Published in final edited form as:

Phys Med Biol. 2011 October 21; 56(20): 6709–6721. doi:10.1088/0031-9155/56/20/013.

Performance studies of four-dimensional cone beam computed tomography

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Abstract

Four-dimensional cone beam computed tomography (4DCBCT) has been proposed to characterize the breathing motion of tumors before radiotherapy treatment. However, when the acquired cone beam projection data are retrospectively gated into several respiratory phases, the available data to reconstruct each phase is under-sampled and thus causes streaking artifacts in the reconstructed images. To solve the under-sampling problem and improve image quality in 4DCBCT, various methods have been developed. This paper presents performance studies of three different 4DCBCT methods based on different reconstruction algorithms. The aims of this paper are to study (1) the relationship between the accuracy of the extracted motion trajectories and the data acquisition time of a 4DCBCT scan and (2) the relationship between the accuracy of the extracted motion trajectories and the number of phase bins used to sort projection data. These aims will be applied to three different 4DCBCT methods: conventional filtered backprojection reconstruction (FBP), FBP with McKinnon–Bates correction (MB) and prior image constrained compressed sensing (PICCS) reconstruction. A hybrid phantom consisting of realistic chest anatomy and a moving elliptical object with known 3D motion trajectories was constructed by superimposing the analytical projection data of the moving object to the simulated projection data from a chest CT volume dataset. CBCT scans with gantry rotation times from 1 to 4 min were simulated, and the generated projection data were sorted into 5, 10 and 20 phase bins before different methods were used to reconstruct 4D images. The motion trajectories of the moving object were extracted using a fast free-form deformable registration algorithm. The root mean square errors (RMSE) of the extracted motion trajectories were evaluated for all simulated cases to quantitatively study the performance. The results demonstrate (1) longer acquisition times result in more accurate motion delineation for each method; (2) ten or more phase bins are necessary in 4DCBCT to ensure sufficient temporal resolution in tumor motion and (3) to achieve the same performance as FBP-4DCBCT with a 4 min data acquisition time, MB-4DCBCT and PICCS-4DCBCT need about 2- and 1 min data acquisition times, respectively.

Introduction

Four-dimensional cone beam computed tomography (4DCBCT) using an on board imager (Sonke *et al* 2005, Chang *et al* 2006, Dietrich *et al* 2006, Li *et al* 2006) has been proposed as a 4D imaging tool for radiotherapy treatment of tumors in the thorax and upper abdomen. Compared with four-dimensional computed tomography (4DCT) using diagnostic CT scanners (Ford *et al* 2003, Low *et al* 2003, Vedam *et al* 2003, Keall 2004, Pan *et al* 2004,

Pan 2005, Rietzel *et al* 2005), 4DCBCT extends 4D imaging capability from the treatment planning stage to the treatment delivery stage. From 4DCBCT images, a tumor motion trajectory can be extracted immediately before the treatment delivery and compared with that from the treatment plan so that the treatment can be adapted to optimize the clinical outcome.

4DCBCT is implemented on the basis of the standard three-dimensional CBCT. First, all projection views acquired from a standard CBCT scan are sorted into several respiratory phase bins according to a respiratory surrogate. Second, image reconstruction is performed for each of the phase bins. In such a way, time resolved image volumes are generated which represent the temporal change of the patient anatomy during a respiratory cycle.

The clinical use of 4DCBCT, however, faces challenges from the data under-sampling problem in image reconstruction. A standard CBCT usually acquires approximately 600 views of projection data through 360 degrees (full scan mode) in approximately 1 min. If the projection views are sorted into ten phase bins, each phase bin only has about 60 views; in addition, these views are usually distributed in a bunched pattern. When the standard filtered-backprojection (FBP) algorithm is used for image reconstruction, streaking artifacts become rampant in the reconstructed images, which pose difficulties in the extraction of accurate and reliable motion information.

Various methods have been proposed to address the data under-sampling problem and therefore improve image quality in 4DCBCT (Sonke *et al* 2005, Li *et al* 2006, 2007, Li and Xing 2007, Lu *et al* 2007, Leng *et al* 2008a, 2008b, Bergner *et al* 2009, Rit *et al* 2009, Zhang *et al* 2010). Most of them can be classified into two categories: (1) slow down the gantry rotation while using the standard FBP reconstruction algorithm or (2) keep the standard gantry rotation time while using novel methods to mitigate streak artifacts.

The data acquisition time of a CBCT scan, at a fixed detector readout speed, is proportional to the total number of the acquired projection views. The data acquisition time and the number of phase bins therefore determine the number of projection views per phase bin. It is straightforward that more total projection views and fewer phase bins will result in fewer under-sampling streak artifacts. These two technical factors, however, have their trade-offs in clinical practice. Longer data acquisition time not only requires hardware modification on current systems, but also increases the likelihood of inadvertent patient motion during the scan and reduces patient throughput. Fewer respiratory phase bins lead to wider phase bins and poorer temporal resolution. Therefore, it is important to study the relationship between the performance of 4DCBCT methods and these technical factors. Such studies will provide a guideline for optimizing the technical factors in clinical applications of 4DCBCT methods.

This paper presents a study on the performance of three 4DCBCT methods. These methods are based on different reconstruction algorithms, including the filtered-backprojection algorithm (FBP), the McKinnon–Bates algorithm (MB) (McKinnon and Bates 1981, Leng *et al* 2008a, Zheng *et al* 2011), and the prior image constrained compressed sensing (PICCS) algorithm (Chen *et al* 2008, Leng *et al* 2008b). The three methods are referred to as FBP-, MB- and PICCS-4DCBCT, respectively, in this paper. Their performance is evaluated through the accuracy of the motion trajectories extracted from the reconstructed 4DCBCT images. The evaluation is focused on the dependence of their performance on two important technical factors in 4DCBCT: the data acquisition time and the number of respiratory phase bins.

Methods and materials

The hybrid digital phantom

A hybrid digital phantom (figure 1) was used to provide realistic chest anatomy as well as the ground truth of the motion trajectory. A CT dataset of a human chest scan was used to simulate the anatomical background, and an ellipsoid was placed inside the left lung cavity of the CT volume to simulate a tumor. The ellipsoid was a sphere of 10 mm in diameter in its home position, and moved and deformed simultaneously during the scan. Its motion was implemented by changing the location of its centroid, and its deformation by changing the lengths of its semi-axes. Both the motion and the deformation of the sphere followed a realistic breathing motion model (Lujan *et al* 1999). The motion of the ellipsoid can be expressed as

$$\begin{aligned}x(t) &= x_0 + A_x \cos^{2n}(\pi t/T - \phi), \\y(t) &= y_0 + A_y \cos^{2n}(\pi t/T - \phi), \\z(t) &= z_0 + A_z \cos^{2n}(\pi t/T - \phi),\end{aligned}\tag{1}$$

where x , y and z are the locations of the ellipsoid in three dimensions, and x_0 , y_0 and z_0 are the corresponding initial values. A_x , A_y and A_z are the motion amplitudes in x -, y - and z -directions, respectively. T is the motion period, ϕ is the phase offset, and n is the order of the cosine function. The deformation of the ellipsoid can be similarly expressed as

$$\begin{aligned}a(t) &= a_0 - A_a \cos^{2n}(\pi t/T - \phi), \\b(t) &= b_0 - A_b \cos^{2n}(\pi t/T - \phi), \\c(t) &= c_0 + A_c \cos^{2n}(\pi t/T - \phi),\end{aligned}\tag{2}$$

where a , b and c are the semi-axis lengths of the ellipsoid in three dimensions, and a_0 , b_0 and c_0 are the corresponding initial values. A_a , A_b and A_c are the amplitudes of the changes in semi-axis lengths of a , b and c , respectively. The parameters used in this study are listed in table 1.

The simulated CBCT scans

Cone beam projection data for the hybrid digital phantom were calculated by superimposing the analytical projection data of the moving ellipsoid to the simulated projection data of the chest CT volume using Siddon's ray tracing algorithm (Siddon 1985). The source-to-isocenter distance was 100 cm, and the source-to-detector distance was 150 cm. The detector was a 512×384 matrix of $40 \text{ cm} \times 30 \text{ cm}$ in size. Statistical noise was introduced to the projection data according to a Poisson model, with the incident photon fluence of 3.3×10^4 per mm^2 .

CBCT scans with gantry rotation times from 1 min to 4 min, in 1 min intervals, are numerically simulated. Assuming a detector readout speed of ten frames per second, 600, 1200, 1800, and 2400 projection views were simulated for scans with rotation times of 1, 2, 3 and 4 min, respectively. For each of the simulated scans, the projection data were sorted into 5, 10 and 20 phase bins, and image reconstruction was performed for each of these phase bins using different reconstruction algorithms.

Note that two detector setup schemes are common for CBCT used in IGRT practice. One is the 'full-fan' mode, in which the detector is symmetrically placed with respect to the center of the field of view (FOV). The other setup is the 'half-fan' mode, in which the detector is displaced toward one side. The half-fan setup is to enlarge the FOV to avoid truncation artifacts in the reconstructed images, which would occur for the full-fan setup when an adult patient is scanned. Both schemes have been used in 4DCBCT investigations. For a full-fan

setup, a strategy to address the truncation problem was to fill in the missing projection measurements (usually corresponding to the peripheral anatomy) based on prior knowledge such as a planning CT. In this paper, the performance of different 4DCBCT methods was studied and evaluated for both detector setup schemes. For the full-fan setup, perfect knowledge of the missing measurements was assumed, which is equivalent to using a sufficiently large detector.

The image reconstruction algorithms

In FBP-based 4DCBCT image reconstruction, the standard FDK algorithm (Feldkamp *et al* 1984), which is an extension of the FBP algorithm to the cone beam case, is used to reconstruct each phase.

MB-4DCBCT uses the MB algorithm (McKinnon and Bates 1981, Leng *et al* 2008a, Zheng *et al* 2011) for image reconstruction for each phase bin. A time averaged image is first reconstructed from all projection views by FDK, and a new projection dataset is generated by forward projecting this time-averaged image at exactly the same view angles as the original scan. Within each phase bin, two images are reconstructed by the FDK algorithm: one is from the original projection data and the other from the new projection data. By subtracting the latter image from the former, a difference image is obtained and then added to the time-averaged image to generate the final reconstructed image for each phase bin.

In the PICCS (Chen *et al* 2008, Leng *et al* 2008b) algorithm, an image is reconstructed by solving the following constrained optimization problem:

$$\min_I (\alpha \|\Psi_1(I - I_p)\|_1 + (1 - \alpha) \|\Psi_2(I)\|_1), s.t. AI = P. \quad (3)$$

In PICCS-4DCBCT, I is the target image to be reconstructed for a phase bin, P is the measured projection data sorted into the corresponding phase bin and I_p is a prior image reconstructed from all the projection views (the FDK algorithm was used in this study). Ψ_1 and Ψ_2 are sparsifying transforms, and the discrete gradient transform was used for both of them in this paper. $\|\cdot\|_1$ is the l_1 -norm of a vectorized image, which is the summation of absolute values from all image pixels.

The minimization of $\|\Psi_1(I - I_p)\|_1$ enforces the similarity between the target image I and the prior image I_p , and serves to transfer the high SNR of I_p to I . Since I_p usually contains motion induced artifacts, the term $\|\Psi_2(I)\|_1$ was introduced to suppress those artifacts by minimizing the variations in I . α is a weighting factor, between 0 and 1, to balance the contributions of the two minimization terms. α was selected as 0.6 for all PICCS reconstructions in this paper. The constraint term, $AI = P$, is to ensure data consistency between the target image and the measured projection data within a respiratory phase bin (A is the system matrix with each element describing the intersection length between an image pixel and a given x-ray path). Applying this constraint will encode the temporal information of the phase bin into the reconstructed image.

The constrained minimization problem was solved in two alternating steps until convergence. The first is to apply the simultaneous algebraic reconstruction technique (SART) to approximately satisfy the $AI = P$ constraint. In the second step, the objective function $\alpha \|\Psi_1(I - I_p)\|_1 + (1 - \alpha) \|\Psi_2(I)\|_1$ is minimized using the gradient descent method.

Motion trajectory extraction using deformable registration

From the reconstructed 4DCBCT images, the motion trajectory of an object of interest can be extracted using a deformable registration algorithm. Instead of a rigid registration

method, a deformable registration is desirable in tumor motion trajectory extraction due to the fact that tumors and organs may change their shapes during motion. To extract the tumor motion trajectory, a two-step procedure was used in this paper: (1) at each respiratory phase, deformable registration is applied to calculate the motion vector for every voxel in the 4DCBCT image with respect to each 4DCBCT image at a given respiratory phase to one at a preselected reference phase, e.g., the 0% phase in this study and (2) the tumor motion trajectory is obtained by tracking the motion vectors of the tumor centroid from each respiratory phase.

Many deformable registration methods have been proposed in recent years (Horn and Schunck 1981, Thirion 1998, Lu *et al* 2004, Modersitzki 2004, Brock *et al* 2005, Wang *et al* 2005, Kessler 2006). In this work, a fast free-form deformable registration algorithm via calculus of variations (Lu *et al* 2004, 2006) was used. In this algorithm, the registration between a target image R and the template image T is accomplished by minimizing the objective function defined as

$$F(\vec{u}) = \int_{\Omega} (R(\vec{x} + \vec{u}) - T(\vec{x}))^2 d\vec{x} + \lambda \int_{\Omega} \|\nabla \vec{u}\|^2 d\vec{x}, \quad (4)$$

where $\vec{x}$ is a vector representing the location of a voxel and $\vec{u}$ is the displacement vector of the voxel. The first term of this objective function measures the dissimilarity between the two images after the motion field is applied, and the second regularizes the smoothness of the motion field. λ is a weighting parameter to control the relative contributions of these two components.

In this paper, the deformable registration was applied to a sub-volume of $64 \times 64 \times 64$ voxel³ surrounding the tumor. The sub-volume is large enough to include the tumor at all phases. The pixel values were linearly normalized to between 0 and 1 before registration. A multi-resolution approach (Lu *et al* 2004, Zhang *et al* 2007) with five resolution levels was taken to accelerate the convergence of the registration. Since the reconstructed images from different methods for different simulated cases have different streaking artifact levels, the choice of λ is customized such that the calculated motion field results in the highest accuracy in motion quantification. It is expected that more weight needs to be put on the smoothness constraint, i.e. a larger λ needs to be used, to achieve the lowest quantification error when more streaking artifacts are present in images. In this paper, λ values are chosen as follows: 0.03 for MB- and PICCS-4DCBCT images and 0.1 for FBP-4DCBCT images. This empirical choice of λ values for different cases was found out to give close to optimal performances in quantifying motion trajectory accuracy.

Evaluation of the accuracy of the extracted motion trajectory

The accuracy of the extracted motion trajectories is evaluated with respect to the ground truth. First, the root mean square error (RMSE) of a motion trajectory is calculated according to the following equation:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (d_i - \bar{d}_i)^2}, \quad (5)$$

where N is the number of phase bins, d_i is the calculated average displacement of the moving object for the i th phase bin, and $\bar{d}_i$ is the true displacement at the center of the same phase bin. The RMSEs are calculated for all three directions. Second, the maximum of the RMSEs along the x -, y - and z -directions, $\text{RMSE}_{\max}$, is used to describe how much the extracted tumor motion deviates from the truth. Since streaking artifact appearance is

strongly dependent on the location with the image and the surrounding anatomy, the motion quantification errors may distribute anisotropically among x -, y - and z -directions. Hence $\text{RMSE}_{\max}$, which highlights the direction component with the largest quantification error, is used as the evaluation metric to assess the performance of the three 4DCBCT methods in different cases.

Results

Evaluation of 4DCBCT images reconstructed by different methods

Figures 2–4 show 4DCBCT images reconstructed around 30% respiratory phase by the FBP, MB and PICCS algorithms when different data acquisition times and numbers of phase bins are used. The voxel size of all reconstructed images is $0.75 \times 0.75 \times 0.75 \text{ mm}^3$. For 4DCBCT images using 5, 10 and 20 phase bins, the selected phase bins shown are [20%, 40%], [20%, 30%] and [25%, 30%], respectively. The ground truth images corresponding to the mid-phase of each selected phase bin are also shown in these figures for comparison.

FBP reconstructed images show the most pronounced streaking artifacts. As presented in figure 2, increasing data acquisition time effectively reduces streaking artifacts in FBP images. MB reconstructed images (figure 3) show considerably reduced streaking artifacts compared with FBP reconstructed ones. The residual streaking artifacts also become less visible as the data acquisition time increases. PICCS reconstructed images, as presented in figure 4, are nearly identical, regardless of the data acquisition time and the number of phase bins. In other words, a 1 min data acquisition time is sufficient for PICCS to reconstruct artifact-free images.

The effect of the number of phase bins on temporal resolution can be easily observed in figures 2–4. The best visualization of this effect comes from the coronal view. Using only five phase bins, the tumor becomes blurred and its shape is distorted compared with ground truth. The blurring and distortion becomes hardly noticeable when 10 or 20 phase bins are used. This effect is independent of the reconstruction algorithm, because the phase bin width is determined in the projection sorting procedure before reconstruction. These observations demonstrate that (1) temporal resolution is crucial in tumor motion imaging and (2) ten or more phase bins are necessary for faithful tumor characterization while it is moving.

Evaluation of motion trajectory accuracy

Extracted motion trajectories of tumor centroid for all simulated cases by different methods are plotted in figures 5–7. These trajectories are from simulated 4DCBCT scans using the full fan setup. The results for the half fan setup are not shown here because of the similarity. The three individual motion components, x , y and z , are plotted separately in these three figures. The ground truth for each phase bin is the programmed tumor motion at the center of that phase bin.

The effect of the number of phase bins on temporal resolution is again observed in these plots. The use of five phase bins provides few sampling points to characterize tumor motion. The large width of these phase bins may lead to systematically biased tumor motion quantification at some phases. For example, the motion in the middle phase bin is always underestimated no matter how long the data acquisition time is. In addition, the use of too few sampling points also results in unstable derivation of a continuous motion trajectory. This is because the corruption of any sampling points may generate large errors in the derived trajectory.

The general trend in three individual motion components with respect to data acquisition time is very similar: for a given number of phase bins, longer gantry rotation time enables

more accurate extraction of motion trajectories. For a given gantry rotation time, motion trajectories from the FBP reconstruction are more inaccurate, while the PICCS reconstruction yields the best results. The MB motion trajectories are much better than the FBP trajectories while they are inferior to the PICCS trajectories.

A cross comparison of FBP-, MB- and PICCS-4DCBCT methods is made by plotting the $RMSE_{max}$ values in figures 8 and 9. Since it has been demonstrated that the use of 5 phase bins is insufficient to provide acceptable tumor definition and motion delineation, only 10 and 20 phase bin cases are included in these plots. Figure 8 shows results from using the full fan setup, and figure 9 shows those from using the half fan setup. The error bars in the plots come from $RMSE_{max}$ measurements for each pixel of a $3 \times 3 \times 3$ pixel³ ROI centered at the tumor centroid.

For each of the three methods, longer data acquisition time results in more accurate tumor motion trajectories. To achieve a certain level of accuracy in motion characterization, different methods require different minimal gantry rotation times. In figure 8 where the full fan setup is used, FBP-4DCBCT reaches the smallest $RMSE_{max}$ (≈ 0.5 mm, $2/3$ of the pixel size, marked by the dashed line) when the data acquisition is 4 min. To reach the same or higher level of accuracy, MB-4DCBCT needs about a 2 min data acquisition time and PICCS-4DCBCT needs about 1 min. As the detector setup scheme changes from ‘full fan’ to half fan, increases in $RMSE_{max}$ values are observed for most data points; however, the relative performances of the three different methods remain unchanged: the minimal $RMSE_{max}$ (≈ 0.75 mm, the size of a single pixel, marked by the dashed line) FBP-4DCBCT achieves using 4 min acquisition can be achieved by MB- and PICCS-4DCBCT using 2 and 1 min acquisition times, respectively. In other words, the relative performances of FBP-, MB- and PICCS-4DCBCT methods are independent of the detector setup scheme.

Conclusions

In conclusion, the performances of three different 4DCBCT methods were studied. The results demonstrate that (1) longer acquisition time results in more accurate motion delineation for each method; (2) ten or more phase bins are necessary in 4DCBCT to ensure sufficient temporal resolution in tumor motion, and (3) 2- and 1 min data acquisition times are sufficient for MB- and PICCS-4DCBCT, respectively, to achieve equivalent or better performance compared to FBP-4DCBCT with a 4 min data acquisition time. However, more clinical studies will be needed to fully demonstrate the potential clinical utility of the 4DCBCT.

Acknowledgments

The work was partially supported by the National Institutes of Health through grant R01EB009699 and Varian Medical Systems. The authors would like to thank Joseph Zambelli and Nicholas Bevins for their editorial assistance in preparation of this manuscript.

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Figure 1.

Hybrid digital phantom used in this study, in which an elliptical object is added into the left lung cavity of a human chest CT data set. (a) Axial view of the phantom at 0% phase. (b, c) Coronal views of the phantom at 0% and 50% phase, respectively. (d) Periodic model used to define the motion and deformation of the tumor-simulating object.

Figure 2. FBP-4DCBCT images using different acquisition times and numbers of phase bins. (a, b) Axial slices and coronal slices, respectively. Column 1–3: 5, 10 and 20 phase bins, respectively. Row 1–4: 1, 2, 3 and 4 min data acquisition times, respectively. The bottom row shows the ground truth. The display window is $[-0.005, 0.03] \text{ mm}^{-1}$.

Figure 3. MB-4DCBCT images using different acquisition times and numbers of phase bins. (a, b) Axial slices and coronal slices, respectively. Column 1–3: 5, 10 and 20 phase bins, respectively. Row 1–4: 1, 2, 3 and 4 min data acquisition times, respectively. The bottom row shows the ground truth. The display window is $[-0.005, 0.03] \text{ mm}^{-1}$.

Figure 4. PICCS-4DCBCT images using different acquisition times and numbers of phase bins. (a, b) Axial slices and coronal slices, respectively. Column 1–3: 5, 10 and 20 phase bins, respectively. Row 1–4: 1, 2, 3 and 4 min data acquisition times, respectively. The bottom row shows the ground truth. The display window is $[-0.005, 0.03] \text{ mm}^{-1}$.

Figure 5. Plots of x -motion trajectories of the tumor centroid using different acquisition times and numbers of phase bins.

Figure 6. Plots of y -motion trajectories of the tumor centroid using different acquisition times and numbers of phase bins.

Figure 7.
Plots of z-motion trajectories of the tumor centroid using different acquisition times and numbers of phase bins.

Figure 8. $RMSE_{max}$ plots of the extracted motion trajectories from 4DCBCT images obtained by different methods. The 'full-fan' setup is used here. (a, b) Use 10 and 20 phase bins, respectively.

Figure 9. $RMSE_{max}$ plots of the extracted motion trajectories from 4DCBCT images obtained by different methods. The 'half-fan' setup is used here. (a, b) Use 10 and 20 phase bins, respectively.

Table 1

Parameters used for equations (1) and (2).

T (s)	ϕ	n	A _x	A _y	A _z	A _a	A _b	A _c
4 s	$\pi/2$	2	5 mm	5 mm	10 mm	0.75 mm	0.75 mm	1.5 mm