Target-specific optimization of four-dimensional cone beam computed tomography

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Purpose: Under-sampling artifacts are a major problem in four-dimensional cone-beam computed tomography (4D-CBCT) and may compromise evaluation of target motion. Several studies have addressed scan parameter selection for minimizing under-sampling artifacts; however, the role of the target characteristics in scan parameter selection has not been investigated. In this work, the authors evaluated 4D-CBCT performance by assessing the accuracy of target motion measurements for various target sizes and motions. The results may serve as patient-specific guidelines for scan parameters selection in 4D-CBCT.

Methods: The authors acquired 4D-CBCT scans of a moving phantom consisting of six water-filled sphere targets of sizes 10–37 mm, using various scan times ranging from 30 s to 3 min., setting the motion to 3-s and 6-s periods. The authors used automatic image registration to extract the target motion trajectories and evaluated these measurements for various target sizes and motions over various combinations of scan parameters including scan time, detector configuration, number of respiration phases, and reconstruction filters.

Results: The most important object parameter to 4D-CBCT performance was the period of motion. Measurements for the 6-s motion were always systematically less accurate than measurements for the 3-s motion for 34 of 36 objects of various sizes and periods of motion. The 6-s motion required a greater scan time than the 3-s motion for equivalent measurement accuracy. The second most influential parameter was the target size. For the 3-s period of motion, objects larger than 13 mm were tracked with sub-millimeter accuracy with a 1-min scan time. For the 6-s period of motion, objects larger than 22-mm were tracked with sub-millimeter accuracy with a 1.5-min scan time. For all sizes and motions, temporal blurring was observed when the number of phases was fewer than 8. Offset detector configuration provided the same performance as centered detector except for small targets (20 mm.) at short scan times (≤ 1 min). Finally, reconstruction filtering and number of respiratory phases did not affect performance.

Conclusions: Scan time should be set according to target size and motion. The authors have provided figures that provide the minimum scan time needed to achieve the particular motion measurement accuracy for a particular size and motion period. © 2012 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4747609>]

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I. INTRODUCTION

Cone-beam computed tomography (CBCT) imaging using kilovoltage flat panel systems integrated with treatment machines has become routine in image-guided radiation therapy (IGRT).^{1–5} The three-dimensional (3D) position of soft tissue structures can be verified with CBCT for accurate target localization. Four-dimensional cone-beam computed tomography (4D-CBCT) has been proposed to extend localization capability to targets influenced by respiratory motion in the thorax and upper abdomen.^{6–8} In 4D-CBCT, the raw projection data are sorted into several phases of the respiratory cycle using a respiration surrogate (e.g., chest wall or abdominal expansion). A 3D image is then reconstructed independently for each phase to produce a set of 4D images (i.e., with respiratory phase as the fourth dimension.) A target motion trajectory may then be measured from the 4D-CBCT and compared with the target model in

the treatment plan, so that the treatment can be adjusted accordingly.

A major challenge for clinical 4D-CBCT is avoiding image artifacts due to under-sampling in the acquisition data. In one continuous gantry rotation, any given projection angle is sampled for only one particular respiratory phase and not for any other phase. This causes large gaps in angular sampling within each phase, causing streak artifacts when the standard filtered back-projection image reconstruction is used. Streak artifacts can distort anatomical boundaries and may make it difficult to accurately measure target motion. One approach to avoiding streak artifacts is to slow the gantry rotation in order to reduce the gaps in angular sampling.^{6–9} Another approach involves using multiple gantry rotations to improve the sampling.¹⁰ Both methods involve long acquisition times (3–6 min), which reduce patient throughput and increase the chance of disrupting patient setup due to inadvertent patient motion.

A different approach to avoiding under-sampling artifacts uses novel reconstruction methods to accommodate under-sampling. There are many algorithms for reconstruction using under-sampled data.^{11–20} Evaluations of the image quality, robustness, convergence, and computational aspects of these reconstruction algorithms have been provided by Bergner *et al.*²¹ and Bian *et al.*²² Although these novel image reconstructions are generally very effective in reducing streak artifacts, each algorithm has some disadvantage. For instance, the McKinnon-Bates^{12,13} and PICCS (Refs. 14 and 15) algorithms sacrifice temporal resolution to some degree. The ASD-POCS (Ref. 16) is a very computationally expensive iterative algorithm. These disadvantages have been noted by Bergner *et al.*²¹ Although computational complexity may not appear to be a concern given advances in computing power, especially in GPU-based reconstruction, POCS and its derivative ASD-POCS cannot reap these gains because they are not parallelizable algorithms.

Given the limitations in the long-scan and novel reconstruction approaches, the 4D-CBCT data acquisitions must be optimized to balance scan time and image quality. Several previous works have studied the relationship between scan time and image quality in 4D-CBCT. These works have assessed image quality using traditional image quality metrics such as signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), or image intensity error (in the case of phantom experiments). For instance, Li and Xing assessed how scan time and number of gantry rotations affect image intensity error.¹⁰ Because it is difficult to relate traditional image quality metrics to clinical significance, a task-based approach to optimizing 4D-CBCT acquisition parameter selection is needed. Qi and Chen have provided such an approach, conducting a 4D-CBCT performance study in which they measured the target motion trajectory using 4D-CBCT with various scan parameters.²³ Although this study included several scan parameters and reconstruction algorithms, it assessed 4D-CBCT performance for only one object and only one object motion.

Intuitively, one expects measuring the trajectory of a smaller object to be more difficult than for a larger one when there are streaky under-sampling artifacts. It is also known that longer respiration periods are associated with greater streak artifacts in 4D-CBCT,¹⁰ one then expects greater errors in tracking small targets with long respiration periods. Because of these dependencies on target characteristics, we propose that 4D-CBCT scan parameters can be further optimized on a patient-specific basis. For example, Lu *et al.*⁹ and Li and Xing¹⁰ have previously suggested setting gantry rotation speed based on the patient breathing period.

In this work, we compared 4D-CBCT performance for various object sizes and motion trajectories. The performance was assessed by the accuracy of target motion trajectories in phantom data using an automatic measurement method. For each object size and motion, we obtained image data using various combinations of scan parameters including scan time, number of 4D-CBCT phases, reconstruction parameters, and detector configurations. The purpose was to optimize scan parameters for a given target size and motion. Last, we have supported our phantom study results with a patient study.

II. METHODS AND MATERIALS

We assessed how object size and motion affect the accuracy of target trajectory measurement in 4D-CBCT. Although the object characteristics cannot be selected in a patient exam, they can be controlled in a phantom study. We therefore designed a phantom study to test various object sizes and motion periods. For each object size and motion, we used various combinations of scan parameters. The most important scan parameter was the scan time, because it directly affected the amount of data available to the task of tracking target motion. Other parameters were: the number of phases used to sort the projection data, the detector configuration (centered or offset detector), and the smoothing filter used in the image reconstruction. The last two parameters are described in the following two sections: II.A. and II.B. All of our experiments were performed using the Varian OBI system (Varian Medical Systems, Palo Alto, CA).

II.A. Offset vs centered detector configuration

We tested two different detector configurations: offset and centered detector. Offset detector configuration²⁴ is often used in clinical CBCT of the thorax or abdomen to enlarge the field-of-view (FOV) for a given size flat-panel detector. Although the FOV is increased without increasing the size of the detector, a trade-off is made in sacrificing half of the x-ray fan data. Because of the popularity of the offset detector configuration, we tested it in our experiment.

The offset detector was shifted by 14.8 cm. The centered detector provided a 25-cm FOV, whereas the offset detector provided a 45-cm FOV. For the centered detector, we acquired projection data over π -plus-fan angle range (200°), whereas for the offset detector, we acquired projection data over a full 360° rotation (a full 360° is required for offset detector). The 200° range was sufficient for the centered detector configuration. On the other hand, some redundant data would be collected from complementary projection angles in a 360° scan in the centered detector configuration.

II.B. Image reconstruction

In this work, we used the standard Feldkamp filtered back-projection for image reconstruction. Feldkamp reconstruction is simply the modification of 2D (planar) filtered back-projection to 3D cone-beam geometry in CBCT.²⁵ In 4D-CBCT, we reconstructed each phase independently using the Feldkamp reconstruction. It is important to emphasize here that many reconstruction algorithms often perform better than filtered back-projection for under-sampled data. Most notable are algorithms based on total-variation (TV) minimization.^{11,14–16,19} These algorithms have produced superior image quality results in both phantom and patient data. However, no single algorithm has been proven superior over others for all clinically imaged objects and situations. Consequently, filtered back-projection remains the only clinically used image reconstruction algorithm in CBCT. Another reason we chose filtered back-projection reconstruction is that

imaging phantoms are biased in favor of TV minimization algorithms because they are usually piecewise constant. TV minimization prefers piecewise constant solutions and is not appropriate for the phantom study in this work.

We tested the performance of smoothing reconstruction filters on the measured trajectory. The purpose of this part of the experiment was to determine whether reconstruction filters affect the motion measurement and whether the filter should be set based on object characteristics. For this part of the experiment, we used the following Butterworth low-pass filters:²⁶

- 1) No smoothing: pure ramp filter (no smoothing),
- 2) Medium smoothing: ramp filter with a Butterworth window with a cutoff of 20% of the Nyquist frequency and order $n = 5$.
- 3) Heavy smoothing: ramp filter with a Butterworth window with a cutoff of 10% of the Nyquist frequency and order $n = 5$.

For our system, the detector spacing was 0.388 mm and the Nyquist frequency was 1.29 line pairs/mm. The medium smoothing filter above provides smoothing similar to typical clinical CBCT.

II.C. Phantom study

We used the IEC NEMA body phantom for this experiment. There were six spheres of 10, 13, 17, 22, 28, and 37 mm diameters in this phantom to simulate different size lung tumors. The phantom was set on a sliding motion platform set to move in a periodic motion along the longitudinal direction of the scanner. Two different motion profiles were used: a 3-s motion period and a 6-s motion period. Most patient respiratory cycle durations are between 3 and 6 s.²⁷ We selected 2-cm motion amplitude to simulate plausible lung tumor motion amplitude, particularly for lesions in the lower lobe.²⁸ Also, a 2-cm motion case benefits from a motion management strategy. We acquired a 3-min scan of the phantom for both the 3-s and 6-s motion profiles. We used the Varian real-time position management (RPM) system to acquire a respiratory signal during the x-ray acquisition, which was used to sort the projection data into phases.

Starting with the 3-min scan data, we simulated shorter scans by removing projection data. We removed data in such a way as to maintain a realistic number of motion cycles for the shorter scans. For instance, removing the data for every alternating cycle represents an acquisition with half of the scan time. By reducing projection data by factors of 1/2, 1/3, 1/4, 1/5, and 1/6 we simulated scan times of 1.5 min, 1 min, 45 s, 36 s, and 30 s. One advantage of *simulating* shorter scan times by removing projection data is that the different simulated scans come from the same actual scan and the images are inherently registered among the scans. We tested 2, 4, 8, and 16 phases. We selected these particular values because they are multiples and their time points in the respiratory cycle are aligned relative to each other. All raw data were used, regardless of the number of phases. We reconstructed each phase and measured the trajectory of each sphere using a rigid image registration method (Sec. II.E).

II.D. Patient study

We performed 4D-CBCT of one lung cancer patient receiving radiotherapy. This patient had a large 40-mm diameter lung tumor in the posterior right lung that moved with a 2.8-s breathing cycle. This patient also had a 10-mm diameter calcified plaque in the posterior left lung. We scanned the patient with a 4.5-min scan time. Using this original 4.5-min scan, we simulated shorter scan times by reducing projection data in the same manner as for the phantom experiment and obtained six different scan times: 45 s, 54 s, 68 s, 1.5 min, 2.25 min, and 4.5 min. We used the Varian RPM system to acquire the respiratory signal for this patient. The RPM data was used to sort the projection data into 2, 4, and 8 phases and reconstruct 4D image sets. We did not use a higher number of phases (e.g., 16, as in the phantom study) because the projection sampling rate for this patient study did not support more than 10 phases. Using the 4D-CBCT image data, we measured the trajectories of both the lung tumor and the calcified plaque for different scan times and number of phases.

We measured the tumor trajectory using a deformable image registration method (Sec. II.E). Although we did not know the “true” trajectory for accuracy assessment, we used the trajectory measured from the 4.5-min scan as our gold standard. We compared the accuracy of the trajectories measured using various scan times against this standard.

II.E. Measurement of image trajectory

The trajectory of the target was measured as it moved through the respiratory cycle. The location of a target in any given phase relative to a reference phase was measured using image registration. By determining the position of the target relative to the position in reference phase in all the phases in the 4D image set, we measured the target trajectory. The following describes the image registration method used.

For the phantom data, we used a rigid, translation-only image registration based on minimizing image intensity difference. We solved this minimization problem using the Levenberg-Marquardt algorithm,^{29–31} which performs small shifts in displacement until the intensity difference is minimized. The displacement c was initialized to zero. For the patient data, we measured the trajectory using deformable image registration instead of rigid registration. We used the method proposed by Lu *et al.* based on the calculus of variations.³² This registration also was an intensity-based approach. This deformable image registration method was also used by Qi and Chen to extract motion trajectories in 4D-CBCT.³³

For both rigid and deformable registration, one phase in the 4D image set was chosen as the reference phase, and the relative target displacement in each of the other phases to the reference phase were measured. To avoid false local minima solutions, we used a multiresolution strategy in which the registration is first performed on low resolution images and the registration result becomes the starting point to the successively higher resolution registrations. In this work, we used four resolution levels for the rigid registration and six levels for the deformable registration. We used the registration result

FIG. 1. Reconstructions of the 3-s period NEMA motion phantom at 50% phase from data corresponding to different scan times: (a) 3 min, (b) 1.5 min, (c) 1 min, (d) 45 s, (e) 36 s, and (f) 30 s.

for one phase as the initial estimate for the registration of the next phase. (For example, the registration of Phase 2 to Phase 1 was used as the initial estimate for the registration of Phase 3 to Phase 1, and so forth. Phase 1 was the reference phase image.)

Once the trajectory was measured, the error for all points along the trajectory was computed by comparison with the true trajectory. The errors in the points along the trajectory were summarized using a root-mean-square (RMS) error metric:

$$\text{RMSError} = \sqrt{\frac{1}{(n-1)} \sum_i |\vec{r}_m^i - \vec{r}_t^i|^2},$$

where r_m^i and r_t^i are the measured and true positions, respectively, of the object in the i th phase. The variable n is the number of phases in the 4D-CBCT data set. The summation was performed over $n - 1$ phases, while one phase was chosen as the reference phase in the image registration-based measurement.

II.E.1. Region-of-interest constraint in image registration

Because lung motion is complex, we simplified the task of measuring motion trajectories by restricting the image registrations (both rigid registration for the phantom and deformable registration for the patient) to a small region-of-interest (ROI) containing the moving target. Within the ROI,

the motion is simpler and approximately rigid with minimal rotation and deformation. For the phantom study, we used the 4D-maximum intensity projection (MIP) image and segmented the MIP to obtain the motion envelope of the sphere. We expanded this region by 5 mm and used this ROI in our image registrations. This is a common margin added to delineated tumor volumes in lung cancer to account for target setup uncertainty and interfractional motion. By adding this margin to our ROI, we ensured that the moving spheres remained inside the ROI. For the patient study, a suitable ROI was already available in the form of the planned treatment volume (PTV) in the patient's radiation treatment plan.³⁴ In this case, the PTV included margins for microscopic extensions of disease (CTV margin) and also for setup errors (PTV margin). These margins are not isotropic expansions and they were chosen specifically for this patient. The CTV and PTV margins added together were roughly 7-mm expansions around the tumor, which is somewhat larger than but close to the 5-mm margin we used for the ROI in the phantom study.

III. RESULTS AND DISCUSSION

III.A. Phantom study

III.A.1. Object size and motion period

Images of the NEMA phantom for both 3-s and 6-s period motions at the end-exhale (50% phase) are shown in Figs. 1 and 2, respectively. Both figures show images for various scan

FIG. 2. Reconstructions of the 6-s period NEMA motion phantom at 50% phase from data corresponding to different scan times: (a) 3 min, (b) 1.5 min, (c) 1 min, (d) 45 s, (e) 36 s, and (f) 30 s.

times from 30 s to 3 min, reconstructed using eight phases. Not surprisingly, the streak artifacts from under-sampling increase as scan time is reduced. The streak artifacts are also worse for the 6-s motion than for the 3-s motion.

For all 12 objects (6 sizes and 2 motion periods), we measured the sphere motion trajectory for the various scan times. The trajectory component in the longitudinal (z-) direction for each object is shown in Fig. 3. We chose 16 for the number of respiratory phases. The first major trend we observed was that errors were consistently greater for the 6-s period than for the 3-s period for short scan times. For the 3-s period, the errors were all less than 2 mm (aside from one exception for the 13-mm sphere) for all scan times and sphere sizes, whereas large errors of 6 mm or greater were observed for spheres smaller than 22 mm with the 6-s period. This suggests that scan times can be set very short for 3-s breathing periods. For the 3-s period, the superior angular sampling produced fewer streak artifacts and more accurate trajectory measurements than for the 6-s period. The second trend observed was that errors became smaller with increasing scan time. This was particularly true for 17-mm or smaller spheres with the 6-s period. A scan time of 1.5 min or greater always produced errors of less than 2 mm. The third trend observed was that larger objects were more accurately tracked. For the 28-mm or larger spheres, the scan time could be reduced to 45 s while keeping the error below 2.5 mm, regardless of period.

Figures 4 and 5 summarize the trajectory errors for different sphere sizes and scan times for a fixed motion period

(either 3 s or 6 s). These figures display our observed trend of increasing error with smaller object size or scan time. We note that our observed trends were not absolute: in a few cases, errors *decreased* with smaller object size or scan time. We attribute these anomalies to the random nature of streak artifacts; a streak artifact may intersect a sphere, causing a trajectory measurement error, or the artifact may not intersect the sphere. For increased confidence in our observed trends, a statistical analysis using many repeat acquisitions would need to be performed; we did not acquire enough data for such an analysis.

One can use Figs. 4 and 5 to optimize a 4D-CBCT acquisition in the following way. Select the appropriate figure based on the motion period. Then, for a given object size and scan time, find the expected trajectory measurement accuracy. Conversely, for a given object size and desired measurement accuracy, one can find the corresponding scan time on the horizontal axis. In this way, the user can minimize the 4D-CBCT scan time for desired measurement accuracy.

We emphasize again that these results were obtained using the Feldkamp (filtered back-projection) image reconstruction algorithm. The errors are expected to be much less for iterative reconstruction using total-variation minimization. Because of the piecewise constant nature of the phantom, we would expect the image reconstruction and trajectory measurement errors to be close to zero for all the targets and acquisition parameters in this study if we had used total-variation minimization reconstruction.

FIG. 3. Measured trajectories of spheres of various sizes and motion periods using various scan times. Displacements along the longitudinal (z-axis) are plotted.

FIG. 4. Root mean square (RMS) trajectory measurement errors of spheres of various sizes with 3-s motion.

FIG. 5. Root mean square (RMS) trajectory measurement errors of spheres of various sizes with 6-s motion.

FIG. 6. Centered and offset detector acquisitions for the 3-s motion period and 3-min scan time. Left column: offset detector, right column: centered detector, top row: axial views, bottom row: sagittal views.

FIG. 7. Centered and offset detector acquisitions for the 3-s motion period and 1-min scan time. Left column: offset detector, right column: centered detector, top row: axial views, bottom row: sagittal views.

FIG. 8. Centered and offset detector acquisitions for the 6-s motion period and 3-min scan time. Left column: offset detector, right column: centered detector, top row: axial views, bottom row: sagittal views.

FIG. 9. Centered and offset detector acquisitions for the 6-s motion period and 3-min scan time. Left column: offset detector, right column: centered detector, top row: axial views, bottom row: sagittal views.

FIG. 10. Comparison of root-mean-square trajectory errors for centered and offset detector configurations for 10-mm/37-mm sizes and 3-s/6-s periods. Errors are plotted against scan time.

III.A.2. Offset vs centered detector configuration

Figures 6–9 show image reconstructions comparing the offset and centered detector configurations. The images with the larger field-of-view correspond to the offset detector configuration. All images are at the peak exhale phase. Figures 6 and 7 show the reconstructions for the phantom moving with

3-s period, scanned with 3-min and 1-min acquisitions, respectively. Figures 8 and 9 show the reconstructions for the phantom moving with 6-s period, scanned with 3-min and 1-min acquisitions, respectively. The offset detector images have slightly more streak artifacts than their centered detector counterparts, especially with 1-min acquisition. Figure 10 shows the errors in the measured sphere trajectories for these

FIG. 11. Root mean square (RMS) trajectory measurement errors of spheres of various sizes with 3-s motion using the offset detector acquisition.

FIG. 12. Root mean square (RMS) trajectory measurement errors of spheres of various sizes with 6-s motion using the offset detector acquisition.

FIG. 13. Reconstructions of the 6-s period NEMA motion phantom from 1-min acquisition data at 50% phase reconstructed using different numbers of respiratory phases: eight phases (a), 4 phases (b), and 2 phases (c). Top row: axial images. Bottom row: sagittal images.

FIG. 14. Measured trajectories of spheres of various sizes and motion periods using various numbers of phases to sort the projection data. Data for “short” scan time (30 s) are shown. Displacements along the longitudinal (z-axis) are plotted.

FIG. 15. Reconstructions of the 6-s period NEMA motion phantom using different reconstruction filters at 50% phase. Top row: 3-min scan: (a) no smoothing, (b) medium smoothing, and (c) heavy smoothing. Bottom row: 36-s scan: (d) no smoothing, (e) medium smoothing, and (f) heavy smoothing.

scans. The two detector configurations showed similar performance. (A useful point of reference is that a typical setup margin in IGRT is 3 mm. Errors less than 3 mm may be considered clinically insignificant.) The only time the performance of the offset and centered detectors showed clinically significant difference was for targets smaller than 20 mm scanned with acquisition time shorter than 1.5 min. Figure 11 (3-s motion) and Fig. 12 (6-s motion) show plots that can be used to optimize the scan time for a desired trajectory measurement

accuracy for a given object size using the offset detector configuration.

III.A.3. Number of respiratory phases

Figure 13 shows images for the 1-min acquisition data of the phantom with 6-s motion period, corresponding to projection sorting using 2, 4, and 8 phases. A clear loss of temporal resolution and motion blurring was evident in the 2-phase reconstruction (Fig. 13, panel c). Streak artifacts were present in all three sorting configurations. Even though the 2-phase reconstruction used more projection data due to the larger temporal width of the phase bin, the visual appearance of the streak artifacts did not improve much. Sacrificing temporal resolution did not appear to be a good strategy for mitigating streak artifacts.

Figure 14 shows the measured trajectories for spheres of various sizes and motions using a short scan time (30 s) and different number of phases. With 2 and 4 phases, the measured motion amplitude was systematically lower than the true value due to motion blurring. There was a systematic error of 6.5 mm when sorting the data into only 2 phase bins. The trajectories for 8 and 16 phases had only submillimeter differences. Eight phases provided sufficient temporal resolution for trajectory measurements. In general, although the streak artifacts were slightly reduced by reducing the number

FIG. 16. Root mean square (RMS) trajectory measurement errors of spheres of various sizes using various reconstruction filters. Data from 36-s scan time. Spheres have 6-s motion period.

FIG. 17. Reconstructions of the patient data corresponding to different scan times at 50% phase: (a) 3 min, (b) 1.5 min, (c) 1 min, (d) 45 s, (e) 36 s, and (f) 30 s.

FIG. 18. Measured trajectories of the lung tumor and calcification for various scan times. Data are based on reconstructions with eight phases.

FIG. 19. Root mean square (RMS) trajectory measurement errors of the lung tumor for different scan times and number of sorting bins.

of phases, this did not improve the accuracy of the measured trajectory.

III.A.4. Smoothing filter in image reconstruction

Figure 15 shows the images reconstructed using different filters corresponding to zero, medium, and heavy smoothing. The top row shows filtered images for “highly sampled” 3-min scans. The bottom row shows filtered images for “under-sampled” 36sec scans. We measured the motion trajectories when different reconstruction filters were used on the under-sampled acquisitions. The RMS trajectory error results (in millimeters) are shown in Fig. 16. The error for any given size was nearly the same regardless of the choice of filter in image reconstruction. The trajectories for the zero, medium, and heavy filters had mostly submillimeter differences amongst each other, even when the errors themselves were as large as 10 mm. In summary, the smoothing filter did not affect the measured trajectory, whether accurate or inaccurate.

III.B. Patient study

Figure 17 shows the reconstructed image sets for the patient study for six different scan times, reconstructed using eight phases. Using the deformable image registration method, we measured the trajectory of both the patient’s lung tumor and the calcified plaque for several scan times and number of phases. Figure 18 shows the x, y, and z components of the trajectories for various scan times. The trajectories for the 4.5-min scan time were considered the truth. The errors in the measured tumor trajectories are shown in Figs. 19 and 20. The tumor most closely resembled the 37-mm size/3-s period sphere from the phantom study. However, the tumor had a 5-mm motion amplitude, whereas the phantom sphere had a 20-mm motion amplitude. The same trends in measurement errors were observed for the patient study as in the phantom study. The errors decreased with increasing scan time, and there was greater error using a smaller number of phases because of motion blurring. Whereas the errors for the 37-mm size/3-s period phantom sphere changed slowly with scan

FIG. 20. Root mean square (RMS) trajectory measurement errors of the calcified plaque for different scan times and number of sorting bins.

time (~ 0.5 mm for all scan times for 8- and 16-phase reconstructions), there was more variation over scan times in the patient study. At short scan times, the errors were larger for the patient study. This suggests that the details of nonrigid motion are lost with decreasing scan time. There was one outlier at the 54-s scan time for the eight phase bin sorting. For this particular scan, strong streak artifacts intersected the tumor, causing large errors in the measured trajectory. As discussed earlier, the streak pattern is largely unpredictable and strongly dependent on both the object and the angular sampling of projections. The calcification in this study most closely resembled the 10-mm size/3-s period sphere from the phantom study. The calcification had a 10-mm motion amplitude, whereas the phantom sphere had a 20-mm motion amplitude. The errors for both the calcification and phantom sphere were ~ 0.5 mm across all scan times (for eight-phase reconstructions). The mostly constant measurement accuracy across scan times for the calcification study may reflect the rigid nature of the calcified lesion. It may also be due to the high contrast of the calcification against the lung tissue background, making the task of tracking the motion equally easy across various scan times.

IV. CONCLUSIONS

This is the first investigation of how object size and motion affect 4D-CBCT performance, specifically the accuracy of trajectory measurements of objects influenced by respiratory motion. The results show that the most important parameter is the object motion period, with shorter periods being more favorable. The second important parameter is object size, with larger objects being more favorable. For the 3-s period of motion, objects larger than 13 mm were tracked with submillimeter accuracy with a 1-min scan time. For the 6-s period of motion, objects larger than 22 mm were tracked with submillimeter accuracy with a 1.5-min scan time. The object’s period of motion and its size together should be used to select the appropriate scan time.

Offset detector configuration did not degrade the 4D-CBCT performance compared to centered detector

configuration except for slow-breathing objects smaller than 20 mm or scanned with acquisition time of 1 min or less. We did not find the number of phases or the reconstruction filters to be important parameters for optimizing 4D-CBCT performance based on object size and motion alone. Object contrast and the degree of nonrigid motion may also have an important effect on 4D-CBCT performance. More phantom studies testing these object parameters are needed to further optimize 4D-CBCT performance. Finally, more clinical studies are needed to validate the results of our phantom study.

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