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Marker-free lung tumour trajectory estimation from a cone beam CT sinogram

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Abstract

An algorithm was developed to estimate the 3D lung tumour position using the projection data forming a cone beam CT sinogram and a template registration method. A pre-existing respiration-correlated CT image was used to generate templates of the target, which were then registered to the individual cone beam CT projections, and estimates of the target position were made for each projection. The registration search region was constrained based on knowledge of the mean tumour position during the cone beam CT scan acquisition. Several template registration algorithms were compared, including correlation coefficient and robust methods such as block correlation, robust correlation coefficient, and robust gradient correlation. Robust registration metrics were found to be less sensitive to occlusions such as overlying tissue and the treatment couch. Mean accuracy of the position estimation was 1.4 mm in phantom with a robust registration algorithm. In two research subjects with peripheral tumours, the mean position and mean target excursion were estimated to within 2.0 mm compared to the results obtained with a '4D' registration of 4D image volumes.

1. Introduction

Motion of an intended radiotherapy target due to respiration can have detrimental consequences for both planning and delivery of treatment. Geometric error in delivery due to target motion can be managed with a variety of methods including the addition of margins (van Herk *et al.*, 2000), gating or tracking the beam (Giraud *et al.*, 2006; Keall *et al.*, 2006; Shirato *et al.*, 2000), patient breath hold (Hanley *et al.*, 1999; Wong *et al.*, 1999), or modulating the beam fluence to compensate for the motion pattern (Chan *et al.*, 2006; Heath *et al.*, 2009; Trofimov *et al.*, 2005; Zhang *et al.*, 2008). All of these methods require knowledge of the target motion pattern prior to planning and during delivery to insure the delivery is accurately localized to the target and to verify the fidelity of the planned treatment to variations in the anatomy or target motion. For example, drift of the target during a fraction (Guckenberger *et al.*, 2007) or an increase in the target motion (Sonke *et al.*, 2008) could detrimentally affect a margin-based management strategy if the margins are not built to account for these changes. Gating or tracking the beam requires target localization at a much higher frequency during delivery (Keall *et al.*, 2006) to localize the target. Probabilistic treatment planning methods, even those robust to variations in the target motion pattern, will likely still need verification of the target motion at some frequency.

Onboard cone beam CT (CBCT) has enabled localization of static soft-tissue targets. For respiration-influenced targets, respiration-correlated CBCT has been developed (Sonke *et al.*, 2005). Respiration-correlated CBCT, similar to other respiration-correlated imaging,

relies on the assumption of a stationary, periodic respiration pattern. Deviations from this assumption may introduce artefacts into respiration correlated CT methods (Yamamoto *et al.*, 2008). Furthermore, respiration-correlated CBCT consists of a set of static CT images representing a single respiration cycle, and therefore cannot adequately capture non-stationary motion, such as drift of the target, or cycle-to-cycle variation in the respiration pattern.

The ability to accurately measure non-stationary or non-periodic respiration would be useful in constructing more accurate patient models for adaptive and probabilistic treatment planning. As respiration-correlated CT does not provide a means to measure these types of motion, interest has arisen in other online modalities. Several groups have developed methods for stereoscopic tracking of fiducials implanted in or near the target (Schweikard *et al.*, 2004; Shirato *et al.*, 2000). While these methods are capable of resolving instantaneous 3D motion, the requirement of multiple, fixed imaging systems to implement them has led to the development of other approaches. The monoscopic, gantry-mounted kilovoltage system used by several vendors for onboard CBCT has been adapted for position estimation (Adamson and Wu, 2008, 2009; Marchant *et al.*, 2008; Poulsen *et al.*, 2008a; Poulsen *et al.*, 2008b). In this approach, implanted fiducials are tracked in each projection as the kilovoltage imaging system is rotated around the patient, forming a partial or full CBCT sinogram. 3D position of the fiducials was estimated from the measured (2D) positions in the projection set using maximum likelihood estimation (Poulsen *et al.*, 2008a) and shortest path approximation (Adamson and Wu, 2008). While these methods are capable of constructing a 3D target position estimation, they require fiducial markers for operation. Methods for marker-free target tracking have been developed by Berbeco *et al.* (Berbeco *et al.*, 2005) and Cui *et al.* (Cui *et al.*, 2008), but these studies have been limited to fluoroscopic tracking at a fixed imaging geometry.

The purpose of this study is to develop and evaluate a system for detecting the 2D position of a target structure without fiducial markers in each projection of a CBCT sinogram, and using this information to estimate the instantaneous 3D trajectory of the structure during the scan acquisition. After a description of the general system, the main studies of this paper are presented, which were designed to evaluate and select the optimal algorithms for template registration and trajectory regularization. Both phantom and clinical data were used for this purpose.

2. Methods and materials

2.1. Method for estimating the target trajectory

The general method for estimating the 3D target position trajectory requires a number of separate modules, as shown in figure 1. A brief overview of the process follows, with a detailed explanation of each module below. An existing 4D patient model is used to generate digitally reconstructed radiographs (DRRs) in the imaging system geometry to serve as templates for a 2D/2D registration. For each projection, a template is selected and a 2D/2D registration is performed to estimate the rigid shift in the target position at the time of projection acquisition, from that in the 4D model. The translated target position in the projection coordinate system is backprojected to estimate the 3D target position in the room coordinate system, as described in detail below. The 3D target position trajectory consists of the estimated per-projection target position as a function of the projection acquisition time.

The patient model consists of the individual phase images from a respiration-correlated CT (RCCT) acquisition, which we assume will be a diagnostic-quality image, as from a CT simulator. In this study, we used a phase-sorted RCCT binned into ten phases, with the first phase representing end of inhalation. The target structure to be tracked is delineated on each

individual phase image, and a mask is applied to each image such that only the target structure (plus a small margin of 5 mm) is visible on any generated DRRs. Thus, at any projection angle, ten DRRs containing an image of only the delineated target at each phase of respiration are produced.

To limit the required registration search space and to provide an initial estimate of the mean position of the target, the reconstructed 3D CBCT scan was rigidly registered to the RCCT using the method described in Hugo et al. (Hugo *et al.*, 2007). Briefly, we constructed the average CT from the RCCT, registered this average CT to the 3D CBCT, and recorded the resulting translation vector as the mean position of the target in the CBCT, which we will denote as $\mathbf{p}_m$. It is assumed here without loss of generality, for simplicity, that the planning isocenter is defined at the mean position of the target centroids for all phases on the RCCT. Prior to DRR generation, all phase images of the RCCT are shifted by $\mathbf{p}_m$ (by shifting the planning isocenter by $-\mathbf{p}_m$) so that the target in the RCCT resides at the daily mean position of the target in the CBCT. Once DRRs are generated, this initial translation will place the target in the DRRs closer to the target in the CBCT projections by removing the mean daily offset of the target.

Figure 2 shows the imaging and room coordinate systems used here. Point coordinates in the room coordinate system will be denoted as $\mathbf{p}$, with components x , y , and z . Points in the imaging coordinate system will be denoted as $\mathbf{p}'$, with components u , v , and w . Note that the origins of both coordinate systems are located at the rotational isocenter of the imaging system, so that in the imaging coordinate system points on the detector plane have a positive w coordinate equal to SDD-SAD. For DRR generation, the planning isocenter is placed at the origin of the room coordinate system. DRRs were generated over the full 360-degree scan range for each of the ten phases of the RCCT. Generating DRRs at the exact projection angles would require 6000–7000 DRRs. Instead, we generated DRRs spaced five degrees apart, for a total of 720 DRRs. In this case, the maximum angular offset between a projection and a template would be 2.5 degrees. Assuming that the target is no more than 2 cm from the imaging isocenter prior to CBCT imaging, the maximum error induced by this angular discrepancy would be 0.8 mm. In cases with the target offset from the imaging isocenter by more than 2 cm, the error could be easily corrected by applying a correction based on the sine of the difference between the DRR angle and the projection angle, or DRRs could be generated at the actual projection angles.

An in-house application using a graphics processing unit (nVidia GeForce 6200) was used to generate the DRRs. The 3D target centroid $\mathbf{p}_c(\varphi)$ as a function of respiration phase φ was also projected onto the detector plane, and the corresponding detector coordinates were recorded as $\mathbf{p}_c'(\varphi)$. The 3D target centroids $\mathbf{p}_c(\varphi)$ were determined from the same delineation used for mask generation.

Rather than trying to detect the 3D target position directly in the CBCT projection, the target trajectory algorithm is based on estimating the offset in $\mathbf{p}_c(\varphi)$ for each CBCT projection. This task is accomplished by first estimating the per-projection offset of $\mathbf{p}_c'(\varphi)$ in the detector plane using 2D/2D template registration

$$\mathbf{p}_d'(\varphi) = \mathbf{p}_c'(\varphi) + \Delta \mathbf{p}'(\varphi) \quad (1)$$

where $\Delta \mathbf{p}'(\varphi)$ is the centroid offset measured in the detector plane and $\mathbf{p}_d'(\varphi)$ is the estimated target centroid position during the CBCT projection acquisition. Then, $\mathbf{p}_d'(\varphi)$ is transformed to $\mathbf{p}_d(\varphi)$ using

$$\begin{pmatrix} u \\ v \\ w \end{pmatrix} = \begin{pmatrix} \frac{SDD[x \cdot \cos(\theta) - y \cdot \sin(\theta)]}{\frac{SAD-d}{z \cdot SDD}} \\ \frac{SAD-d}{SDD-d} \end{pmatrix} \quad (2)$$

where u and v are the estimated centroid positions in the detector plane, w is the detector plane position, d is the estimated depth of the target centroid (from isocenter) normal to the detector plane, and θ is the projection angle.

One key issue is that template registration will only provide the location of $\mathbf{p}_d(\varphi)$ in the detector plane (with a w coordinate equal to $SDD-SAD$). In order to generate an accurate transformation to $\mathbf{p}_d(\varphi)$, the actual depth d must be known. If the point to be localized is stationary or moving in a periodic manner, it would be possible to use two orthogonal projections to estimate $\mathbf{p}_d(\varphi)$. However, as we are intending to track possibly non-stationary and non-periodic motion, this assumption is not valid. Instead, equation 1 is used to calculate d_m from the estimated mean position $\mathbf{p}_m$. Using d_m instead of the actual d to calculate $\mathbf{p}_d(\varphi)$ will introduce error in the xy plane parallel to the projection direction. The 3D position estimate perpendicular to the imaging plane is simply the depth estimate d_m , so error in this estimate will propagate to the 3D position estimate at certain angles. Thus, the x position and y position estimates will not be correct at certain projection angles. However, xy motion will only impact the depth estimate if the motion varies by a large amount from the prior measured motion in the RCCT, since the location of the target in the phase image is used as the starting point for registration, and could be used as the starting point for depth estimate if the xy motion was large. Such high variability from the prior estimate is unlikely, and thus was not considered here. Error will be also introduced indirectly parallel to the imaging plane and in the z direction due to the influence of d on the magnification as shown in equation 2. Assuming a maximum error between d and d_m of 1 cm, an SAD of 100 cm, and an SDD of 150 cm, the maximum error in $\mathbf{p}_d(\varphi)$ parallel to the detector plane would be 0.15% of the distance of the point in the uv plane from the origin of the detector. For a large field of view of radius 20 cm, the maximum error would be 0.3 mm.

The accuracy of template registration with four different similarity metrics was evaluated. Normalized cross correlation (NCC) was initially implemented as the similarity metric for template registration. NCC is based on the assumption that, once corrected for the mean intensity, the distributions of intensity are most correlated between two images that are most similar. However, occlusions inside the patient such as overlying tissue (ribs, spine, diaphragm) or outside the patient such as the treatment table may interfere with the correlation (Kim and Fessler, 2004). To evaluate and counteract this effect, we developed a new registration metric which here we will call ‘block normalized cross-correlation’ (BCC). Briefly, BCC divides the overlap region between the template and test image into subregions, or blocks (figure 3). Each block is individually normalized and the NCC for each individual block is calculated. Essentially, BCC acts as a kind of high-pass filter before NCC. Blocks of 10×10 pixels in size were found to achieve best results. For overlap regions that were not integer multiples of 10 pixels, the last row and column of blocks was the size of the remainder. From the set of correlation coefficients for all blocks, the mean NCC is calculated. This mean NCC is then used as the similarity metric for BCC-based template registration.

Additionally, two robust correlation metrics, fast robust correlation coefficient (Fitch *et al.*, 2005) and robust gradient correlation (Fitch *et al.*, 2002) were also implemented as similarity metrics. Robust correlation coefficient-based (RCC) registration is based on a similar hypothesis as that supporting BCC-based registration: Underlying image features

will have locally high correlation, but occlusions will introduce outliers in the correlation distribution. Robust correlation methods are designed to reduce the effect of such outliers on the similarity metric. Robust gradient correlation (RGC) also uses a robust correlation coefficient for similarity, but computes the robust correlation of the gradient image. First, the finite differences along and across each image (test and template) are computed to estimate the local gradients in the image. Then, complex numbers are used to represent the magnitude and direction of the gradient image at each pixel in each image, termed the complex finite difference of the image. Finally, the RCC of the resulting gradient maps is calculated.

Previously, multiple templates spanning the range of breathing phases have been used to aid in phase correlation and gating (Berbeco *et al.*, 2005; Cui *et al.*, 2007). Here we perform an analogous, but inverse, procedure to select a single template based on the estimated breathing phase in order to limit the required number of template registrations for each projection. The respiration phase during each projection acquisition was estimated by detecting the location of the diaphragm apex in the z direction for each projection, constructing a phase-time plot diagram, and binning each projection into one of ten phases following a method described by Sonke *et al.* (Sonke *et al.*, 2005). This process was performed using in-house software.

2.2. Phantom evaluation

An oscillating phantom was constructed using a positioning stage with an acrylic platform for radiographic transparency, and a 5 cm diameter rubber sphere with an 1 cm diameter hollow cylinder through the centre was mounted to the platform for use as a target object. The stage was oscillated in the z direction only, in a sawtooth pattern with a peak to trough excursion of 2 cm and a period of 12 s (the period of motion was limited by the maximum velocity of the positioning stage). A planning RCCT scan was acquired on a CT simulator (Brilliance Big Bore, Philips Healthcare, Andover, MA, USA) and reconstructed into ten phases. The sphere was delineated on each phase image volume using an automatic thresholding technique in a research version of a treatment planning system (Pinnacle v8.1t, Philips Healthcare, Andover, MA, USA). Two CBCT scans were acquired on a Synergy accelerator (Elekta Oncology Systems, Crawley, UK). For the first scan, the phantom was nominally shifted 1 cm in x , y , and z . The target object was localized while stationary with a conventional CBCT scan, then the target object was oscillated with the same motion pattern, excursion, and period as during RCCT acquisition. The target-tracking algorithm described above was used to measure the target centroid trajectory. For the second scan, the phantom was kept in the same offset position as for the first scan. The phantom was set oscillating with the same motion shape, an excursion of 3 cm, and a period of 12 s. Another CBCT was acquired, and the target trajectory was estimated from this scan.

To estimate the accuracy of target centroid trajectory detection, the detected target trajectories were compared to the nominal motion patterns. The nominal motion pattern was constructed by recording the encoder position of the motion platform during scan acquisition, and verified by manual observation using the CBCT system in fluoroscopic mode after the CBCT acquisition was completed. Absolute target position detection error distributions were calculated by taking the absolute value of the difference between the measured and nominal target centroid 3D positions for each projection.

2.3. Clinical data evaluation

The target trajectory estimation process was evaluated on two clinical CBCT scans, each from a different patient with a T2 non-small cell lung cancer lesion (figure 4). Subject 1 had a 24 cc left lower lobe lesion. 701 projections were acquired over 128 s for Subject 1.

Subject 2 had a 31.8 cc right lower lobe lesion, and the available scan was 702 projections over 128 s. Nominal trajectory data was not available for either patient scan. Therefore, a respiration-correlated CBCT scan was reconstructed and registered to an RCCT scan acquired for planning purposes following the method of Hugo et al. (Hugo *et al.*, 2007). Briefly, the CBCT scan was sorted into ten phase bins using the phase sorting algorithm described above and reconstructed into ten phase images. The target in each phase image was rigidly registered to a reference phase (end inhalation) to produce a target trajectory during CBCT acquisition. To determine the offset of the mean position, the reference phase from CBCT was registered to the reference phase from the RCCT. From this mean offset, the offset of each individual phase was computed to produce the mean target trajectory during CBCT acquisition.

The resulting target trajectory from this respiration-correlated registration was used as a reference trajectory for comparison. Breathing variations during CBCT acquisition result in blurring and consistency artefacts in the reconstructed phase images. It is difficult to decompose these variations from the phase images themselves. Because of this, the target trajectory obtained from respiration-correlated registration approximates the mean trajectory over the entire CBCT acquisition, averaged over the breathing variations. As the detected trajectory measures breathing variation directly, rather than averaging over it, the detected target trajectory and this reference trajectory cannot be directly compared as for the phantom study. To compare the reference trajectory to the detected target trajectory, the detected trajectory was sorted by respiration phase into ten phase bins using the already-described algorithm. The mean position of the target centroid for each phase was calculated to produce a mean trajectory. The mean excursion (mean difference between the mean end inhalation and mean end exhalation target centroid positions) was calculated. This mean excursion was compared to that obtained from the respiration-correlated registration.

3. Results and discussion

3.1. Phantom evaluation

Figure 5 shows a lateral and an anterior projection of the phantom; a) the unregistered DRR and CBCT projection from the end of inspiration phase, b) same DRR and projection once the correction by p_m has been applied, c) same DRR and projection once registration has been performed. Note that if the measured offset $\Delta p'$ is zero, the resulting target trajectory would be the centroid position trajectory $p_c(\varphi)$, shifted by p_m , the measured mean target position during the scan. This trajectory would occur (given no measurement error) only if the target shape remained the same from fraction to fraction, and if the motion pattern exactly matched that during planning with no variation in amplitude and shape, and no drift during the scan acquisition. Thus, the offset $\Delta p'$ only represents deviations due to non-periodicity, non-stationary drift, and measurement error, and therefore should be a relatively small magnitude in relation to the mean target position offset p_m and the periodic amplitude of breathing, constraining the template registration spatially which should improve the accuracy of the algorithm.

Figure 6 shows the nominal target trajectory and detected trajectory in the z (cranio-caudal) direction for the phantom when the position of the target has been shifted by 1 cm and with the same motion pattern during RCCT and CBCT. Figure 7 shows box plots of the absolute position detection error for this scan for all template registration algorithms. The BCC registration algorithm was most accurate overall for this scan, with median absolute error (90% confidence level) of 0.8 (1.8), 0.9 (2.7), and 1.4 (3.2) mm in x , y , and z , respectively, for this scan. In the x direction, 90% of the projections had an absolute error of less than 2.4 mm for NCC and 2.0 mm for the other algorithms. In the y direction, the 90% level was 8.2 mm for NCC and 2.7 to 4.8 mm for the robust algorithms. The phantom was not moving in

the xy plane for this scan; the substantial difference in detection error between the x and y directions can be explained by occlusions in the CBCT projection images. When trying to resolve position in the y direction, lateral CBCT projections were used. These projections often contained occlusions such as the treatment couch and the motion platform itself (see figure 5, for example), contributing to reduced detection accuracy. Robust algorithms, as the results demonstrate, were more adept at reducing the effect of such occlusions on detection accuracy.

Figure 8 shows the absolute detection error for the second phantom scan, where the motion pattern was changed by increasing the excursion from 2 cm to 3 cm, for all template-matching algorithms. Absolute error distributions for this test scan were similar to those for the first test scan (without a motion pattern change). The BCC algorithm was again most accurate overall, although the NCC algorithm produced the most accurate detection in the z direction. For this scan, the NCC algorithm mean absolute error (90% error level) was 1.3 (2.8) mm in x , 1.2 (8.1) mm in y , and 1.2 (2.2) mm in z . For BCC, the mean absolute error was 0.8 (1.9) mm in x , 1.0 (2.6) mm in y , and 1.2 (3.0) mm in z . Robust algorithms produced less frequent large errors in comparison to the NCC algorithm (as demonstrated by a reduction in the 90% error level) in the xy -direction, although not in the direction of motion (z direction).

3.2. Clinical data evaluation

Figure 9 shows a measured projection and a masked template at one view angle for Subject 2. Figure 10 shows the detected target centroid trajectory in the z direction for the first research subject CBCT scan. The ‘nominal’ mean end exhalation and mean end inhalation positions (from the respiration-correlated registration) are also shown. For the two research subject cases, the difference in mean trajectory from the respiration-correlated registration results are presented in table 1. Only the NCC, BCC, and RCC results are listed, as the results for RGC were similar to those for RCC. The results demonstrate that the trajectory detection algorithm was able to determine the mean target centroid position and excursion to within 3.0 mm of the values calculated using a ‘4D’ respiration-correlated registration technique. Furthermore, one of the robust algorithms was able to determine the target position and excursion within 2.0 mm, although the robust algorithm producing this result was not consistent between the two subjects.

4. Discussion

Eventually, the goal of developing this system is to use this trajectory information to complement the corresponding 3D CBCT image acquisition for use in probabilistic or adaptive treatment planning development and verification. While processes are being developed to enable adaptive replanning for variations in respiration-induced motion over the treatment course, it is not yet well understood what magnitudes and types of variations occur, and how to optimally correct for them. Sonke et al., Britton et al. and others have evaluated changes in the respiration pattern and mean tumour position over the course of treatment using 4DCT and 4DCBCT (Britton *et al.*, 2007; Sonke *et al.*, 2008). However, these imaging modalities cannot be directly used to evaluate the effect of intrafraction changes such as cycle to cycle variation in respiration amplitude and pattern, temporal drifting (‘trending’) of the tumour position, or transient effects such as coughing, as a trajectory tracking algorithm can. The combination of trajectory tracking and 4DCBCT analysis could provide such complementary data for an analysis of the effect of all of these types of respiration variation.

The algorithm and study as designed has some limitations that need to be discussed. Depth estimation was simplistic, relying on the estimate of p_m . As described above, this process

could introduce some error into 3D position estimation. Other methods of depth estimation are available, as implemented independently by Adamson and Poulsen (Adamson and Wu, 2008; Poulsen *et al.*, 2008a). DRR template generation separately for each CBCT acquisition is time-consuming, even with our optimized GPU-based algorithm. To counteract this, we are implementing offline template generation and an online per-template shift based on the estimate of p_m . Only cranio-caudal motion was evaluated in phantom. Significant lateral or anterior-posterior motion may impact the trajectory detection accuracy, but we were unable to evaluate this possibility in this study due to mechanical limitations of the motion platform. Finally, this algorithm relies on the assumption that the tumour shape is static from fraction to fraction and has sufficient contrast for template registration. Our analysis with clinical data here demonstrates this assumption is acceptable for peripheral lesions. However, adjustments to the algorithm will most likely be required for central lesions and nodal targets, including conditioning of the registration with a predictive filter and possible use of anatomical surrogates.

Marker-less trajectory tracking of the tumour could be used to guide real-time tumour tracking during therapy, particularly during arc therapy, or for implementing a tumour trailing strategy (Trofimov *et al.*, 2008). However, the current algorithm was not designed with this purpose in mind and would require several modifications to be useful for online, near real-time operation. In the current algorithm, p_m is estimated from the reconstructed CBCT corresponding to the projections used for tracking. An estimate of p_m prior to CBCT acquisition would need to be made, either from a prior CBCT during the same fraction, or by some other estimator. DRR template generation would need to be performed offline and templates quickly adjusted for each CBCT acquisition, as described above. Finally, the code would need to be optimized for speed of operation and the system integrated into a CBCT acquisition system such that projections were immediately available for processing as they were acquired.

5. Conclusions

An algorithm for extraction of the target position centroid from a set of CBCT projections was developed and evaluated in phantom and in two clinical research subjects with peripheral tumors. Template registration search regions were constrained through estimation of the mean centroid position and a prior estimate of tumour excursion from a planning RCCT. Occlusions such as the treatment table and overlying tissue were found to produce error for a standard template registration algorithm. Robust template registration reduced the frequency of large errors, although the mean accuracy of the algorithm remained similar. The target position trajectory was estimated with a mean accuracy of 1.4 mm in phantom. With clinical data, the algorithm estimated the mean position and excursion to within 2.0 mm of that obtained from a full '4D' registration.

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Figure 1.
Schematic of the target trajectory estimation algorithm.

Figure 2.

Coordinate systems of the CBCT imaging equipment used in this study. The kilovoltage source position ('Source' in the figure) rotates in the xy plane, with the z direction corresponding to the patient cranio-caudal axis, with positive z pointing away from the linac gantry. The uvw coordinate system is fixed to the imaging system, and rotates with the source and detector. The xyz coordinate system is the world coordinate system and is stationary.

Figure 3.

Illustration of BCC algorithm. The template and test image are overlaid (left). The overlap region is divided into 10×10 pixel blocks, and NCC is computed independently for each block. Finally, the mean NCC over all blocks is calculated. The process is repeated for each overlaid pose of the test and template images.

Figure 4.
(Top) Axial and coronal images for Subject 1, end inhalation phase from the pRCCT.
(Bottom) Axial and coronal images for Subject 2. The tumor is demarcated by the yellow arrows.

Figure 5.

DRR templates (green) and CBCT projections (magenta) of the phantom used for trajectory evaluation studies. The top row of the figure shows a projection along the y axis (anterior/posterior axis) and the bottom row is a projection along the x axis (lateral axis). The leftmost panel shows the target object in the DRR templates in the planned position and in the CBCT projections offset by 1 cm in x , y , and z . In the middle panel, the DRR templates have been generated with the offset $\mathbf{p}_m$ applied, shifting the templates to match the mean position of the object during CBCT acquisition. Notice that application of this estimated mean position offset reduces the search area for the registration. In the rightmost panel, the template and projection have been registered using the RCC algorithm.

Figure 6. Nominal trajectory (solid) and detected trajectory (dashed) in the z direction for the phantom scan with the same amplitude during planning and CBCT acquisition, using the RCC algorithm.

Figure 7.

Box plots of position detection error, all registration algorithms, for the phantom scan with the same amplitude during planning and CBCT acquisition. Boxes show the upper and lower quartile and median. Whiskers show the 10th and 90th percentile error.

Figure 8.

Box plots of position detection error, all registration algorithms, for the phantom scan with the change in amplitude from 2 cm during planning to 3 cm during CBCT acquisition. Boxes show the upper and lower quartile and median. Whiskers show the 10th and 90th percentile error.

Figure 9. Measured projection for Subject 2 (left). The arrow shows the location of the tumor. Masked tumor template at the same view angle (right).

Figure 10.

Estimated target position in the z direction for an example research subject. The estimated trajectory is shown in black. The mean end exhalation position from the '4D' respiration-correlated registration is shown in red, and the mean end inhalation position is shown in dotted green.

Difference in mean target centroid position and mean target excursion, trajectory detection algorithm vs. respiration-correlated registration.

Table 1

Subject	Algorithm	Difference, mean position (mm)			Difference, mean excursion (mm)		
		x	y	z	x	y	z
1	NCC	-2.4	0.3	0.5	-0.2	0.4	3.0
1	BCC	-2.3	0.6	1.9	0.2	1.4	2.9
1	RCC	-0.6	0.1	-0.1	0.1	0.7	1.6
2	NCC	0.8	1.9	-0.9	-0.6	-0.6	3.1
2	BCC	0.3	2.0	0.2	-0.8	-0.1	1.9
2	RCC	1.4	3.2	1.7	-1.4	-1.1	2.6