A FRAMEWORK FOR AUTOMATIC, ACCURATE, AND FAST 2-D+T/3-D REGISTRATION APPLIED TO TRANS-CATHETER AORTIC VALVE IMPLANTATION (TAVI) PROCEDURES

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ABSTRACT

Presentation of detailed anatomical structures via 3-D models of the aortic root helps navigation and deployment of the prosthetic valve during TAVI procedures. Accurate 2-D/3-D registration of the 3-D model with one static X-ray image has been achieved using a hybrid method in [1]. In this paper, we extend the above method to register the 3-D model to a sequence of angiographic images that can be used for dynamic 2-D/3-D fusion. The key idea is to iterate the processes of motion-model construction and motion-model-guided 2-D/3-D registration. This iterative process starts from the frames with a good contrast presence, and extends gradually to those frames with less contrast and hence requires the motion-model to boost the registration performance. Image-based automatic motion-phase detection and contrast agent detection are utilized to fully explore the pseudo-cyclic property of the aortic motion and makes our framework fully automatic. Compared to the naïve frame-by-frame 2-D/3-D registration approach, the proposed method reduced the registration error and the computational time by a factor of 6 and 12 respectively, and boosted the success rate from ~50% to ~100%, on five clinical TAVI data.

Index Terms— 2-D+t/3-D Registration, Trans-catheter Aortic Valve Implantation (TAVI), Automatic Contrast Detection

1. INTRODUCTION

Aortic valve disease is the most common valvular problem in aged people. A minimal invasive trans-catheter aortic valve implantation can be performed in high risk patients. Accurate 2-D/3-D registration of the 3-D model from pre-operative volumes (CT, MR etc.) with one static X-ray image has been proposed in [1] (Fig.1). Extensions of the registration with one image to a sequence of angiographic frames can be helpful for dynamic 2-D/3-D fusion and patient-specific motion modeling. However, naïve extension of the method in [1] by a frame-by-frame manner will not lead to a satisfactory performance, because the contrast agent washes out very quickly in the aorta so that a lot of frames in the sequence contain only very faint, partial, and/or barely visible contrast. Also the computational cost could be relatively high when the temporal information is not fully utilized in the frame-by-frame approach.

In this paper we propose a framework for fully automatic, accurate, and efficient 2-D+t/3-D registration of the 3-D model to an angiographic sequence. The key idea is to periodically update the patient-specific motion-model using the frames that have been registered, starting from the frames with most contrast and hence highly reliable for registration purpose. The constructed motion-model is then used to supervise the registration of the more challenging frames with less contrast and refined when more frames are registered. To the authors' best knowledge, this is the first systematic framework on 2-D+t/3-D registration. 2-D+t/3-D+t registration has been shown in [2] for coronary applications. It requires however a 4-D data that is typically unavailable and unnecessary for aortic procedures because the deformation coming from heat beat is much less at the aortic root compared to the coronary artery. In addition, our method estimates the rigid-body motion across time via a sequence of 2-D/3-D registration, while the method in [2] performs only one 2-D/3-D registration and estimates the deformation across time using the 4-D data.

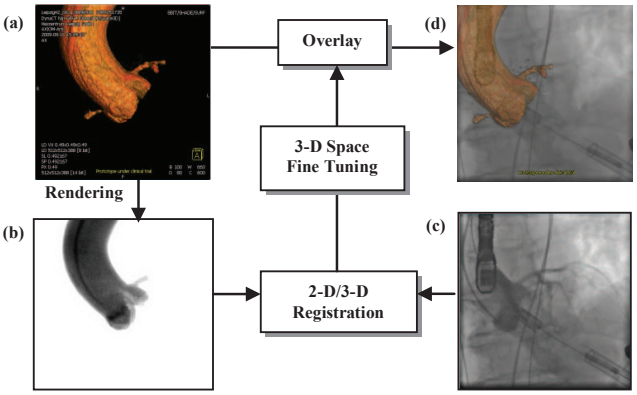


Fig.1. Illustration of 2-D/3-D Registration for TAVI. (a) A 3-D aortic volume. (b) The rendered DRR image. (c) A 2-D X-ray image with contrast injection. (d) Overlay of The 3-D volume onto X-Ray image.

2. METHODS

2.1 Workflow of 2-D+t/3-D Registration

The workflow of 2-D+t/3-D registration (Fig.2) consists of three steps: motion phase detection, motion cycle ordering, and 2-D+t/3-D registration. The motion of the aorta is quasi-periodic consisting of cardiac and respiratory motion. Therefore the motion estimated for one frame could provide a reliable prediction for the aortic root location on other frames at a similar cardiac phase, given a translational correction for respiratory motion. Based on the contrast feature curve [3] and the detected motion phase, the 3-D aortic model is first registered to the frames in one cardiac cycle that has most contrast presence, and an initial motion-model is constructed from this cycle of registration. The constructed motion-model is then used to supervise the registration of the frames in other cycles with less contrast. The process of motion-model update and motion-model-guided 2-D/3-D registration iterates until all frames in the sequence are registered.

2.2 Motion Phase Detection

Since the electrocardiogram (ECG) and respiratory signals are not ubiquitously available clinically, we adopt the image-based

method in [4] for motion phase detection. Given a fixed ROI Ω in the image, the energy change between consecutive frames in the spectral domain could be calculated by:

$$E = \int_{\Omega} \frac{F(I_t)^* \cdot F(I_{t+1})}{|F(I_t)^* \cdot F(I_{t+1})|} df \qquad (1)$$

Where $F(I_t)$ is the Fourier transform of the frame at time t. It can be shown [4] that under certain assumptions the energy change can be approximated as a quasi-periodic function in the temporal space (Fig. 3(a)), which could be an estimate of the motion phase for the corresponding frame in a periodic system. Note that the ROI Ω should not include the aorta, since the injected contrast agent would introduce extra intensity change and violate the quasi-periodic property.

Suppose that two consecutive local peaks on the motion phase curve correspond to the frames at time t and $t+n$, we further normalize the phase for the frame at time i as follows:

$$phase(i) = \frac{i-t}{n-1}, \qquad t \le i \le t+n-1 \qquad (2)$$

After normalization, each frame is associated with a motion phase value ranging from 0 to 1 as shown in Fig. 3(b).

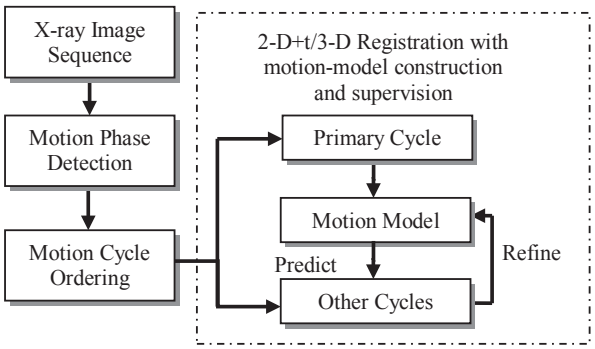


Fig.2. The workflow of 2-D+t/3-D registration.

2.3 Motion Cycle Ordering

Given the motion phase curve, we further order the multiple motion cycles according to their level of contrast presence. A contrast feature curve is calculated using the method in [2] (Fig. 3(c)), and the frame with most contrast, i.e. the highest contrast feature value, is denoted as I_p. The motion cycle containing the frame I_p is named as the primary cycle C_p, which shows the most prominent contrast agent and is used for the construction of the initial motion-model.

Next, we divide the rest of the cycles into two groups: $G_L = \{C_1, C_2, \dots, C_{p-1}\}$ and $G_R = \{C_{p+1}, C_{p+2}, \dots, C_m\}$ for the cycles before and after C_p respectively. A contrast weight is assigned to each of the cycles, which is the average contrast feature value for all the frames within that cycle. These cycles are then ordered as follows: each time one cycle from each group G_L or G_R is selected and the cycles must be selected in a descending (ascending) order for group G_L (G_R). The cycle with a higher contrast weight will be the next cycle to be registered. The motivation for the ordering scheme is to guarantee that for a cycle to be registered, there always exists a cycle in its neighborhood that has already been registered, for the purpose of respiratory motion compensation (details are given in Section 2.4).

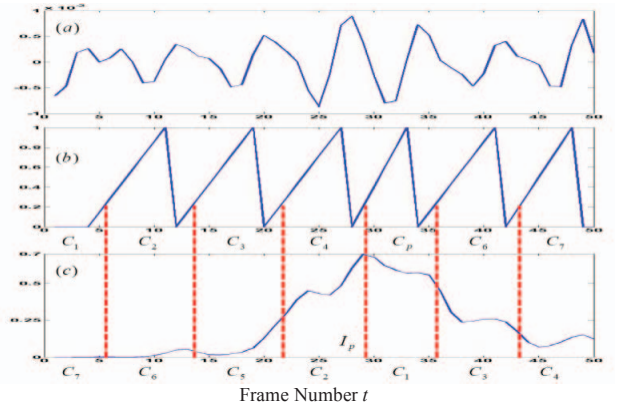


Fig. 3. (a) Quasi-periodic motion phase curve, (b) Normalized motion phase curve, (c) Contrast feature curve.

2.4 2-D+t/3-D Registration

A Rigid-body registration is performed in the proposed method due to the observation that the deformable motion at the aortic root is relatively small, and the fact that 2-D/3-D registration is by-nature an ill-posed problem for which a single-view 2-D image could not lead to a reliable estimation of the deformation, if any. The pose vector for a rigid-body transformation is denoted as $M_t = [x_t, y_t, z_t, \alpha_t, \beta_t, \gamma_t]$, and $t \in [1, m]$ for an angiographic sequence containing m frames. The goal is to find the optimal pose vector M_t $(t = 1 \dots m)$ for each frame in the sequence.

2.4.1 2-D/3-D Registration of The Primary Cycle

For the first frame in the primary cycle, i.e. frame I_p with the peak contrast feature value, we could reliably get the pose vector M_p using the method in [1], which essentially measures the gradient correlation of the aorta boundary between the optimized DRR and the X-ray image. For the rest frames in the primary cycle, since the shape of the aorta is relatively clear with a good contrast presence, we use the standard Horn-Schunck optical flow method [5] to estimate the motion of the aorta between frames I_t and I_{t+1}. Suppose that we obtain N motion vectors $S = \{(u_i, v_i)\}_{i=1}^{N}$ from the boundary of the aorta in the frame I_p using the optical flow method, and let the motion transform in the homogeneous coordinate system between these two frames be:

$$\begin{bmatrix} x^{t+1} \\ y^{t+1} \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & t_x \\ -b & a & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x^t \\ y^t \\ 1 \end{bmatrix} \qquad (3)$$

We then apply linear least square to estimate the parameter vector $\varepsilon = \{(a, b, t_x, t_y)\}^T$ by fitting the motion vectors in S into the transform model as follows:

$$Y = \begin{bmatrix} x_1^{t+1} \\ y_1^{t+1} \\ \vdots \\ x_N^{t+1} \\ y_N^{t+1} \end{bmatrix} = \begin{bmatrix} x_1^t + u_1 \\ y_1^t + v_1 \\ \vdots \\ x_N^t + u_N \\ y_N^t + v_N \end{bmatrix}_{2N \times 1}, \qquad X = \begin{bmatrix} x_1^t & y_1^t & 1 & 0 \\ y_1^t & -x_1^t & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_N^t & y_N^t & 1 & 0 \\ y_N^t & -x_N^t & 0 & 1 \end{bmatrix}_{2N \times 4}$$

and

$$Y = X\varepsilon \qquad (4)$$

Hence, we have the solution $\hat{\varepsilon}$ based on linear least square:

$$\hat{\varepsilon} = (X^T X)^{-1} X^T Y \quad (5)$$

In addition, we apply RANSAC [6] to further remove outliers. In particular, one parameter vector ε could be determined from any two motion vector (u_i, v_i) and (u_j, v_j). Hence, each time we randomly select two motion vectors from S and calculate the corresponding parameter vector ε. Then, the rest of the motion vectors in S are used to test how good the estimated transform model is. When the number of random sampling is large enough, a sufficient number of motion vectors with a well-fitted transform model can be selected and applied in Eq. (4-5) to derive the optimal parameters vector $\hat{\varepsilon}$.

Based on the estimated transform model, the 3-D model is moved in 3-D correspondingly by an approximation of 3-D translations and in-plane rotation. Then a fine tuning of 2-D/3-D registration using the method in [1] is performed in a small neighborhood of the predicted position to obtain M_{t+1}. Essentially the frames in C_p are registered by the combination of an optical flow-based 2-D motion analysis on X-ray images and a fine tuning of 2-D/3-D registration between the 3-D model and the X-ray image. This is much faster than naïve frame-by-frame method, and more accurate than the fine level 2-D/3-D registration alone that has a very small capture range.

2.4.2 2-D/3-D Registration of Other Cycles

Although the above optical flow-based 2-D motion analysis is efficient, it is reliable only for frames with a sufficient contrast presence. For other cycles with partial or very faint contrast, we propose an iterative scheme to perform the registration. The basic strategy is to build a motion-model (MM), based on the pose vectors of the registered cycles, and use the constructed motion-model to predict the pose vectors for the frames in the query cycle. In this way, the pseudo-cyclic property of the aortic motion is fully explored to boost the registration accuracy and efficiency. An example is shown in Fig. 4(a). All the frames in cycle C_1 have been registered. Cycle C_2 is the next one to register according to the ordering. To build the motion-model MM for cycle C_1, let $M^{C_1} = \{M_t\}_{t=p}^{p+n-1}$ be the set of discrete pose vectors for the n frames in C_1. Cubic-Spline interpolation is then used to build a continuous 6-D pose function from the discrete pose vectors:

$$M^{C_1} \rightarrow M^{C_1}(k), \qquad k \in [0,1] \quad (6)$$

where k is the motion phase described in Section 2.2, and

$$MM = \{M^{C_1}(k)\} \quad (7)$$

For any given frame in cycle C_2 with a motion phase $\tau \in [0,1]$, the predicted pose vector from MM is $M^{C_1}(\tau) = [x_\tau^{C_1}, y_\tau^{C_1}, z_\tau^{C_1}, \alpha_\tau^{C_1}, \beta_\tau^{C_1}, \gamma_\tau^{C_1}]$. Next a fine tuning of 2-D/3-D registration using the method in [1] in the local neighborhood of $M^{C_1}(\tau)$ is performed to find the optimal pose vector for this query frame in cycle C_2. After all the frames in cycle C_2 are registered, their pose vectors will be used to create $M^{C_2}(k)$, in a similar way to $M^{C_1}(k)$. The motion model is then updated as $MM = \{M^{C_1}(k), M^{C_2}(k)\}$, and is used for pose vector prediction for frames in the cycles C_3 and after.

The aortic motion comes from both cardiac movement and respiration. It is however difficult to separate accurately respiration motion from cardiac motion without additional information about the respiratory phase. In our method, accurate separation of cardiac and respiratory motion is not the goal, and we approximate respiratory motion based on two observations: 1) within one cardiac cycle the magnitude of respiratory motion is much smaller than that of cardiac motion, and 2) respiratory motion is mostly translational. Let $C^r = \{C_1, C_2, \ldots, C_L\}$ include all the L registered cycles, and $MM = \{M^{C_1}(k), M^{C_2}(k), \ldots, M^{C_L}(k)\}$. Given a query cycle C_q, we can always find a registered cycle $C_n \in C^r$, which is in the neighborhood of C_q according to our order scheme. For each registered cycle $C_i \in C^r$, a respiratory motion compensation vector $R_i = [x_i^r, y_i^r, 0,0,0,0]$ is calculated:

$$x_i^r = \frac{1}{N} \sum_{j=k_1}^{k_N} (M_x^{C_i}(j) - M_x^{C_n}(j)) \quad (8)$$

$$y_i^r = \frac{1}{N} \sum_{j=k_1}^{k_N} (M_y^{C_i}(j) - M_y^{C_n}(j)) \quad (9)$$

where $j = \{k_1, k_2, \ldots, k_N\}$ are N phase points sampled in the interval $[0,1]$, and $M_x^{C_i}(j)$ and $M_y^{C_i}(j)$ are the predicted first two dimensions from $M^{C_i}(k)$ given the phase j. Essentially x_i^r and y_i^r are the average shifts in horizontal and vertical directions in the imaging plane, approximating the average respiratory motion between cycles C_i and C_n. In Fig. 4(a-b), we use the smooth curve connecting cycles to represent the respiratory motion between cycles. The predicted pose vector M_{I_q} for frame I_q in cycle C_q with phase τ is then calculated as:

$$M_{I_q} = \frac{1}{L} \sum_{C_i \in C^r} (M^{C_i}(\tau) - R_i) \quad (10)$$

It can be seen that with the expansion of the motion-model MM to include multiple registered cycles, the predication for a future cycle can potentially become more robust by averaging out the residue respiratory motion within one cardiac cycle as well as when there is discrepancy in the motion patterns for a given cycle. Lastly a fine tuning of 2-D/3-D registration in a small local neighborhood of M_{I_q} is performed to get the final optimal pose vector for the frame I_q. The step-size and search range in the fine tuning is set to be smaller when the contrast weight for the query frame gets smaller, meaning that the supervision from the constructed motion-model becomes more important when the image content is deemed less reliable for registration purpose due to the faint contrast. With the reliable motion prediction from the motion-model and the constrained search space in the fine tuning step, both the accuracy and the efficiency can be significantly boosted.

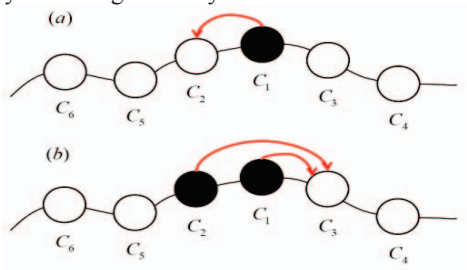


Fig. 4. (a) Registration of cycle C_2 utilizing the motion-model built from registered C_1, (b) Registration of cycle C_3 utilizing the motion-model built from registered C_1 and C_2.

3. EXPERIMENTAL RESULTS

The proposed 2-D+t/3-D registration method was tested on five clinical data from five patients, acquired during TAVI procedures on Siemens AXIOM Artis C-arm system. In the frame-by-frame method, all frames were treated independently by using the registered position for the frame I_p with a peak contrast as the starting position for registering all other frames, and a search range was limited to 1/3 of the image width and height around this initial position. This is for a fair comparison to minimize the accumulation of errors (drifting), which was often reported in tracking literatures when the tracking result for the current frame is used as the starting position for the next frame, and was also observed in our experiments that is not reported in this paper due to the space limit.

The accuracy was evaluated by comparing the registration result with the aortic root position manually localized by an expert. For the frames without a reliable contrast medium, the calcium at the bottom of the aortic root was used as the reference for the aortic root location. The 2-D re-projection target registration error (TRE) is the average 2-D Euclidean distance between the transformed position and the ground truth for the several landmarks, i.e. the hinge plane and the coronary ostia. Performance evaluation on the 2-D plane is appropriate for TAVI procedures, because the C-ARM angulation does not change after the optimal angle is selected, and the most important guidance is the coronary ostia and the hinge plane on the optimal projection. In addition, a registration is considered to be successful when the 2-D TRE is less than 3 pixels, which maps to less than 1 mm in 3-D for a typical C-ARM setting for TAVI procedures. Fig. 6 shows the TRE (y-axis) versus the frame number (x-axis) for one sequence. It can be seen that the proposed method had a consistently better accuracy on the frames with a reasonably good contrast, and still performed robustly and registered successfully for those frames with a faint contrast, for which the frame-by-frame method completely failed (off). Similar results were also obtained for the other four datasets, and the results are summarized in Table 1.

In addition, the total running time of the proposed framework was divided by the number of frames in the sequence to get the average running time for each data. As for the frame-by-frame method, the time for registering each frame was recorded and its mean and standard deviation was calculated. The speed was tested on a common Dell Precision M4500 computer without multi-core optimization. It can be seen that our proposed framework was more than 10 times faster than the frame-by-frame approach.

4. CONCLUSION

In this paper, we developed an automatic, fast, and accurate 2-D+t/3-D registration framework that fully takes advantages of the quasi-periodic property of the aortic motion and automatic detection of motion phase and contrast agent. Both the accuracy and efficiency are significantly improved compared to the frame-by-frame method. Our future work includes more comprehensive testing and clinical trial of the proposed method, as well as a more comprehensive strategy for motion-model utilization, e.g. by not only providing the predicted position and the searching range for the fine-tuning of 2-D/3-D registration, but also modifying the similarity measure with a generated confidence map for the potential motion space.

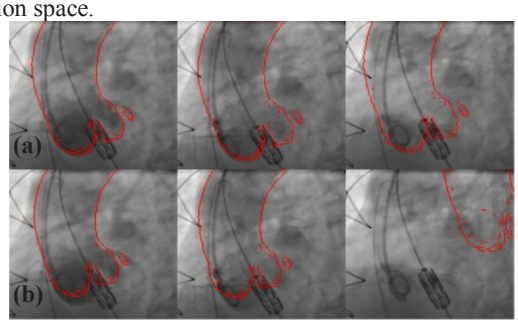


Fig.5. Comparison of registration examples using naïve frame-by-frame method and the proposed method. (a) The proposed method; (b) The frame-by-frame method, which can completely fail when the frame contains only very faint contrast.

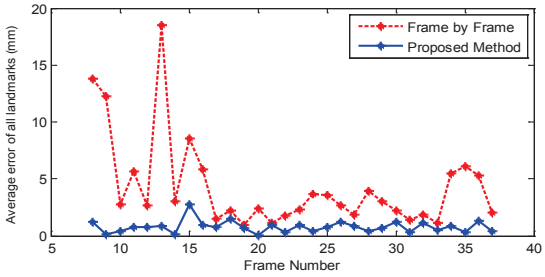


Fig. 6. Registration error across all the frames in one sequence.

Table 1. Comparison of the proposed 2-D+t/3-D registration framework and the frame-by-frame (*F-B-F*) approach.

Data set	*Accuracy (pixel)*		*Success Rate*		*Speed (second)*	
	Prop.	*F-B-F*	*Prop.*	*F-B-F*	*Prop.*	*F-B-F*
1	0.24±0.22	3.45±4.64	100%	78.57%	0.23	3.78±0.61
2	1.68±0.84	8.45±8.85	96.67%	46.88%	0.34	3.58±0.49
3	1.67±0.93	11.89±11.95	100%	50.00%	0.24	3.32±0.53
4	0.99±0.78	4.82±6.21	96.67%	66.67%	0.26	4.06±0.54
5	0.78±0.54	4.31±4.07	100%	53.33%	0.24	3.23±0.40

5. ACKNOWLEDGEMENTS

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