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Nonrigid Motion Correction with 3D Image-based Navigators for Coronary MR Angiography

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Abstract

Purpose—To develop a retrospective nonrigid motion-correction method based on 3D image-based navigators (iNAVs) for free-breathing whole-heart coronary magnetic resonance angiography (MRA).

Methods—The proposed method detects global rigid-body motion and localized nonrigid motion from 3D iNAVs and compensates them with an autofocusing algorithm. To model the global motion, 3D rotation and translation are estimated from the 3D iNAVs. Two sets of localized nonrigid motions are obtained from deformation fields between 3D iNAVs and reconstructed binned images, respectively. A bank of motion-corrected images is generated and the final image is assembled pixel-by-pixel by selecting the best focused pixel from this bank. In vivo studies with six healthy volunteers were conducted to compare the performance of the proposed method with 3D translational motion correction and no correction.

Results—In vivo studies showed that compared to no correction, 3D translational motion correction and the proposed method increased the vessel sharpness by $13\% \pm 13\%$ and $19\% \pm 16\%$, respectively. Out of 90 vessel segments, 75 segments showed improvement with the proposed method compared to 3D translational correction.

Conclusion—We have developed a nonrigid motion-correction method based on 3D iNAVs and an autofocusing algorithm that improves the vessel sharpness of free-breathing whole-heart coronary MRA.

Keywords

coronary MRA; motion correction; nonrigid; navigators; autofocusing

Introduction

Motion is one of the most significant challenges in free-breathing three-dimensional (3D) coronary magnetic resonance angiography (MRA) (1). To achieve high spatial resolution and

whole-heart coverage, a coronary MRA scan typically spans many respiratory and cardiac cycles, resulting in artifacts such as blurring and ghosting. Several approaches have been proposed to address motion in coronary MRA. Respiratory gating limits data acquisition to an end-expiratory window, but significantly prolongs the scan time, which may lead to patient discomfort and respiratory pattern drifts (2, 3). Prospective methods assume rigid-body motion (4) or affine motion (5), and adaptively adjust the imaging location and gradients according to the real-time measured motion. While these methods demonstrate flexibility in selecting the motion-tracking region and real-time correction, they are limited to affine motion.

Various retrospective methods have also been developed. Motion information can be tracked simultaneously or interleaved with the actual data acquisition, and compensated with translational or affine correction. To track the motion simultaneously with the data acquisition, the repeatedly acquired data in the center of k-space are utilized to reconstruct projections of the heart or low-resolution images (6–9). In the other approach, 1D images of pencil beams over the diaphragm (10) or whole-heart projections (11), 2D images of a thin slice over the heart (12, 13) or 3D low-resolution whole-heart volume images (14–16), or images of the fat (17–19) are acquired interleaved with the actual data acquisition. Motion estimation can be obtained through beat-by-beat image registration, or image registration between bins classified by respiratory phases (20–23). A two-step motion correction approach that is based on beat-to-beat translational correction and bin-to-bin motion correction extracted from 2D image navigator has also been developed (24). These methods have demonstrated promising results, but they are based on global motion estimation and do not fully consider localized motion.

Another approach is model-based motion correction which formulates the motion correction as a matrix inverse problem and incorporates arbitrary motion (25–28). Motion-weighted and iterative reconstruction are also emerging methods that use the motion information as weighted coefficients in an optimization formulation of the image reconstruction (29, 30). Autofocusing methods are another type of nonrigid motion correction (31–35), which reconstruct a bank of motion-compensated images from a set of motion trajectory estimates and use a focusing metric to assemble the final image from this bank of images. The quality of the final image depends on the accuracy of the motion estimates and the focusing metric.

In this work, we proposed a motion-correction method that extracts both global and localized motion trajectories from 3D image-based navigators (iNAVs) with 4.4 mm isotropic spatial resolution and 176 ms temporal resolution, and compensates them with an autofocusing algorithm. We apply this motion-correction method to free-breathing coronary MRA and assess the performance with volunteer studies. Vessel sharpness is compared between no motion correction, 3D translational motion correction and the proposed method.

Methods

Motion Tracking with 3D iNAVs

Motion information is tracked with 3D iNAVs acquired every heartbeat. Figure 1(a) shows the free-breathing whole-heart coronary MRA acquisition scheme (13,36). To reduce cardiac

motion, the acquisition is cardiac gated and the full set of 3D cones k-space data is segmented over multiple heartbeats and acquired in sequential order. In each heartbeat (R-R interval), a fat suppression module is applied for additional fat suppression, followed by an alternating repetition time balanced steady-state free precession (ATR-SSFP) readout sequence, which provides high blood-muscle contrast while suppressing fat, is used for the 3D cones acquisition (37). Following the 3D cones image acquisition, a 3D iNAV is acquired with 32 cones readouts during the same ATR-SSFP train, in which only one catalyzation module is required for the main acquisition and the 3D iNAV acquisition. The duration of the 3D iNAV acquisition is significantly reduced to 176 ms by a variable-density 3D cones trajectory design (36,38) and iterative reconstruction with L1-ESPIRiT (39). The 3D iNAVs have $28 \times 28 \times 14 \text{ cm}^3$ FOV and isotropic 4.4 mm resolution. As shown in Fig. 1(b), 3D iNAVs cover the whole imaging volume and allow nonrigid localized motion to be tracked throughout the scan.

Motion Correction

To investigate and utilize the motion information in the 3D iNAVs, we propose a motion-correction method that estimates both global rigid-body motion and localized nonrigid motion. As displayed in Fig. 2(a), 3D rigid-body motion correction is first applied to the raw k-space data. Two sets of residual localized motion that trade off between spatial and temporal resolution differently are estimated after the global motion correction (localized motion A for high temporal resolution and localized motion B for high spatial resolution). An autofocusing algorithm is applied with a bank of images generated with global motion correction only and with global motion correction followed by localized 3D translational motion correction based on localized motion A or localized motion B. The details are described below.

Step 1: Global rigid-body motion correction—To correct the major motion component of the heart, frame-by-frame global 3D rigid-body motion correction is applied as follows. First, to select a reference 3D iNAV time frame (heartbeat), we calculate a similarity matrix by comparing each 3D iNAV with all others using a mutual information metric (40, 41). A good reference time frame should be similar to as many other time frames as possible. Therefore, we select the reference time frame to be the one with the largest sum of similarities with all other time frames. Second, a 3D rigid-body motion model (including a rotation matrix A and a translation vector b) is estimated at every time frame by image registration to the reference time frame. In the registration, a 3D ellipsoid mask covering the whole heart is prescribed and mean square error within this mask is used as the metric for registration. The rigid-body motion model is estimated with the MATLAB Optimization Toolbox (The Mathworks, Natick, MA). Rigid-body motion correction can be achieved by rotating the k-space trajectory and applying linear phase compensation (22,42)

$$\begin{aligned} \mathcal{F}(k) &= \exp(i2\pi k' \cdot b) \mathcal{F}'(k') \\ k &= A^{-1}k' \end{aligned}$$

where $\mathcal{F}'(k')$ is the acquired k-space data, k' is the designed k-space trajectory, $\mathcal{F}(k)$ is the motion-corrected k-space data, and k is the motion-corrected k-space trajectory.

Step 2: Autofocusing motion correction

(a) Localized motion estimation: After Step 1, both the 3D iNAV and regular scan data have undergone rigid-body motion correction. Because there are potential nonrigid motion components that cannot be corrected with rigid-body motion, two approaches are proposed to detect residual nonrigid motion with deformation-field estimation. The first approach (localized motion A) directly extracts nonrigid motion from the 3D iNAVs after rigid-body motion correction, which has high temporal resolution (per heartbeat) but low spatial resolution (4.4 mm). In the second approach, higher spatial resolution images are reconstructed by binning the 1.2 mm resolution coronary MRA k-space data into several motion states, and corresponding binned images are used to derive additional nonrigid motion estimates to augment those obtained from the 3D iNAVs.

The flowchart of localized motion A estimation is shown in Fig. 2(b). First, frame-by-frame deformation field estimation is performed on the registered 3D iNAVs using the MATLAB Image Processing Toolbox (The Mathworks, Natick, MA). These deformation fields are used to compute a set of localized motion trajectories that describe the dominant motion patterns within the heart. Then k-means clustering is performed to cluster pixels with similar deformation fields over time and 3D translational motion trajectories can be generated by averaging the deformation fields in each cluster. Correlation is used as the similarity criterion for the clustering. The number of clusters is empirically set to 32. For the six datasets, the minimum cluster size ranges from 0.9% to 1.7%, and the maximum cluster size ranges from 4.3% to 8.8%. Figure 3 shows an example of the region-of-interest (ROI) formed with clustered pixels.

Figure 2(c) shows the procedure for localized motion B estimation. To obtain images with resolution higher than 3D iNAVs, the k-space data is divided into three bins according to the similarity matrix of registered 3D iNAVs. The number of bins is empirically selected. Spectral clustering is used for binning, which generates low-dimensional features from the similarity matrix and uses them as inputs for k-means clustering (43, 44). As shown in Fig. 4(a)–(b), time frames with high similarity are clustered after binning. For each bin, a high-resolution image can be reconstructed with 3D gridding (Fig. 4(c)). The average and maximum undersampling factor of the bins in the six datasets are 3.4 and 5.1, respectively. The following processing is similar to localized motion A estimation. Deformation fields between the high-resolution binned images are estimated, and the reference bin is chosen as the bin that includes the reference time frame in the global motion estimation. Then k-means clustering is performed to cluster pixels with similar deformation fields and the number of clusters is empirically set to 16. Mean square error is used as the similarity criterion for the clustering. A 3D translational motion trajectory is generated for each cluster by averaging the deformation fields in that cluster. Localized motion B has high spatial resolution (approximately isotropic 1.2 mm) but low temporal resolution (three bins). Because localized motion A and B are residual motion after global motion correction, the scale is small. Different motion trajectory candidates also have slightly different motion ranges. The

median value of SI motion in each candidate for different volunteers is similar (less than 2 mm). The max value of SI motion in each candidate for different volunteers ranges from 4.5 mm to 12 mm. Examples of motion trajectories for localized motions are shown in Fig. 5.

(b) Image bank and final image formation: As motion trajectories in localized motion A and localized motion B are 3D translational motions, motion-corrected images can be generated by corresponding linear-phase compensation on the global-motion-corrected k-space data. Therefore, images with global motion correction only (one image), global motion correction followed by localized motion A correction (32 images) or localized motion B correction (16 images) comprise the bank of motion-corrected images. The final image is assembled pixelwise by choosing the best-focused pixel from the bank of motion-corrected images (33,35). Localized gradient entropy is used as the focusing metric, which is minimized for images with sharp edges (45).

Imaging Experiments

To test the proposed motion-correction algorithm, scans on six healthy volunteers (4 males, 2 females, age range of 26 to 40) were performed on a 1.5 T GE Signa Excite scanner with a maximum gradient amplitude of 40 mT/m and a maximum gradient slew rate of 150 mT/m/ms. An eight-channel cardiac array was used for signal reception, and cardiac triggering was performed with a peripheral plethysmograph (with which the trigger time is closer to the diastolic cardiac phase compared to ECG gating (46)). This study was approved by the IRB, and written informed consent was obtained from all participants. A fully sampled 3D cones trajectory with $28 \times 28 \times 14 \text{ cm}^3$ FOV and 1.2 mm isotropic resolution was used. Other imaging parameters for the coronary MRA sequence were: TE = 0.57 ms, TR₁/TR₂ = 4.29/1.15 ms, flip angle = 70°, receiver bandwidth = $\pm 125 \text{ kHz}$, and 100% respiratory navigator efficiency. The acquisition time per heartbeat is 99 ms and the total acquisition time is 508 heartbeats (7 min 49 s in the case of 65 heartbeats per minute).

All images were reconstructed at 0.6 mm isotropic voxel size using two-fold interpolation by k-space zero-padding. Quantitative analysis of vessel sharpness was performed with the image edge profile acutance (IEPA) (13, 47, 48) for the right coronary artery (RCA), left anterior descending (LAD), and left circumflex (LCx) arteries. For each subject, cross-sectional ROIs of the RCA, LAD and LCx from five different segments spanning from proximal to distal segments were obtained with OsiriX (Pixmeo, Geneva, Switzerland) and exported to MATLAB (The Mathworks, Natick, MA). The same location was selected between the three methods (no motion correction, 3D translational motion correction and the proposed method). In total, 90 coronary segments were compared. 32 evenly distributed radial profiles were extracted from every segment and the IEPA was calculated as the average root-mean-squared of all the gradients along the radial profiles scaled by a factor of 100. Higher IEPA scores correspond to higher vessel sharpness. The mean IEPA scores were compared between reconstruction with no motion correction, conventional 3D translational motion correction, and the proposed method. The conventional 3D translational motion correction was based on a motion trajectory derived with global translational image-registration of the 3D iNAVs. Paired two-tailed Student's t-tests were used to analyze the IEPA scores, with $P < 0.025$ considered statistically significant (49) (P value threshold is

adjusted with Bonferroni correction (50)). The signal-to-noise ratio of the left ventricle (LV) ($\text{SNR} = S_{\text{LV}}/\sigma_{\text{LV}}$) and the contrast-to-noise ratio ($\text{CNR} = (S_{\text{LV}} - S_{\text{MYO}})/\sigma_{\text{LV}}$) are also measured, where S_{LV} and σ_{LV} are the average and standard deviation of signal in an ROI of the left ventricle and S_{MYO} is the average signal of an ROI in the myocardium. To analyze the contribution of each motion trajectory type (global motion only, global motion correction followed by localized motion A or localized motion B), the ratios of the pixels selected with every trajectory type were calculated within a 3D masked region covering the heart.

Results

Figure 6 shows representative thin-slab maximum intensity projection (MIP) images from the in vivo coronary MRA scans. Images reconstructed with no motion correction, 3D translational motion correction, and proposed method are displayed. Figures 6(a) (b) and (c) show reformats of the RCA, LAD and LCx respectively, and Fig. 6(d) shows a reformatted short-axis view. When no motion correction is applied, the images are blurred and the coronaries are not visualized well. The edge between the myocardium and ventricle is also blurred. With 3D translational motion correction, the image quality is improved. The proposed method further increases the vessel sharpness and the edge sharpness between myocardium and ventricle. The improvement in vessel sharpness can also be observed in the magnified cross-sectional views (inset images). The motion maps, which represent the selected motion trajectory with different gray levels, are also shown in Fig. 6. The black area represents regions in which the autofocus algorithm selected the global motion trajectory. Different motion trajectories are used throughout the heart.

The results of the quantitative analysis are presented in Fig. 7. Over all subjects (Fig. 7(a)), the IEPA of the RCA, LCx and LAD without motion correction are 1.78 ± 0.42 , 1.29 ± 0.37 and 1.31 ± 0.42 . 3D translational motion correction improves the IEPA scores to 1.95 ± 0.45 , 1.45 ± 0.31 and 1.46 ± 0.41 . The proposed method gives the highest scores, which is 2.05 ± 0.45 , 1.52 ± 0.32 and 1.53 ± 0.42 . The IEPA score of the RCA, LAD and LCx are all significantly different between the proposed method and no motion correction ($P < 0.001$), as well as between the proposed method and 3D translational motion correction ($P < 0.001$). The average and standard deviation of IEPA scores from each subject are displayed in Fig. 7(b) - (d). In the RCA and LCx (Fig. 7(b)(d)), the proposed method shows improvement over 3D translational motion correction in all subjects. In the LAD (Fig. 7(c)), the IEPA of 3D translational motion correction of Subject 4 is 0.920 while the proposed method is 0.902, but the proposed method performs better in all other subjects. In total, 75 out of 90 segments have the highest IEPA score with the proposed method. The SNR and CNR are comparable among no motion correction (17.6 ± 2.7 and 9.3 ± 1.5), 3D translational motion correction (17.5 ± 3.3 and 9.0 ± 1.8) and the proposed method (18.0 ± 3.3 and 9.8 ± 2.1).

Table 1 gives a breakdown of the mean IEPA scores for the proximal, mid and distal segments of the RCA and LAD. Compared to no motion correction, the proposed method results in higher IEPA scores that are statistically different ($P < 0.005$) in all segments except the mid-LAD ($P = 0.064$). When compared to 3D translational motion correction, a similar trend toward improved IEPA with the proposed method is observed for all segments,

although statistically significant improvements are measured in only the mid-RCA and distal-LAD segments ($P < 0.025$).

The distribution of selected motion trajectories for each subject is shown in Fig. 8(a), which varies with datasets. For example, reconstructed images of Subject 2 are dominated by localized motion B (green color region in Fig. 8(b)); reconstructed images of Subject 5 have a larger portion of global motion (black color region in Fig. 8(c)) compared to other datasets; reconstructed images of Subject 6 are mainly compensated with localized motion A (magenta color region in Fig. 8(d)). The autofocusing metric selects motion candidates that have better localized motion estimates most of the time, indicating that simple global motion may not be sufficient to correct the motion corruption.

Discussion

We have presented a motion-correction method that extracts global and localized motion information from 3D iNAVs, and compensates for motion with an autofocusing algorithm. This method was applied to free-breathing whole-heart coronary MRA. Compared to 1D or 2D navigators, 3D iNAVs provide tracking of every region of the heart, which enables 3D rigid-body motion and deformation-field estimation, and avoids errors from through-plane motion. By providing localized motion information directly, the acquisition of 3D iNAVs reduces the search space of the autofocusing algorithm compared to using 2D iNAVs (35). The total processing time was approximately 6.2 hours on a Linux system with dual 2.6 GHz Xeon x5650 CPUs and 72 GB RAM. It was dominated by reconstructing the 3D iNAVs with ESPIRiT (4 hours). The processing time of global 3D rigid-body motion correction, localized motion A estimation, localized motion B estimate and autofocusing algorithm was approximately 0.15 hour, 1.1 hours, 0.25 hour and 0.67 hours respectively. The processing time for estimating localized motion A is dominated by the deformation field estimation for all the time frames. The processing time for 3D iNAVs reconstruction and localized motion A estimation can be reduced with more efficient programming and parallel computing.

Three types of motion are considered in the proposed method. In the first step, the global motion captures the major bulk motion of the heart. Although a 3D rigid-body motion model is used in this method, a 3D affine motion model can also be extracted from the 3D iNAVs, which potentially provides more accurate motion correction. There is a trade-off between model complexity and parameter estimation accuracy.

In the second step, two types of localized motion are estimated after the global motion correction is applied. 3D iNAVs offer the flexibility to do both binning and direct beat-to-beat localized nonrigid motion estimation. Separating the global and localized motion benefits the clustering of deformation fields of 3D iNAVs, and improves the quality of images reconstructed from each bin. The high temporal resolution of localized motion A provides the possibility to capture beat-to-beat nonrigid motion. Localized motion B augments localized motion A with high spatial resolution by trading off the temporal resolution. Moreover, compared to localized motion A which is the motion of 3D iNAVs, localized motion B is estimated from the main acquisition data and is more accurate in terms of the timing of measured motion.

Because subjects have different motion properties, the distribution of selected motion trajectories varies and the improvements of the proposed method over 3D translational motion correction also varies. For Subject 5, the IEPA score is close between the proposed method and 3D translational motion correction, consistent with the fact that this dataset has the highest portion of global motion among the six datasets. The improvements are larger for Subjects 1, 2, 3 and 6 in which the portion of global motion is smaller. In other words, the nonrigid motion is better characterized by the localized motion estimates and not by the global motion estimate in these datasets. For Subject 4 though, the average IEPA of the LAD with 3D translational motion correction is higher than with the proposed method. This result may be due to the greater amount of aliasing that existed in the 3D iNAV's of this subject. Overall, while the six volunteers studied here demonstrate the potential utility of the method, further studies investigating the benefits in patients are warranted.

There are several limitations and issues with the proposed method. First, a significant limitation of our study is the lack of comparisons with conventional methods such as Cartesian navigator-gated scanning. The scope of this study stayed within our navigator-corrected 3D cones method, focusing on the additional improvements achieved by our new processing method. Second, several parameters in the proposed motion-correction method (number of bins, number of clusters in localized motion A and localized motion B) were selected empirically. While these parameters performed well for the datasets presented, a preferred approach is to select the parameters based on the particular dataset, given variations in motion properties with different subjects. One possibility is use to a criterion such as average silhouette (51), which indicates how tightly data are grouped in their clusters and to select the parameters based on this criterion. Third, localized motion A has a larger feature dimension (1521, three spatial direction multiplied by (number of heartbeats - 1)) than localized motion B (6, three spatial direction multiplied by (number of bins - 1)). Therefore correlation is used as the similarity criterion for localized motion A while mean square error is used for localized motion B empirically. An analysis of the performance of different similarity criteria will be important. Fourth, no attempt was made at this stage to reduce the relatively long reconstruction time for use in a clinical setting. Fifth, 3D iNAV's are collected after the main acquisition and over a duration of 176 ms. An approach that enabled 3D iNAV's to be derived from the main acquisition itself or with shorter duration would be desirable. Lastly, our approach for selecting the reference respiratory frame does not necessarily lead to one at the end-expiratory phase as is widely done (52). An investigation comparing methods of reference-frame selection would be useful.

The proposed method with a 3D iNAV acquisition can be applied to other applications. For example, for respiratory-phase and cardiac-phase resolved whole-heart coronary MRA (53, 54), a 3D iNAV acquisition can be interleaved with the main acquisition, and the proposed motion-correction method can bin the data into different respiratory and cardiac phases to derive motion-trajectory estimates. However, the scan time will be increased to compensate for the cardiac phases missed due to the acquisition of 3D iNAV's. Alternatively, one possibility to avoid missing cardiac phases is to track motion simultaneously and reconstruct 3D iNAV's from the main acquisition.

Conclusion

We have presented a motion-correction method for free-breathing whole-heart coronary MRA that tracks motion with 3D iNAV and compensates for motion with an autofocusing algorithm. Both global rigid motion and localized nonrigid motion were considered in the proposed motion-correction method. In vivo studies showed that the proposed method improves the coronary vessel sharpness compared to 3D translational motion correction in 75 out of 90 segments.

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Figure 1.

(a) Timing diagram of the coronary MRA sequence. FS: fat suppression. 3D CONES ATR-SSFP: 3D cones main acquisition. 3D iNAV: 3D variable-density cones acquisition for image-based navigators. (b) Three cross-sections (coronal, sagittal and axial) of a representative 3D iNAV.

Figure 2.

(a) Flowchart of the proposed method. 3D rigid-body motion correction is first applied, followed by autofocusing motion correction. A bank of images is constructed with no additional motion correction and with two sets of localized motion correction. The final image is assembled pixel-by-pixel from the bank of images. (b) Localized motion A is estimated from deformation fields between registered 3D iNAVs, which has high temporal resolution (per heartbeat) and low spatial resolution (4.4 mm). (c) Localized motion B is estimated from the binned images reconstructed from segmented data, which has low temporal resolution (three frames) and high spatial resolution (1.2 mm).

Figure 3.

(a) Deformation fields are automatically clustered to select localized ROIs with similar localized motion. The deformation fields within each cluster are averaged to yield localized motion trajectories (localized motion A). The corresponding anatomy is displayed in (b). For the six datasets, the minimum cluster size ranges from 0.9% to 1.7%, and the maximum cluster size ranges from 4.3% to 8.8%.

Figure 4.

(a) Similarity matrix before binning. (b) Spectral clustering is performed with a similarity matrix, which clusters time frames with high similarities to the same bin. (c) Reconstructed coronal images from each bin (left: bin 1, middle: bin 2, right: bin 3). Differences can be observed; e.g. the LAD (arrow) and superior position of the heart (arrowhead). The average and maximum undersampling factor of the bins are 3.4 and 5.1, respectively.

Figure 5.

Examples of motion trajectories from localized motion A and localized motion B. Localized motion A has frame-to-frame variation, while localized motion B has higher spatial resolution. As localized motion B has low temporal resolution (three bins), the motion of time frames in the same bin shares the same value. Localized motion A and B are residual motion after global motion correction, so the scale is small. Different motion trajectory candidates also has slightly different motion range. The median value of SI motion in each candidate for different volunteers is similar (less than 2 mm). The max value of SI motion in each candidate for different volunteers ranges from 4.5 mm to 12 mm.

Figure 6.

Representative thin-slab MIPs from different subjects reconstructed without motion correction (left), 3D translational motion correction (middle left), and the proposed method (middle right), along with the selected motion trajectory map (right). Reformatted views of the RCA (a), LAD (b), LCx (c), and short-axis (d). Magnified 2D cross-sectional views of the coronaries at the segment denoted by red dash-line are shown in the inset images. The proposed method improves the vessel sharpness compared to 3D translational motion correction and no motion correction. Different gray levels in the motion map indicate that different motion trajectories were selected throughout the heart. The black region represents the selection of global motion.

Figure 7.

Quantitative analysis of the reconstructed images. IEPA scores of the RCA, LAD and LCx were measured for a total of 90 segments from six subjects. The average IEPA scores of all 90 segments are shown in (a), and IEPA scores for each subject are shown in (b)–(d), for the RCA, LAD and LCx respectively. The SNR (e) and CNR (f) are comparable among the three methods.

Figure 8.

(a) The distribution of selected motion trajectories is calculated for each subject. Simple global motion is not sufficient to correct for the nonrigid motion corruption because in most regions, the algorithm is selecting motion candidates that have better localized motion estimates. (b) – (d) Representative motion maps of an axial slice from Subject 2, 5, 6 also show that the distribution of selected motion trajectories varies with datasets. Magenta color denotes localized motion A, green color denotes localized motion B, and black denotes global motion.

Table 1

IEPA scores for different segments of the RCA and LAD

		Proximal	Mid	Distal
RCA	No motion correction	1.77±0.44	1.79±0.45	1.90±0.35
	Translation	1.96±0.55	1.95±0.48	2.10±0.33
	Proposed	2.02±0.53	2.06±0.45	2.21±0.33
LAD	No motion correction	1.15±0.39	1.42±0.29	1.20±0.23
	Translation	1.40±0.28	1.46±0.30	1.43±0.24
	Proposed	1.48±0.25	1.51±0.28	1.51±0.25