidating the pathophysiology of CVD, as the mechanisms behind many of these conditions are still not fully understood. In addition, the recovery of dense myocardial motion displacement from 4D echocardiography can have a significant impact in applications such as modeling, simulation, and training.

While much work has been done in the field of speckle tracking and motion flow estimation for 2D+time US images, much less has been reported thus far for 4DUS. Important path-leading research into this real time volumetric imaging modality has emphasized correlation-based approaches [4, 5]. This paper extends our ISBI 2011 work [6], where we proposed a variational approach to compute 3D myocardial velocity vectors. In this paper, we present a more thorough performance evaluation using several data sources, including (a) real intraoperative 4D transesophageal (4D TEE) sequences, (b) synthetic sequences, and (c) phantom sequences.

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2. METHOD

Following the derivation in [6] of our variational approach to myocardial motion computation, the brightness constancy constraint on the intensity value of a voxel in a given 4DUS frame at time t and at location $[x, y, z]$, states that

$$I(x, y, z, t) = I(x + u, y + v, z + w, t + 1) \tag{1}$$

where x, y, z, and t can be combined to form a vector $\mathbf{x} = (x, y, z, t)^\top$ and u, v, and w can be combined to form a displacement vector $\mathbf{d} = (u, v, w, 1)^\top$. We form an energy function that penalizes differences in voxel value between pairs of frames:

$$E_{Data}(u, v, w, t) = \int \Psi(|I(\mathbf{x} + \mathbf{d}) - I(\mathbf{x})|^2) d\mathbf{x} \tag{2}$$

where the function $\Psi(s^2) = \sqrt{s^2 + \epsilon^2}$ constitutes an $L2$ norm, which allows the application of quadratic optimization techniques, while behaving as a robust $L1$ norm when $\epsilon \to 0$.

Following [6, 7, 8, 9], the use of a single constraint for three unknowns $[u, v, w]$ leads to an ill-posed problem, thus an additional spatiotemporal smoothness constraint is incorporated by forming an energy function that penalizes large gradients in flow vectors:

$$E_{Smooth}(u, v, w, t) = \int \Psi(|\nabla u|^2 + |\nabla v|^2 + |\nabla w|^2) d\mathbf{x} \tag{3}$$

A new objective function is formed by summing together the two previously discussed energy components. To allow for the amount of flow vector smoothness to be adjusted as desired, the smoothness function is weighted by some $\alpha > 0$:

$$E(u, v, w, t) = E_{Data} + \alpha E_{Smooth} \tag{4}$$

To minimize the objective function, which involves an unknown under an integral operator, the Euler-Lagrange equation is used. The resulting nonlinear equations are solved using a fixed point iteration method, as in [7]. An improved coarse-to-fine multiscale image warping approach is utilized, where median filtering is applied to estimated displacement vectors at each level of the coarse-to-fine pyramid (see [6, 9]).

3. COMPARATIVE PERFORMANCE EVALUATION

3.1. Intraoperative Data

To qualitatively evaluate our method and discover any challenges associated with the clinical application of our method, we performed

tests on real human TEE data. We collected intraoperative real-time 4D TEE data from patients at the Johns Hopkins University's School of Medicine. The acquisition was performed under a protocol approved by the JHU Institutional Review Board.

4D TEE acquisition was performed using an iE33 Philips console fitted with a Philips X2-T Live 4D TEE probe (Philips Medical Systems, Bothell, WA). The resulting TEE cube sizes were 224×208×208. The 4D TEE probe was run at frequencies ranging from 3 to 5 MHz resulting in spatial resolutions from approximately 0.4 to 1 mm. The data was collected intraoperatively using ECG-gating and a 7 breath-hold protocol leading to a frame rate of close to 50 Hz.

The breath-hold procedure minimizes stitching artifacts caused by the spurious motion of the patient's breathing apparatus. Before acquiring a TEE volume, the anesthesiologist temporarily deactivates the patient's respirator and allows the patient's chest to steady. While the patient is still breathing, deactivating the patient's respirator noticeably decreases the amount of artifacts present in a cube.

To prevent the computation and subsequent evaluation of flow vectors in areas where flow is not well defined (e.g., regions of uniform intensity), we remove empty and/or blood-filled cavities from our data and process only the myocardium. Simple k-means clustering, after compensating for attenuation, is used to group all the voxels of our cube into two clusters: a darker cluster, and a lighter cluster. Optical flow is then computed using only the brighter intensity cluster.

3D optical flow was computed on a sequence of frames spanning one full heart cycle. A total of 28 sequences from multiple patients were used, where each sequence consisted of between 30 and 50 cubes. After computing 3D optical flow, movies were generated for each sequence displaying flow vector and heat map overlays. As shown in Table 1, these generated movies containing our 3D optical flow results were then evaluated by a cardiologist for flow vector plausibility in both direction and magnitude, as well as overall image quality. Most notably, across sequences of varying image quality, all but one sequence obtained the highest marks for direction and magnitude plausibility.

3.2. Intraoperative Data with Synthetic Motion

To quantitatively assess algorithm performance, we used synthetically generated sequences by subjecting clinical 3D volumes to known motion transformations. Our synthetic flow results correspond closely with those found by [10] using similar synthetic transformations, with the only difference being that the proposed method's results are in 3D rather than 2D.

As a side note, while we reproduce metrics currently used by researchers in the field, there are many factors that can reduce the meaningfulness of a comparison between methods. Perhaps one of the most important factors is that we are simply not processing the same data. As can be seen from Table 6, even in 2D, different source images can have a profound impact on resulting error values. For this reason, for purposes of comparisons, we implemented one of the most commonly used 4DUS motion technique, i.e. correlation-based motion flow, so that we could compare the performance to our method when applied to identical data. The technique, demonstrated in [11], computes the cross-correlation coefficient r across a given search window centered around every 5×5×5 volume according to the following equation:

$$r = \frac{\sum(I(\mathbf{x},t)I(\mathbf{x}+\mathbf{u},t+1))}{\sqrt{\sum(I(\mathbf{x},t)^2)\sum(I(\mathbf{x}+\mathbf{u},t+1)^2)}} \tag{5}$$

The synthetic motion transformations that we used, restated from [10], were translation, rotation, and deformation. Translation was performed by shifting a sub-cube of our data by a known number of voxels in either the lateral (x), elevational (y), or axial (z) directions (Table 3 contains resulting error values). By shifting only a sub-cube of our data, we eliminate the effects of hidden texture from our error values. Translation can be expressed by the following equation:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} u \\ v \\ w \end{pmatrix} \tag{6}$$

Rotation and deformation transformations were performed plane-wise, and can be expressed by the following equation:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} \alpha\cos\theta & -\beta\sin\theta & 0 \\ \alpha\sin\theta & \beta\cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} \tag{7}$$

where α and β represent the amount of lateral and elevational deformation, and θ represents rotation. The product of α and β are set equal to one, per an incompressibility constraint. Table 4 compares flow error values for rotational transformations where α and β are both set equal to 0, but θ is changed according to the number of degrees rotation desired. In contrast, table 5 is obtained by setting θ to 0 and varying α (and consequently β) according to the percentage deformation desired. Note that 1% lateral deformation is achieved when $\alpha = 1.01$ and $\beta = \frac{1}{1.01}$.

After applying the previously discussed transformations to our data and calculating both the commonly used angular and endpoint error values, we found that the translation of volumes resulted in low angular and endpoint error for both our variational and correlation-based methods, mimicking results shown by [12]. Because our method relies on coarse-to-fine and variational approaches, it is difficult to solve for flow (even after simple transformations such as translation) without obtaining some very small, albeit not identically zero, amount of error. On the other hand, the correlation-based method is able to match two identical windows for simple transformations such as translation, and thus obtain zero error, as expected. However, once more complex transformations such as rotation and deformation are used, the correlation-based method begins to deviate considerably from the expected flow, whereas the variational approach does not.

3.3. Phantom Data

For a more comprehensive quantitative assessment of optical flow algorithms, by incorporating the artifacts and anomalies commonly found in real data, we perform a series of experiments on data obtained using a multipurpose tissue-equivalent ultrasound phantom (Nuclear Associates, Carle Place, NY, Model#: 84-317). The phantom is composed of Zerdine (a solid-elastic water-based polymer) that is designed to emulate liver tissue. Embedded within the phantom are numerous nylon wires and cyst-like structures that, for our purposes, add a degree of heterogeneity to the data.

Ultrasound acquisition was performed using an Ultrasonix SonixTouch Research console (Vancouver, BC) and 4DC7-3/40 probe. The probe contains 128 elements in a curved linear array that is panned by a motor with 410 steps, where each step tilts the array by 0.183°. Volumes with a resolution of 484×364×90 were collected using a depth of 15 cm, transmit frequency of 3.3 MHz, and focus depth of 7.5 cm, resulting in an approximate spatial resolution of 0.485 mm. The ultrasound probe and phantom are placed inside

Table 1: Expert evaluation: Vector Motion ranges from 1 - plausible, to 5 - not plausible; Image Quality ranges from 1 - high quality/no artifacts, to 5 - poor quality/many artifacts

Seq ID	Vector Motion	Image Quality	Seq ID	Vector Motion	Image Quality
1	1	2	2	1	2
3	1	3	4	2	2
5	1	2	6	1	1
7	1	1	8	1	1
9	1	2	10	1	2
11	1	2	12	1	2
13	1	1	14	1	2
15	1	2	16	1	2
17	1	2	18	1	2
19	1	1	20	1	2
21	1	2	22	1	2
23	1	2	24	1	3
25	1	3	26	1	3
27	1	2	28	1	2

an apparatus that maintains their positions, contacts the probe with the phantom, and allows for controlled and measurable movement.

Due to the lack of a simple and controllable method to deform the phantom, experiments were performed by simply translating the phantom a known distance. As can be seen from Table 2, the variational approach performs significantly better than the correlation-based approach on translational phantom data. While the correlation-based approach is able to successfully match some regions within the phantom, for others it produces flow vectors with very high error values. On the other hand, our variational approach produces relatively consistent, low-error flow vectors across the entire volume of the phantom.

For most applications that involve combining flow results over time (e.g., tracking), it is important to realize that the error values reported here will compound over time. As such, we believe that the variational method will show even more significant improvements over correlation-based methods when integrated into real-world systems.

4. CONCLUSION AND FUTURE WORK

We present a novel method for the estimation of dense 3D myocardial displacement from 4D TEE. Tests were performed on synthetic, phantom, and intraoperative TEE data, and demonstrate a considerable reduction in error. This method may be applied to biomechanical simulations, myocardial strain computation, elastography, and automated diagnostics of pathologies.

Future work will include further quantization of clinical performance, investigation into algorithmic performance on data from different modalities, as well as the adaptation of techniques that may be used to boost algorithmic performance (such as those used in [13, 14]).

Table 2: Phantom translation flow error values

Angular Error (deg)				
Translation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1 mm	15.68°	9.27°	26.10°	24.07°
2 mm	14.98°	15.46°	27.67°	33.92°
3 mm	13.55°	18.97°	46.77°	43.37°
4 mm	13.87°	20.39°	71.93°	42.29°
5 mm	16.88°	25.42°	81.02°	39.40°
6 mm	20.10°	29.27°	83.68°	38.84°
Endpoint Error (vox)				
Translation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1 mm	0.36	0.19	0.95	1.01
2 mm	0.60	0.48	1.37	1.35
3 mm	0.97	1.01	2.86	2.21
4 mm	1.47	1.63	5.48	2.24
5 mm	2.35	2.51	7.68	2.19
6 mm	3.49	3.44	9.61	2.21

Table 3: Synthetic translation flow error values

Angular Error (deg)				
Translation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1	0.09°	0.73°	0°	0°
2	0.06°	0.46°	0°	0°
3	0.04°	0.33°	0°	0°
4	0.03°	0.26°	0°	0°
5	0.03°	0.20°	0°	0°
6	0.02°	0.16°	0°	0°
Endpoint Error (vox)				
Translation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1	0.00	0.02	0	0
2	0.00	0.02	0	0
3	0.00	0.02	0	0
4	0.00	0.02	0	0
5	0.00	0.02	0	0
6	0.00	0.02	0	0

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Table 4: Synthetic rotation flow error values

Angular Error (deg)				
Rotation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1°	0.73°	2.64°	1.43°	7.95°
2°	0.78°	2.83°	2.22°	10.03°
3°	1.01°	3.91°	3.55°	12.32°
4°	1.13°	5.26°	9.43°	21.34°
5°	1.28°	6.40°	21.79°	34.22°
6°	1.52°	7.86°	35.43°	41.54°
Endpoint Error (vox)				
Rotation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1°	0.02	0.09	0.04	0.22
2°	0.04	0.14	0.09	0.41
3°	0.07	0.20	0.26	0.75
4°	0.10	0.31	0.93	1.60
5°	0.14	0.43	2.14	2.68
6°	0.18	0.61	3.55	3.42

Table 5: Synthetic lateral deformation flow error values

Angular Error (deg)				
Deformation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1%	1.16°	0.94°	20.77°	7.75°
2%	1.15°	0.71°	14.05°	8.58°
3%	1.39°	0.67°	10.98°	7.60°
4%	1.71°	0.72°	9.36°	8.54°
5%	2.07°	0.81°	8.78°	10.22°
6%	2.44°	0.92°	9.20°	12.31°
Endpoint Error (vox)				
Deformation	Variational		Cross-Correlation	
	Mean	Stdev.	Mean	Stdev.
1%	0.02	0.02	0.46	0.24
2%	0.03	0.02	0.41	0.29
3%	0.05	0.03	0.41	0.25
4%	0.09	0.04	0.44	0.37
5%	0.13	0.06	0.51	0.58
6%	0.18	0.08	0.68	0.85

Table 6: Middlebury public dataset [15] error values for flow computed using 2D versions of the variational and cross-correlation methods

Variational Method				
Image Pair	Angular Error (deg)		Endpoint Error (pix)	
	Mean	Stdev.	Mean	Stdev.
Dimetrodon	3.21°	5.71°	0.21	0.33
Grove2	2.87°	8.07°	0.20	0.47
Grove3	7.36°	18.71°	0.81	1.54
Hydrangea	2.67°	7.59°	0.26	0.51
RubberWhale	10.14°	27.05°	0.23	0.49
Urban2	4.40°	13.38°	0.48	1.49
Urban3	6.57°	24.03°	0.80	1.96
Venus	12.41°	34.53°	0.65	1.01
Cross-Correlation Method				
Image Pair	Angular Error (deg)		Endpoint Error (pix)	
	Mean	Stdev.	Mean	Stdev.
Dimetrodon	17.71°	26.84°	0.79	1.13
Grove2	13.77°	24.87°	0.83	1.14
Grove3	39.42°	43.41°	2.90	3.18
Hydrangea	25.70°	39.18°	1.88	2.11
RubberWhale	11.92°	17.17°	0.42	0.62
Urban2	54.06°	46.70°	7.97	8.50
Urban3	68.43°	51.45°	7.01	5.21
Venus	42.46°	45.48°	2.90	2.80

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