Motion tracking of left ventricle and coronaries in 4D CTA

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ABSTRACT

In this paper, we present a novel approach for simultaneous motion tracking of left ventricle and coronary arteries from cardiac Computed Tomography Angiography (CTA) images. We first use the multi-scale vesselness filter proposed by Frangi *et al.*[1] to enhance vessels in the cardiac CTA images. The vessel centrelines are then extracted as the minimal cost path from the enhanced images. The centrelines at end-diastolic (ED) are used as prior input for the motion tracking. All other centrelines are used to evaluate the accuracy of the motion tracking. To segment the left ventricle automatically, we perform three levels of registration using a cardiac atlas obtained from MR images. The cardiac motion is derived from cardiac CTA sequences by using local-phase based non-rigid registration. The CTA image at each time frame is registered to the ED frame by maximising the proposed similarity function and following a serial propagation scheme. Once the images have been aligned, a dynamic motion model of the left ventricle can be obtained by applying the computed free-form deformations to the segmented left ventricle at ED phase. A similar propagation method also applies to the coronary arteries. To validate the accuracy of the motion model we compare the actual position of the coronaries and left ventricle in each time frame with the predicted ones as estimated from the proposed tracking method.

Keywords: Image-Guided Therapy, Motion Analysis, Registration, Segmentation, Cardiac Imaging

1. INTRODUCTION

1.1 Purpose

As one of the leading causes of death worldwide, coronary artery disease occurs due to the failure of the blood circulation to supply adequate oxygen and nutrition to cardiac tissues. It is typically caused by the excessive accumulation of atheromatous plaques and fatty deposits within certain regions of the arteries which restrict the blood flow. As one way of treating this disease, arteries or veins grafted from the patient's body are used to bypass the blockages and restore the supply to the heart muscle.

Conventional bypass surgery requires invasive sternotomy and the use of a cardiopulmonary bypass machine, which leads to long recovery period for the patient and has high infectious potential. Using an image-guided robotic surgical system, totally endoscopic coronary artery bypass (TECAB) surgery techniques have been developed to allow clinicians to perform bypass surgery off-pump with three pin-hole incisions in the chest cavity, through which two robotic arms and one stereo endoscopic camera are inserted. However, 20-30% conversion rates from TECAB surgery to conventional invasive surgical approach[2,3] have been reported due to the vessel misidentification and mis-localization caused by the restricted field of view of the stereo endoscopic images.

To reduce this conversion rate and facilitate the TECAB procedure, we aim to construct a patient-specific 4D left ventricle and coronary artery motion model from preoperative cardiac CTA sequence. The main challenge of this work is first to obtain automatic segmentation of both structures and follow the deformation of them accurately. In this paper, we propose an atlas-based segmentation method and registration-based motion tracking framework to achieve this. Finally, through temporally and spatially aligning the coronary motion model with the intraoperative endoscopic views of the patient's beating heart, this work has the potential to assist the surgeon to identify and locate the correct coronaries during the robotically-controlled TECAB procedures.

1.2 Related Work

The extraction of blood vessel has been studied extensively in the past two decades. A very recent and comprehensive review about vessel extraction can be found in Lesage *et al.*[4] For cardiac segmentation, two publications by Peters *et al.*[5] and Zhuang *et al.*[6] are closely related to our work. As for cardiac motion tracking, non-rigid registration based on a free-form deformation (FFD) model has shown promising results.[7,8]

2. METHODS

A 4D motion model of the beating heart with coronary arteries is needed for guiding the TECAB procedure. Prior to motion modelling to assist the TECAB surgery, it is essential to segment the left ventricle (LV) and coronary arteries accurately. To achieve this, we first segment the left ventricle and extract the vessel centerlines from the ED time frame of the CTA image sequence. Secondly, we align the sequence of cardiac CTA images to the ED time frame by using our proposed registration method. Finally, we apply the derived deformation to the segmented ventricle and extracted coronaries. The resulting patient-specific motion model can then be used to augment the intraoperative view from endoscope cameras by 2D3D alignment.

2.1 Coronary Artery Extraction

The CTA images are first processed with multiscale Hessian-based vessel enhancement filter.[1] The filter utilizes 2nd order derivatives of the image at multiple scales to identify bright tubular-like structures. The maximum response map over a set of scales is collected to provide a coarse segmentation of the coronary arteries. The vesselness of each voxel is computed from the analysis of the Hessian matrix of second derivatives in the local area after convolving with Gaussian kernel at pre-selected scale value. The centrelines of coronary arteries are then extracted as minimal cost path connecting the start and end nodes as in section 2.2 in Zhang *et al.*[9]

2.2 Left Ventricle Segmentation

The segmentation of the left ventricle (myocardium) from CTA images is achieved using an atlas propagation scheme.[6] The atlas used here is constructed from MR images for the whole heart segmentation in.[11] A number of MR images acquired using the same MRI sequence from various subjects are used to construct this atlas. All MR images are registered to a selected reference image. An atlas intensity image is then computed as the mean intensity image from this group of registered MR images, shown in Figure 1 (a). A labelled atlas image, as shown in Figure 1 (b), is also created by manually labelling each anatomical structure of the reference image, including the blood pool of each chamber, great vessels and left ventricle myocardium. By using the normalized mutual information (NMI) as the similarity measure, the MR atlas can be used to segment CTA images as well as it was argued in Zhuang *et al.*[6]

Figure 1. the MR intensity image of the atlas; label image of the atlas.

The registration framework for whole heart segmentation from CTA image is illustrated in Figure 2. The gradient ascent method and the multiresolution scheme as in[10] are used to optimise the similarity metric. Given the 3D cardiac atlas, the main challenges of the segmentation for any new patient scan are the initialisation of the substructures and imposition of shape constraints. This segmentation scheme is based on a registration framework consisting of three steps:[11]

1. A global affine registration for localization;
2. A locally affine registration method (LARM) for substructure initialization;
3. A nonrigid free-form deformation (FFD) registration for refining the segmentation results from previous stage.

This registration scheme has been shown to be robust against the large variability of the heart shape,[6] and it is particularly useful for our application as our CTA data mainly come from pathological cases.

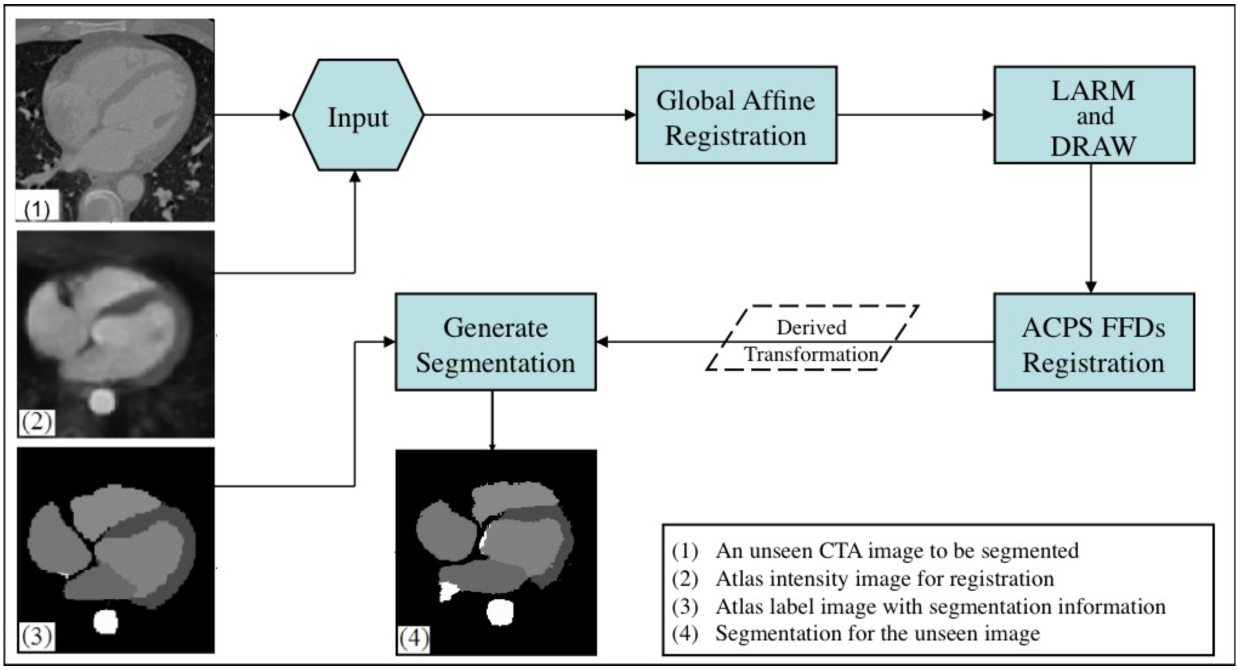


Figure 2. The framework of automatic whole heart segmentation based on atlas propagation (adapted from[11]).

2.3 Cardiac Motion Extraction by Image Registration

NMI registration has been widely used for nonrigid registration. To align two images using NMI, the structures of interest should be initialized close enough to guarantee a majority overlap. However, this is practically difficult for the registration of coronary artery because of its thin and elongated shape, as shown in Figure 3(c) shows. Furthermore, the thin structure of vessels has little impact on the NMI similarity measure when the similarity is computed for registering the whole heart. As a result, the NMI similarity measure may not capture the motion of vessels sufficiently.

To tackle this problem, in this work we propose to use local phase[12,13] to capture the deformation and register the thin structure of coronary arteries. The local phase ϕ is derived using the monogenic signal:[13]

$$\phi(\mathtt{x}) = \mathrm{atan2}\Big(\sqrt{\sum_{i=1}^{3}(g(\mathtt{x}) * h_i(\mathtt{x}) * I(\mathtt{x}))^2},\ g(\mathtt{x}) * I(\mathtt{x})\Big), \tag{1}$$

where g is a zero mean bandpass filter such as the log-Gabor filter,[13] convolved with I to constitute the even component of the signal; $\{h_i\}$ are the odd anti-symmetric filters in the spatial domain, $i = 1, 2, 3$, whose expression in frequency domain H_i is:

$$H_i(u_1, u_2, u_3) = \frac{u_i}{\sqrt{u_1^2 + u_2^2 + u_3^2}}. \tag{2}$$

The local orientation of the signal can be estimated as:

$$O_d(\mathtt{x}) = \frac{g(\mathtt{x}) * h_d(\mathtt{x}) * I(\mathtt{x})}{\sqrt{\sum_{d=1}^{3}(g(\mathtt{x}) * h_d(\mathtt{x}) * I(\mathtt{x}))^2}} \tag{3}$$

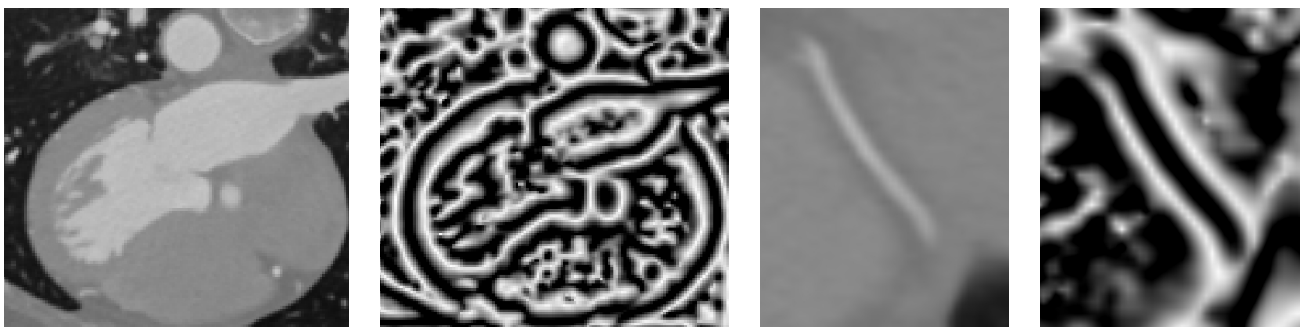
Local phase provides a quantitative and continuous description of local features, such as the thin structure of vessels in CTA images. Figure 3 shows the CTA images and their corresponding phase images.

For the registration of other substructure of interests such as ventricles, we need the intensity information for computing the similarity measure. Therefore, we combine both the intensity and local phase for the computation of the similarity function, as follows:

$$\mathcal{C}(I_t, I_s, T) = w_c\mathcal{S}(I_t, I_s, T) + w_f\mathcal{S}(\phi_t, \phi_s, T) - w_p\mathcal{P}(T) \ , \tag{4}$$

where I_t and I_s denote the target and source image respectively, T is the free-form deformation; $\mathcal{S}$ is similarity metric such as NMI or normalized cross correlation (NCC) for the image intensity and local phase, $\mathcal{P}(T)$ is the bending energy of T for smoothness regularisation as in Rueckert *et al.*;[14] parameters w_c, w_f and w_p are weightings for the three terms respectively.

To register different frames of a CTA dataset to a selected reference frame, we use the *serial propagation* registration to model the large deformation field required for the registration between two frames that are far apart from each other, such as between the ED and ES frames. In the serial propagation, we first register the two neighboring frames to the reference frame. The resulting transformation is used to initialize the registration of next pair. It continues until all images are aligned with the reference, as shown in Fig.1 of Zhang *et al.*[9]



(a) (b) (c) (d)

Figure 3. The CT image (a) and its local phase image (b), the coronary artery (c) and its local phase (d).

3. RESULTS AND EVALUATIONS

Figure 4 and Figure 5 shows the automatically segmented cardiac structures, including left ventricle using the proposed method in Section 2.2 from four patients' CTA scans. By visual inspection, these results are promising. However, quantitative assessment should be performed for clinical evaluation in future.

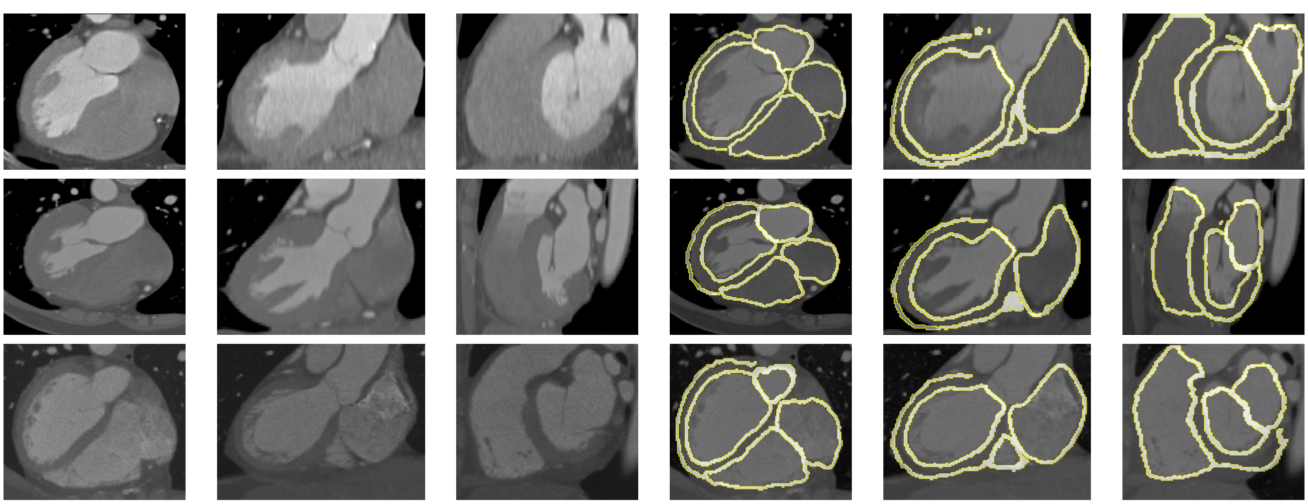


Figure 4. Examples of CTA image segmentation. For each row, (1st, 2nd and 3rd columns): CTA example images in three views; (4th, 5th and 6th columns): the CTA images overlaid with segmentation surfaces shown in light-grey with yellow contour.

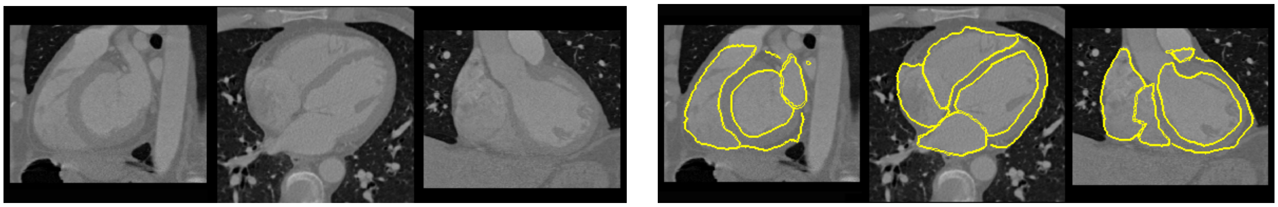
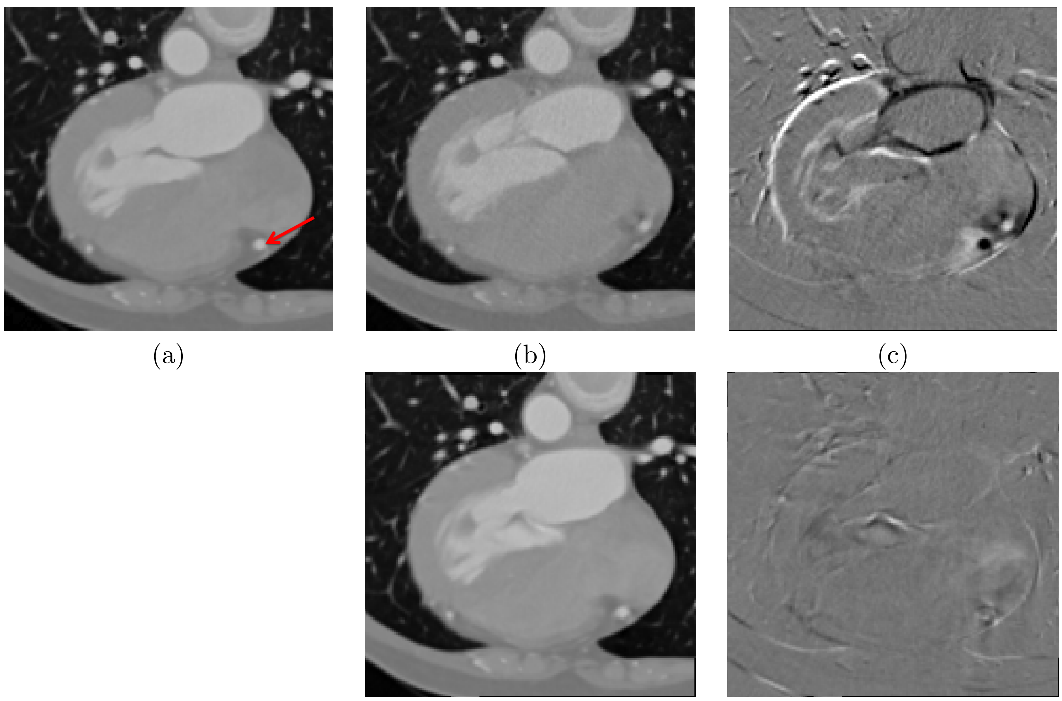


Figure 5. a CTA example image; CTA image with segmentation surface.

The cardiac motion extracted by the method in Section 2.3 is used to predict the motion of left ventricles and coronaries here. The coronaries and left ventricles extracted from ED phase are deformed according to the obtained deformation information to all other phases to form the coronary and left ventricle motion models. Figure 6 shows an example of registration results, both the left ventricle and coronary artery (pointed by red arrow) are aligned after using proposed registration scheme.



(a) (b) (c) (d) (e)

Figure 6. Registration results using local phase based method. (a): Reference image; (b): Source image; (c): Subtraction of (a) and (b) before registration. (d): Deformed image of (b) after registration; (e): Subtraction of (a) and (d). Note the red arrow points to a coronary artery cross-section in reference image (a).

For future quantitative evaluation, we propose to assess the motion tracking accuracy for the left ventricle and coronary arteries separately. For the left ventricle, we compute the distance between the manually annotated surface and the surface computed from our proposed motion tracking as in Zhuang *et al.*[6] To assess the quality of coronary motion model, coronary centerlines are extracted semi-automatically from all time frames of the CTA sequence. We propose to compare the predicted location of the centrelines obtained by applying the non-rigid deformation with the extractions of the centrelines.

4. CONCLUSIONS

We present an approach for simultaneous patient-specific left ventricle and coronary tree motion tracking from CTA sequences to assist the totally endoscopic coronary artery bypass surgery. The proposed method has been tested on the clinical CT datasets acquired from four subjects where good results have been observed. Further tests and quantitative analysis are to be performed in the near future.

By aligning the 4D coronary and left ventricle model with the series of 2D endoscopic images captured during the operation, this work has the potential to assist the planning and conducting of TECAB surgery, and also reduce the conversion rate from TECAB to more invasive conventional procedures.

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