

Motion-compensated Image Reconstruction for Cardiac CT with Sinogram-Based Motion Estimation

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Abstract—Motion-compensated image reconstruction (MCIR) has been widely studied to reduce artifacts induced by cardiac motion. In this paper, we propose a new approach to estimating the motion of the coronary arteries. We use a simple linear model for the motion of each coronary artery during an axial scan and we estimate the model parameters in the sinogram domain. The purpose of the method is not to estimate the motion of the coronary arteries precisely, but rather to provide good initial estimates for subsequent joint image reconstruction and motion estimation. The idea was evaluated with a cardiac CT simulation. Simulation results illustrate that our proposed method can provide reasonably good motion estimates that may be useful for initializing the joint estimation of both motion parameters and reconstructed images.

I. INTRODUCTION

MOTION of a patient induces artifacts such as streaks and blurring in the reconstructed CT images, and thus inhibits accurate diagnosis. Even with the fast gantry rotation speed of the state-of-the-art scanners, obtaining a motion-free image is challenging, especially for cardiac CT imaging due to rapid heart motion. Different types of methods were proposed to mitigate the issue [1]–[3]. One potentially promising category of these methods is motion-compensated image reconstruction, which utilizes known or estimated motion information when reconstructing the image. Compared to gated reconstructions that suffer from limited temporal resolution and dose inefficiency, motion-compensated methods can provide better dose efficiency and image quality if accurate motion estimates are provided.

Since the accuracy of the estimated motion significantly affects the reconstructed images, obtaining precise motion estimates is very important. However, estimating the motion of the entire heart or even just the coronary arteries is a very challenging problem. Many approaches have been proposed to address the problem [4]–[6]. However, most of these methods require extra measurements in addition to the short scan, which has angular span of $\pi + 2\gamma$ where γ is the fan angle of the projection, or depend on the initial gated reconstructions. Joint estimation of both the motion parameters and the reconstructed image may compensate for inaccurate initial motion estimates, but having decent initial estimates is still very desirable.

This work is supported in part by GE Healthcare and CPU donations from Intel Corporation.

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We propose a new approach to estimate the motion of the coronary arteries by using only the short scan measurements. The proposed method tracks the motion of the coronary arteries in the sinogram domain, and provides reasonable estimates of their motion. The acquired motion information can be used to obtain reconstructed images with reduced artifacts. However, the main purpose of this method is not perfectly estimating the motion of the coronary arteries, but rather providing good initial estimates for subsequent joint estimation of both the motion parameters and the image. The method was investigated with a simulation of cardiac CT with the XCAT phantom.

II. MOTION-COMPENSATED IMAGE RECONSTRUCTION FOR CT

A. Measurement Model

The unknown object is denoted as $x(\mathbf{r}, t)$ where t is time and \mathbf{r} is the spatial location. The measurements \mathbf{y}_m corresponding to the motion-free state of the object at m th frame are assumed to be linearly related to the object $\mathbf{x}_m = x(\cdot, t_m)$ as follows:

$$\mathbf{y}_m = \mathbf{A}_m \mathbf{x}_m + \epsilon_m, \quad m = 1, \dots, N_f, \quad (1)$$

where t_m denotes the time of m th frame, \mathbf{A}_m is the system model for m th frame, ϵ_m is the noise and N_f is the assumed number of frames. Here we assume $\mathbf{x}_m = \mathbf{T}_m(\underline{\alpha}_m) \mathbf{x}$ where $\mathbf{T}_m(\underline{\alpha}_m)$ is a warp matrix based on estimated motion parameters $\underline{\alpha}_m$. The goal is to obtain $\underline{\alpha}_m$ that reduces motion artifacts when reconstructing \mathbf{x} from $\{\mathbf{y}_m\}$.

B. Problem Formulation

Consider the following penalized weighted least squares (PWLS) formulation of motion-compensated CT image reconstruction:

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \{\Psi(\mathbf{x}) \triangleq \mathbf{L}(\mathbf{x}) + \mathbf{R}(\mathbf{C}\mathbf{x})\}, \quad (2)$$

$$\mathbf{L}(\mathbf{x}) = \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{T}(\underline{\alpha})\mathbf{x}\|_{\mathbf{W}}^2, \quad \mathbf{R}(\mathbf{C}\mathbf{x}) = \beta \sum_{k=1}^K \kappa_k \psi_k([\mathbf{C}\mathbf{x}]_k),$$

$$\mathbf{A} = \text{diag}\{\mathbf{A}_1, \dots, \mathbf{A}_{N_f}\}, \quad \mathbf{T} = [\mathbf{T}_1(\underline{\alpha}_1)' \dots \mathbf{T}_{N_f}(\underline{\alpha}_{N_f})']',$$

where $\mathbf{x} \in \mathbb{R}^N$ is the discretized version of the object being reconstructed, \mathbf{A} is the forward projector, $\mathbf{T}(\underline{\alpha})$ is the warp matrix, $\underline{\alpha}$ is the motion parameters, $\mathbf{W} = \text{diag}\{w_i\}$ is a statistical weighting matrix, β is the regularization parameter,

κ_k is the user-defined weight for controlling spatial resolution in the reconstructed image, ψ_k is the potential function, C is a matrix that performs finite differences between neighboring voxels, and K is the number of neighbors.

Joint estimation of motion parameters and image reconstruction can be formulated as follows:

$$(\hat{x}, \hat{\alpha}) = \arg \min_{x, \alpha} \{\Psi(x, \alpha) \triangleq \mathbf{L}(x, \alpha) + R(Cx) + R_{inv}(\alpha)\}, \quad (3)$$

$$R_{inv}(\alpha) = \sum_{m=1}^{N_f} \beta_{inv,m} R_{\alpha}(\alpha_m), \quad (4)$$

where R_{inv} enforces invertibility to the motion parameters, R_{α} is the piecewise quadratic regularizer for the motion parameters of each frame, and $\beta_{inv,m}$ is the regularization parameter for m th frame [7].

To minimize (3) one can use a variety of iterative algorithms including alternating minimization [8] and ADMM methods [9]. All such iterative algorithms require initial values for the parameters α and the next section describes a proposed method for computing initial motion estimates.

III. PROPOSED METHOD

The basic idea is to track the motion of each coronary artery using its trajectory in the sinogram. Given a stationary point in the image domain, we know its exact path in the sinogram domain. In turn, from the path of a point in the sinogram, we can estimate its location during the scan. This information is then used to obtain the warp between frames.

We use 3rd generation CT geometry for the derivation of the method, and only consider the 2D fan beam case for simplicity. However, the proposed method can be applied to any other scanner geometry with proper modifications. We also assume that the displacement of the coronary artery is small, and can be modeled as a linear function of the view angle. In other words, we assume that the midpoint of the artery moves at a constant velocity during the short scan. Finally, we need approximate locations of the center of each coronary artery. Coronary artery centerline extraction methods or manual inputs can be used to obtain this information, which we only use to determine the approximate region-of-interest (ROI) around each coronary artery.

A. Coronary artery motion estimation

To extract the trajectory of each coronary artery from the measurements, it is helpful to remove the projections corresponding to the objects outside the ROI. By reconstructing only the ROI and subtracting it from the fully reconstructed image, we can obtain the objects outside the ROI. We use filtered back-projection (FBP) method to reconstruct these initial images. For coronary arteries near the boundary of the heart, we fill the very low intensity regions such as air with approximate myocardium CT value before the subtraction. This procedure helps the tracking process to be more accurate. Subtracting the re-projection of this non-ROI image from the original measurements will approximately give the projections of only the ROI region (See Fig. 1).

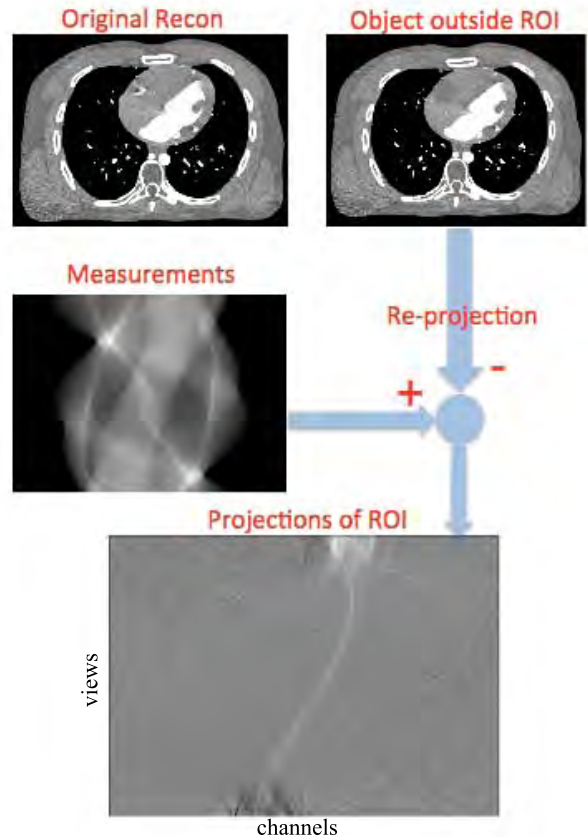


Fig. 1. Flow chart for obtaining the projections for the ROI around right coronary artery. (RCA)

Given the projections of only the ROI region, we identify the trajectory of the target coronary artery using the following procedure:

- Apply filters to enhance ROI projections. Filters such as bilateral, low-pass or matched filter can be used to remove noise and help identifying the trajectory. We used a Hanning filter.
- Track the maximum value at each view angle.

With above procedures, we have the trajectory of the center of a coronary artery in the sinogram domain, $s_{\theta}(x, y)$ where θ is the view angle (See Fig. 2). From the geometry of the scanner, we have the following relationship:

$$s_{\theta}(x, y) = Dsd \arctan\left(\frac{x_{\theta}}{Dso - y_{\theta}}\right) + \epsilon, \quad (5)$$

$$x_{\theta} = x \cos \theta + y \sin \theta, \quad (6)$$

$$y_{\theta} = -x \sin \theta + y \cos \theta, \quad (7)$$

where (x, y) is the true location of the center of a coronary artery, Dsd is the distance from the source to the detector, Dso is the distance from the source to the iso-center, and ϵ is the noise in the measurement. We obtain the following

approximation from (5):

$$\begin{aligned} z_\theta &\triangleq \tan\left(\frac{s_\theta}{Dsd}\right) \approx \frac{x_\theta}{Dso - y_\theta}, \\ (Dso - y_\theta) z_\theta &\approx x_\theta, \\ Dsoz_\theta &\approx x_\theta + z_\theta y_\theta. \end{aligned}$$

Let $x = x_0 + tdx$ and $y = y_0 + tdy$ where $t \in [0, 1]$, x_0 and y_0 are the initial locations of the coronary artery, and dx and dy are the displacement to the final locations:

$$\begin{aligned} Dsoz_\theta &\approx (x_0 + tdx) \cos \theta + (y_0 + tdy) \sin \theta \\ &+ z_\theta \{-(x_0 + tdx) \sin \theta + (y_0 + tdy) \cos \theta\}. \end{aligned}$$

We estimate the 4 parameters of each artery's motion (center and displacement) by minimizing the following cost function:

$$\arg \min_{\mathbf{u}} \|\mathbf{z} - \mathbf{B}\mathbf{u}\|_1,$$

where

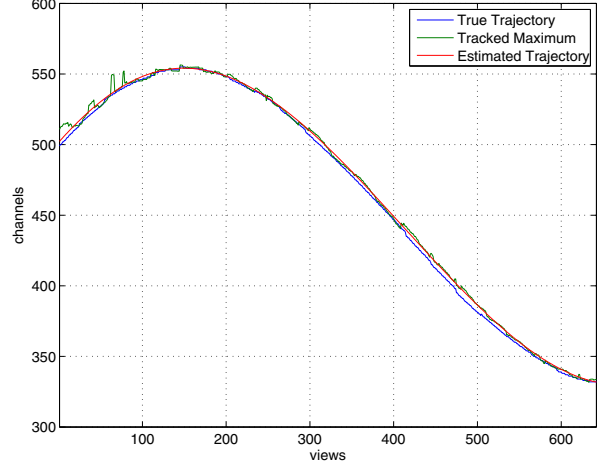
$$\begin{aligned} \mathbf{z} &= [\dots Dsoz_\theta \dots]', \\ \mathbf{B} &= \begin{bmatrix} \cos \theta - z_\theta \sin \theta & & & \\ \dots & \sin \theta + z_\theta \cos \theta & \dots & \\ t \cos \theta - tz_\theta \sin \theta & & & \\ t \sin \theta + tz_\theta \cos \theta & & & \end{bmatrix}', \\ \mathbf{u} &= [x_0 \quad y_0 \quad dx \quad dy]'. \end{aligned}$$

By estimating \mathbf{u} , we determine the initial location of the coronary artery and its displacement during the scan. Since z_θ can be noisy, we use L1 regression instead of least squares fitting. Fig. 2 shows the estimated trajectory of the center of the right coronary artery, which agrees well with the true trajectory.

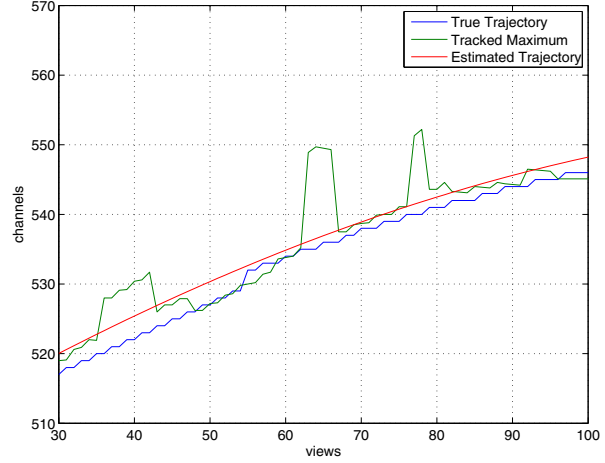
The above procedure estimates the motion for each coronary artery only, whereas MCIR needs motion estimates over the entire heart. To extend the initial motion estimates to cover the entire heart, we need a method to properly extrapolate these coronary artery motions. This is a challenging problem and remains as our future work. In this study, we focus only on local deformation around each coronary artery for our MCIR, and introduce an approach to obtain the entire heart motion in the results section. We can define the warp between the frames by using the deformation model with thin plate splines (TPS) or B-splines. We used cubic B-splines to model the warp.

IV. RESULTS

The proposed algorithm was demonstrated on a 2D CT image reconstruction problem with the XCAT phantom [10], which provides realistic cardiac motion. We assumed homogeneous and complete enhancement of coronary arteries and left ventricle, which can be achieved with proper contrast medium protocol. Saline chasing, which is a protocol that injects bolus of saline immediately after the iodinated contrast medium bolus, was assumed to achieve such arterial enhancements [11]. Simulated heart rate was 75 bpm, and the case of imperfect cardiac gating was assumed. A short scan of a 3rd-generation fan-beam CT system was simulated, and the system has 888 channels per view spaced 1.0239 mm apart, and 642



(a)



(b)

Fig. 2. Estimated trajectory of the center of the right coronary artery in the sinogram domain. (a) For entire view range [1 642] (b) for partial view range [30 100].

evenly spaced view angles. Reconstructed images use pixels $(0.9766\text{mm})^2$ in size with 512^2 voxels.

We focussed on estimating the motion of two coronary arteries with large displacements including the right coronary artery (see Fig. 3 (a) for their locations). We selected manually the approximate location of each coronary artery, and a circular region with 15 voxel radius centered at the location was selected as ROI. We assumed seven frames, $N_f = 7$, and the warp between each frame and the reference frame was obtained using nonrigid image registration and the estimated motion of each coronary artery.

For the regularizer of the image in (3), we used the Fair potential function to provide edge-preservation and a certainty-based penalty to obtain more uniform resolution. Poisson noise was added to the measurement, and the weights in the data-fit term in (2) were chosen as $w_i = \exp(-[\mathbf{A}\mathbf{x}]_i)$. The regularization parameter β was selected (without considering the warps) such that the target PSF has a full-width at half-maximum (FWHM) of approximately 1.3 mm.

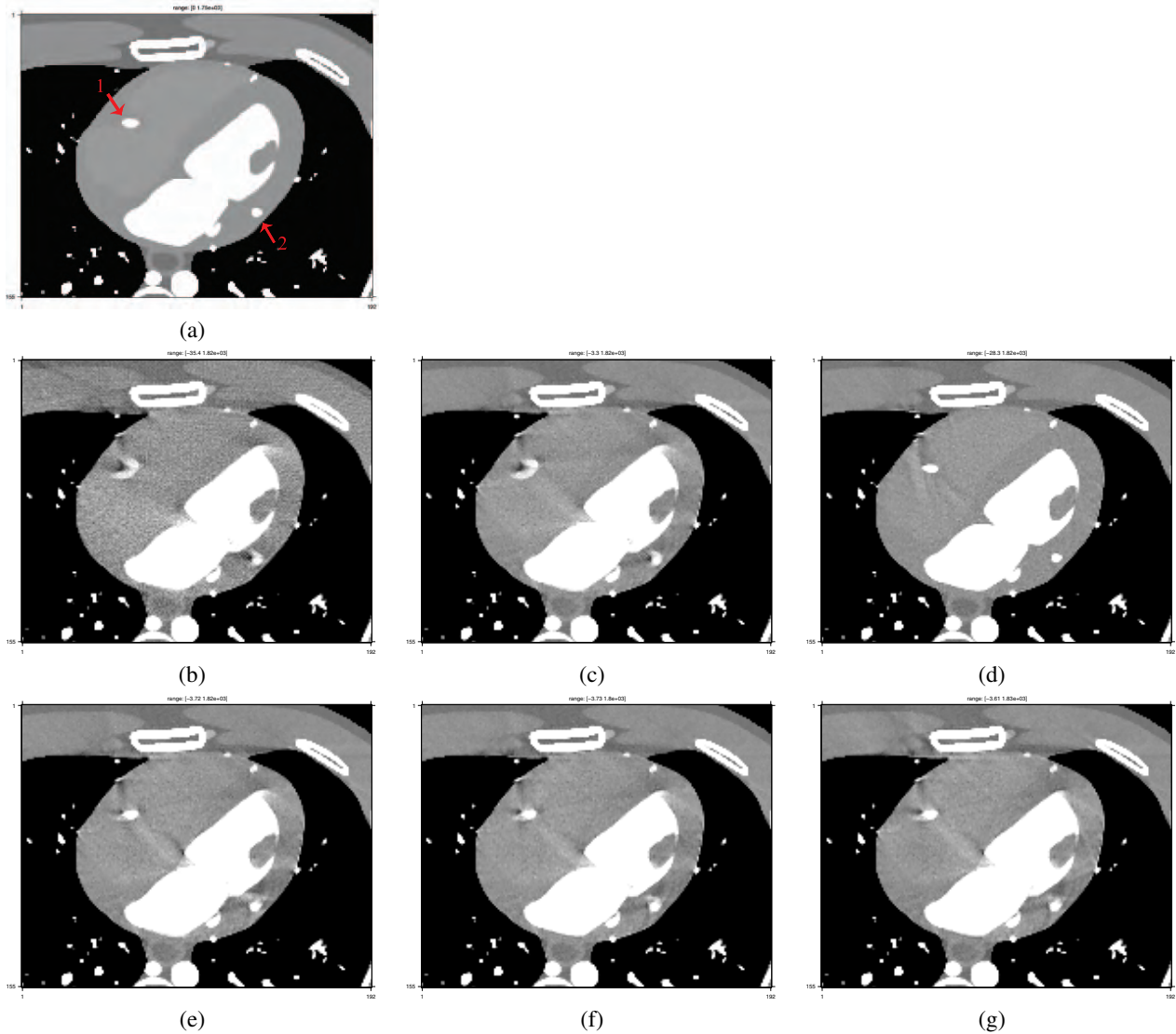


Fig. 3. Images in the ROI of (a) XCAT phantom; (b) FBP reconstruction; (c) Iterative reconstruction without motion compensation using conjugate gradient (CG); (d) MCIR with the motion estimated directly from the XCAT phantom; (e) MCIR with the motion estimates obtained by the proposed method; (f) MCIR with the motion estimates between (e) and adjacent short scans; (g) Joint estimation results with the motion estimates of (f) as a initial starting point.

Fig. 3 shows the reconstructed images with various methods. Using FBP or iterative reconstruction without any motion compensation leads to reconstructed images corrupted with motion artifacts. When accurate motion information is available, MCIR methods can reconstruct images almost without motion artifacts, as shown in Fig. 3 (d) where motion estimates were obtained by using nonrigid image registration directly to the phantom. However, there still exist some residual motion artifacts due to imperfect image registration, which suggests the difficulty of obtaining perfect motion estimates.

With motion estimated using our proposed method, the motion-compensated image reconstruction [Fig. 3 (e)] greatly reduces the motion artifacts, especially around the right coronary artery, compared to the conventional reconstruction methods without any compensation. The shape of each coronary artery became more realistic and close to the truth. However,

the reconstructed image still has residual motion artifacts due to suboptimal motion estimation. Using joint estimation may help reducing these residual artifacts, but most of these improvements will be limited to coronary artery regions. The limitation of the proposed method is that it provides local motion estimations only near coronary arteries. Even though these estimates can significantly reduce the motion artifacts around coronary arteries, which are the main focus of cardiac CT imaging, the reconstructed images still suffer from motion artifacts of other parts of the heart such as left ventricle. In addition to our coronary artery motion estimates, we want to obtain decent motion estimates for the entire heart for our joint estimation scheme.

Here, we introduce one approach. In standard cardiac CT scanning protocol, some additional measurements are collected in addition to the short scan. We use these additional

measurements to obtain multiple short scan reconstructions with slightly different motion status. This can be done by considering the entire scan as several overlapping short scan measurements and reconstructing each of them separately. Since each short scan reconstructions are corrupted by severe motion artifacts, estimating motion between these images is not informative. Instead, we estimate motion between our motion-compensated image [Fig. 3 (e)] to these adjacent short scan reconstructions. Still, due to motion artifacts in these short scan reconstructions, the estimated motion may not be very useful, but it may be used as a better initial condition for our joint estimation compared to having no initial information at all.

Fig. 3 (f) shows a result of motion-compensated reconstruction using motion estimates between coronary-artery-corrected image and adjacent short scans. Some of the motion artifacts were reduced compared to Fig. 3 (e). Finally, Fig. 3 (g) shows the reconstructed image with joint estimation of both motion parameters and image, which has further reduced motion artifacts, especially around the left ventricle. Joint estimation involves many parameters and they were not optimized in this study. Further investigation on these parameters is required and is likely to provide better results.

	Oracle	FBP	Iterative w/o correction	MCIR (coronary only)	MCIR (entire heart)	Joint MCIR
1	20.5	60.9	56.5	29.8	30.4	29.1
2	21.9	98.6	102.4	106.5	106.8	101.7
ROI	14.9	41.7	34.8	33.9	33.5	32.9

TABLE I
RMSE (IN HU) OF DIFFERENT METHODS WITH RESPECT TO THE TRUTH (FIG. 3 (A)). SEE FIG. 3 (A) FOR THE INDEX OF EACH CORONARY ARTERY. ROI WAS DEFINED TO CONTAIN THE ENTIRE HEART.

To quantitatively verify the improvements, we computed the root-mean-squared error (RMSE) around each coronary artery and overall ROI with respect to the XCAT phantom (See Table I). The results confirm that our proposed methods effectively reduce severe artifacts around right coronary artery. However, our methods did not work well for the other coronary artery. This is mainly because this coronary artery is located very close to left ventricle. Movement during the scan and high contrast of left ventricle prohibits accurate estimation of the trajectory for this coronary artery. Also, our simple motion model can be another reason for unsatisfying performance. We'll work further to solve these issues.

V. DISCUSSION

We presented a new coronary artery motion estimation method for the motion-compensated image reconstruction problem. The proposed method greatly reduced the motion artifacts without requiring any other information or excessive scan padding. The estimated motion is limited to the coronary artery, and the estimated motion still suffers from residual motion artifacts because of the suboptimal motion. However, as mentioned in the introduction, the purpose of this method is to provide a good starting point for the following joint

estimation step, which showed promise. Also, joint estimation will be more closely investigated to obtain better results.

Filtering and trajectory estimation in the coronary artery motion estimation procedure may be further refined with more sophisticated methods. Sinogram segmentation or morphological top-hat filtering can be used to remove unnecessary structures to help isolate the coronary artery [12].

Finally, the proposed method was applied to a 2D case with a digital phantom. Our future work will focus on extending the method to 3-D CT and applying to real patient data.

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