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Reconstructing Cone-beam CT with Spatially Varying Qualities for Adaptive Radiotherapy, a Proof-of-Principle Study¹

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Abstract

With the aim of maximally reducing imaging dose while meeting requirements for adaptive radiation therapy (ART), we propose in this paper a new cone beam CT (CBCT) acquisition and reconstruction method that delivers images with a low noise level inside a region of interest (ROI) and a relatively high noise level outside the ROI. The acquired projection images include two groups: densely sampled projections at a low exposure with a large field of view (FOV) and sparsely sampled projections at a high exposure with a small FOV corresponding to the ROI. A new algorithm combining the conventional filtered back-projection algorithm and the tight-frame iterative reconstruction algorithm is also designed to reconstruct the CBCT based on these projection data. We have validated our method on a simulated head-and-neck (HN) patient case, a semi-real experiment conducted on a HN cancer patient under a full-fan scan mode, as well as a Catphan phantom under a half-fan scan mode. Relative root-mean-square errors (RRMSE) of less than 3% for the entire image and ~1% within the ROI compared to the ground truth have been observed. These numbers demonstrate the ability of our proposed method to reconstruct high-quality images inside the ROI. As for the part outside ROI, although the images are relatively noisy, it can still provide sufficient information for radiation dose calculations in ART. Dose distributions calculated on our CBCT image and on a standard CBCT image are in agreement, with a mean relative difference of 0.082% inside the ROI and 0.038% outside the ROI. Compared with the standard clinical CBCT scheme, an imaging dose reduction of approximately 3–6 times inside the ROI was achieved, as well as an 8 times outside the ROI. Regarding computational efficiency, it takes 1–3 min to reconstruct a CBCT image depending on the number of projections used. These results indicate that the proposed method has the potential for application in ART.

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1. Introduction

Cone-beam computed tomography (CBCT) (Jaffray *et al.*, 1999; Jaffray *et al.*, 2002) has become one of the most valuable tools in image guided radiation therapy (IGRT). At present, it is widely employed to visualize patient's anatomy prior to a treatment for treatment set-up purposes. Its gain in terms of setup accuracy has been recognized (Chang *et al.*, 2007; van Kranen *et al.*, 2009; Wang *et al.*, 2009; Topolnjak *et al.*, 2010; Jiang *et al.*, 2012). Recently, along with the great desire of realizing adaptive radiotherapy (ART) (Yan *et al.*, 1997), more advanced utilizations of CBCT have also been proposed. For instance, delivered dose could be reconstructed on the daily CBCT geometry, which is further accumulated to a reference geometry, yielding a total delivered dose to date to assess the needs of treatment adaptations in the remaining treatment fractions (Wen *et al.*, 2007; Lee *et al.*, 2008; Dipasquale *et al.*, 2013; Bosse *et al.*, 2014). The available patient anatomy on the day of treatment also serves as a basis for online ART, where a treatment plan could be developed based on it in order to maintain plan optimality despite inter-fraction anatomy variations (Wu *et al.*, 2008; Vestergaard *et al.*, 2013; Otto and Mestrovic, 2014).

Nonetheless, excessive imaging dose from repeated uses of CBCT has become a clinical concern. This fact has limited the frequency of CBCT in current practice, e.g. only once per week, as well as the scope of CBCT, e.g. only to adult patients. Even in some scenarios where CBCT dose is not a limiting factor, it is still desirable to reduce the imaging dose due to the ALARA (As Low As Reasonably Achievable) principle. For these reasons, much research has been conducted focusing on developing novel CBCT reconstruction algorithms to retrieve high quality CBCT images based on projection data acquired at a low exposure level (mAs per projection) and/or reduced number of projections. Regularization methods have been utilized to maintain image quality and suppress artifacts, such as total variation and its variants (Sidky *et al.*, 2006; Song *et al.*, 2007; Sidky and Pan, 2008; Tang *et al.*, 2009; Bian *et al.*, 2010; Jia *et al.*, 2010b; Choi *et al.*, 2010; Defrise *et al.*, 2011; Ritschl *et al.*, 2011; Tian *et al.*, 2011), tight frame (Jia *et al.*, 2010a; Yan *et al.*, 2012), soft-thresholding (Yu and Wang, 2009, 2010), dictionary-based methods (Xu *et al.*, 2012; Lu *et al.*, 2012), and prior image-based methods (Chen *et al.*, 2008a; Lee *et al.*, 2012; Yan *et al.*, 2013). Although these novel approaches have demonstrated a great potential to substantially reduce radiation doses to patients, technical difficulties, such as high computational burdens, still prevent them from clinical practice.

Another possible way of reducing imaging dose is to collimate x-ray beams to acquire projection data for only a particular region of interest (ROI) and to reconstruct the image inside the ROI. Since the standard Feldkamp-Davis-Kress (FDK) reconstruction algorithm (Feldkamp *et al.*, 1984) leads to truncation artifacts under this circumstance, great efforts have been made over the years to improve image quality in this so-called interior tomography problem. Examples include interchanging the orders of back-projection and differential operators (Noo *et al.*, 2004; Zou *et al.*, 2005; Pan *et al.*, 2005; Tang *et al.*, 2006; Yu *et al.*, 2007; Cho *et al.*, 2008; Dennerlein and Maier, 2013), extrapolating truncated projection data (Rajgopal and Anoop, 2006), borrowing prior information to ensure the uniqueness of the solution (Ye *et al.*, 2007; Yu *et al.*, 2008; Courdurier *et al.*, 2008; Kudo *et al.*, 2008) or taking advantages of compressed sensing approaches (Yu and Wang, 2009).

Nonetheless, reconstructing the image inside ROI alone cannot meet the requirements of radiotherapy, particularly in ART. Although the tumor area can be visualized in an ROI image, other anatomy landmarks cannot, which are usually required as well to help patient positioning. The limited size of the ROI poses an even more severe problem for ART, as the missing anatomy outside the ROI makes it impossible to perform radiation dose calculations for dose assessments and treatment replanning.

With the aim of maximally reducing imaging dose while meeting the needs of radiotherapy, we propose in this paper a new CBCT method that yields a volumetric image with a spatially varying image quality. High image quality with a low noise level is achieved inside a circular ROI, which will fulfill the purpose of tumor visualization in the patient-positioning stage. The region outside the ROI has a relatively high noise level, but still contains full patient anatomy, which facilitates treatment setup and radiation dose calculations. A new scheme for projection data acquisition, along with a reconstruction algorithm, is proposed to achieve this new CBCT method.

2. Methods and Materials

2.1 Method

2.1.1 Scan protocol—The proposed CBCT method utilizes a scan protocol that acquires two groups of x-ray projections with different mAs levels and x-ray collimations depending on projection angles. It is our objective to reconstruct a CBCT image based on the two groups of measurements that has a high quality inside the ROI and a relatively low quality, specifically a high noise level, outside the ROI. As such, in the first group (P1), a number of N_1 projections are acquired equally spaced in an angular range needed for the reconstruction, e.g. 364 projections are equally distributed over a 200° range in a full-fan mode. These projections are taken under a low mAs level per projection and without collimating the x-ray source. Because of the large field of view (FOV), these projections are sufficient to generate a CBCT image without truncation, while the image noise is relatively high due to the low mAs used. The purpose of acquiring these projections is to yield a relatively reasonable estimation of the CBCT image outside the ROI with a minimal amount of imaging dose. In the second group (P2), a number of $N_2 < N_1$ projections are also acquired at sparsely located projection angles equally spaced in the scan range. They are associated with a relatively high mAs level. The x-ray source is collimated to a small FOV according to the ROI. These projections, after correction for the truncation issue based on the CBCT outside the ROI reconstructed using data in P1, will be sufficient for the reconstruction of the CBCT inside the ROI. Sparsely acquired projections at N_2 directions are used, as opposed to at densely placed angles, since we would like to maximally reduce the imaging dose. This scan protocol is illustrated in Fig. 1.

2.1.2 Reconstruction method—Along with the acquired projection data, we propose the following CBCT reconstruction algorithm as shown in Fig. 2, which consists of the following 6 steps. (1) The dense acquired projections from P1 are reconstructed via the conventional FDK type algorithm (Feldkamp *et al.*, 1984) for simplicity, yielding a noisy overview of the whole CBCT image. (2) The reconstructed image is then split into two spatially disjoint parts, namely inside the ROI and outside the ROI. (3) The image outside

the ROI is forward projected using a digital reconstructed radiograph (DRR) algorithm (Folkerts *et al.*, 2013) along the projection angles where the P2 projections are acquired. (4) The forward projection data is subtracted from the measured data acquired in P2. This step effectively removes contributions in the projection images from the CBCT volume outside the ROI, and the results are x-ray projections for the CBCT inside the ROI only. Note that a relatively noisy CBCT reconstructed using low-mAs projections is utilized to calculate the forward projections. This may lead to inaccuracy in the calculated forward projections. Yet, it is our assumption that the line integral in the forward projection calculations can effectively reduce noise in the calculated projections. (5) Based on the corrected projection data at a set of sparsely located angles, a volumetric image inside the ROI is reconstructed via our in-house developed, tight-frame (TF)-based iterative CBCT reconstruction algorithm (Jia *et al.*, 2010a). In this method, a patient volumetric image can be obtained by solving an optimization problem $f = \operatorname{argmin}_f |Pf - y|^2 + \mu J_{TF}(f)$. Here P and y are projection operator and projection data, respectively. J_{TF} is the TF regularization term, which ensures the sparsity of the image under a TF transform, an overcomplete wavelet-based transform. μ is a tuning parameter which controls the regularization term. In principle, a lower μ pushes for a more stringent agreement between the projection data and the reconstructed image, which can help reveal finer image details but can also lead to amplified noise. On the other hand, a higher μ can effectively promote image smoothness at the cost of blurring high-spatial-frequency details. This optimization problem is solved via an iterative algorithm. (6) Finally, the noisy image outside the ROI and the high-quality ROI image are combined to produce the final volumetric image.

Step 4 relies on the accuracy of the forward projection estimation based on the noisy CBCT image outside the ROI. We would like to comment on this assumption. For a projection ray line, the projection value $p = \int_L f(x)dl$, where $f(x)$ is the CBCT image. Once there is noise on $f(x)$, the impact on the projection value is $\delta p = \int_L \delta f(x)dl$. Hence, the mean value $E[\delta p] = \int_L E[\delta f(x)]dl = 0$ due to the zero mean value of the noise. Assuming there is no spatial correlation of the image noise, i.e. $E[\delta f(x) \delta f(y)] = \sigma(x)^2 \delta(x - y)$, it follows that $E[\delta p^2] = \int_L \sigma(x)^2 dl$. Therefore, the standard deviation of the projection

$\sigma_p = \sqrt{E[\delta p^2] - E[\delta p]^2} = \sqrt{\int_L \sigma(x)^2 dl} \sim \sqrt{L}$, where L is the length of the integral. Since the projection value $p = \int_L f(x)dl \sim L$, the relative error of the estimated projection value

$\frac{\sigma_p}{p} \sim 1/\sqrt{L}$. While both the error and the projection value increase after the projection, the latter increases faster, making the relative error small.

In our study, all the components for this reconstruction algorithm have been implemented on a computer graphics processing unit (GPU) platform, which has been demonstrated previously to improve the computational efficiency of CBCT image reconstructions (Xu and Mueller, 2005, 2007; Li *et al.*, 2007; Sharp *et al.*, 2007; Yan *et al.*, 2008; Jia *et al.*, 2010a; Jia *et al.*, 2014).

2.2 Validation studies

2.2.1 Test cases—In this proof-of-principle study, our method was tested in a set of cases at different levels of realism. In all cases, the voxel resolution is $512 \times 512 \times 70$ with a voxel

size of $0.05 \times 0.05 \times 0.2 \text{ cm}^3$. The ROI is a cylindrical area around the isocenter with a radius of 3–4 cm. First, a head-and-neck (HN) cancer patient case was studied via simulations. The x-ray projections were generated in a full-fan scan range of 200 degrees in a realistic manner using Monte Carlo (MC) simulation (Jia *et al.*, 2011). The projection numbers for the two groups of P1 and P2 are $N_1 = 364$ and $N_2 = 60$, respectively. The mAs levels for the two scans are 0.05 and 0.4 mAs/projection. Second, a semi-real experiment was conducted on a HN cancer patient case. 364 regular CBCT projections with a scan angle range of about 200 degrees were acquired on an on-board imaging system mounted on a Varian Trilogy linear accelerator (Varian Medical System, Inc., Palo Alto, CA) under a full-fan mode with a standard protocol of 0.4mAs/projection. Sixty equally spaced x-ray projections were extracted and only the part of each projection corresponding to a small FOV was further selected, to mimic the data acquisition under P2. Noise was then added to those 364 regular CBCT projections to mimic the projection acquired under P1. Lastly, a real experiment was performed on a Catphan phantom (Phantom Laboratory, Inc., Salem, NY) in the Varian on-board imaging system. Two separate scans were conducted to acquire the two groups of projection data P1 and P2. Both scans were performed in a half-fan mode with projections acquired in a 360-degree range. For P1, $N_1 = 676$ and 0.05mAs/projection were used. As for P2, $N_2 = 170$ and 0.4mAs/projection were used and the x-ray blades were set at appropriate locations according to the ROI to collimate the source.

To compare our approach with others, we also conducted studies using projection data acquired or simulated under other protocols. Scan Protocol 1 (SP1) refers to the scans with the standard setting used in the current clinic, e.g. 0.4 mAs/projection for both the HN cases and 1.04mAs/projection for the half-fan cases. The x-ray source was not collimated and the projections were acquired at 364 angles in a 200-degree range for the HN cases as well as for the semi-real experiment, and at 676 angles in a full rotation for the half-fan case. Applying the FDK algorithm to these data yields high-quality images with a low noise level. SP2 is conducted with low exposure level of 0.05 mAs per projection. Other parameters are the same as those in SP1. These data lead to noisy CBCT images due to the amplified noise levels in the projections.

2.2.2 Evaluations—Our method was evaluated from multiple aspects, beginning with image quality. In addition to visually inspecting the reconstructed images, we also quantified reconstruction accuracy using relative root mean square error (RRMSE), which is defined as $RRMSE = \|f - f^{ref}\|_2 / \|f^{ref}\|_2$, where f represent the evaluation image and f^{ref} is the ground truth image reconstructed from SP1 by the FDK method. The RRMSE values inside the ROI, outside the ROI, as well as for the whole image are reported.

Second, we evaluated the image dose reduction achieved by our method. Since dose reduction is expected to be spatially non-uniform due to the use of collimated x-ray projections in some of the projection measurements, we computed the imaging dose using our in-house-developed GPU-based Monte Carlo dose calculation engine (Jia *et al.*, 2012; Montanari *et al.*, 2014) to give a clear understanding of the dose distribution under our method.

Third, since one of the motivations of developing this new CBCT method was to reconstruct a non-truncated volumetric image for radiation calculations in ART, we also demonstrate that the resulting image can meet this goal. Specifically, we selected an intensity modulated radiation therapy (IMRT) treatment plan for a HN cancer patient case, which was designed on a planning CT. We first rigid registered the CBCT image reconstructed by the FDK method using the protocol SP1 and the planning CT, and recomputed the plan dose on the CBCT image using a finite-size pencil beam algorithm with 3D density corrections (Gu *et al.*, 2009; Gu *et al.*, 2011). This mimics the process of calculating delivered dose on a daily patient geometry (Wen *et al.*, 2007; Kan *et al.*, 2008; Ding and Coffey, 2009; Huang *et al.*, 2011; Block *et al.*, 2012; Stanic *et al.*, 2012; Liu *et al.*, 2013). The resulting dose distribution is regarded as the ground truth. We then computed the same plan dose but in the CBCT image reconstructed by our method and compared the resulting dose distribution with the ground truth one. Visual inspections of the dose distributions and dose volume histograms (DVHs) of key organs were used to evaluate their agreement. Quantitative measures, e.g. the difference of dose distributions between our CBCT image and the ground truth one were also calculated. All the computations in this step were conducted in our research platform Supercomputing Online Re-planning Environment (SCORE) which employs GPU for high computational efficiency (Gautier *et al.*, 2013).

Lastly, we report computation time of the reconstruction. Since the workflow shown in Fig. 2 has multiple components, we report the computation time for each of the key components, as well as the total time.

3. Results

3.1 Image quality

Results of the MC-simulated HN case are shown in Fig. 3. First of all, even though the data extrapolation is taken into consideration, truncation artifacts are still obvious in the FDK-based ROI image under SP1 (Fig. 3(b)). In contrast, our proposed method is able to reconstruct a high quality image inside the ROI that is free of truncation artifacts (Fig. 3(a)). It is visually also very close to the ground truth image. As for the image outside the ROI, our result is noisy as expected (Fig. 3(d)). The entire image has a spatially varying quality, as opposed to the uniform quality of conventional approaches (Fig. 3(e)–(f)). Fig. 4 shows the results of the semi-real experiment conducted on a HN cancer patient case in one transverse slice. Similar image quality to that in the previous case has been achieved.

As for the Catphan experiment, we have shown both the resolution and contrast slices in Fig. 5. When comparing the results of our method against the CBCT image reconstructed by the FDK algorithm under the low-dose scan SP2, the line pairs are much more distinguishable and are comparable to that of the SP1 high dose scan. Profiles of five line pairs are shown. For the contrast slice shown on the second row, we have also zoomed in to the ROI region. Due to the large amount of noise in SP2, the dotted structure indicated by the arrow is hardly visible. In contrast, its visibility is maintained to a good degree in our method as well as in SP1.

To quantify the reconstruction accuracy in our study, we computed the RRMSE for our method. It was found that our CBCT image attains an RRMSE of 2.42%, 2.61% and 2.89% for the MC-simulated HN case, the semi-real experiment and the Catphan experiment, respectively, over the entire image region. The RRMSE in the ROI region is 0.98%, 1.03% and 1.13% for the three cases, while those for the outside part are 4.36%, 4.68% and 5.47%. These numbers clearly demonstrate the agreement of the image inside the ROI with the ground truth.

3.2 Imaging dose

We have calculated the imaging dose using our GPU-based MC dose calculation code, gCTD (Jia *et al.*, 2012), on the MC-simulated HN patient case and the experimental Catphan case. The results are shown in Fig. 6. Compared with the dose in our proposed method, the dose in SP1 is much higher. Dose profiles for both cases (Fig. 6(i), (j)) are also used to illustrate the dose reduction. The profiles of step 1 and step 2 represent the doses under P1 and P2, respectively. By adding these two together, we can find the total imaging dose delivered by using the proposed CBCT method. As for the MC-simulated HN case, compared with the clinical standard scheme SP1 (Fig. 6(d)), the dose is reduced by approximately 6 times inside the ROI and up to 8 times outside the ROI. As for the half-fan case, 170 projection data were used in P2 for the reconstruction of the ROI. This led to a focused dose in the ROI area as indicated in Fig. 6(f). In this case, a dose reduction of about 3 times and 8 times was achieved inside and outside the ROI, respectively.

3.3 Radiation dose calculations

Radiation dose calculations were performed in our SCORE research platform using a finite-size pencil beam algorithm with 3D density correction (Gu *et al.*, 2009; Gu *et al.*, 2011). Distribution maps of radiation dose D calculated on our CBCT images are shown in Fig. 7(a)–(c). The dose values have been normalized by the prescription dose of the plan D_p . This dose distribution agrees well with D_{ref} , the one computed on the CBCT image under the SP1 high-dose scan, as indicated by the difference images in Fig. 7(d)–(f). Quantitatively, we computed the relative dose difference $\langle D - D_{ref} \rangle / D_p$, where $\langle . \rangle$ indicates a spatial average of voxels. It was found that the difference is 0.082% inside the ROI, and 0.038% outside the ROI. Throughout the whole image, the 95-percentile dose difference is 0.0093%. Those voxels with relatively large dose differences (>5%) are found in the air cavity due to the noisy image in these areas and the high sensitivity of dose values in the low-density region. However, they are not of clinical importance. To demonstrate the gain of the proposed method, we also compared D_{SP2} , the dose distribution calculated on the CBCT image under the SP2 low-dose scan, with D_{ref} . The difference images are displayed in Fig. 7(g)–(i). The relative dose difference $\langle D_{SP2} - D_{ref} \rangle / D_p$ is also computed. In this case, the difference is 0.302% inside the ROI, and 0.0495% outside the ROI. Throughout the whole image, the 95-percentile dose difference is 0.0294%. Furthermore, the DVH curves of PTV, brain stem, spinal cord, and brain for the three dose distributions are also compared in Fig. 7(j). While DVH curves for our CBCT agree well with those for the scan SP1, there is an apparent difference between the curves for SP1 and those for SP2. These results demonstrate that even though the image outside the ROI is noisy, it has a negligible effect on dose calculations.

3.4 Computation time

The total computation time is ~50 seconds for the case with a resolution $512 \times 512 \times 70$ under full-fan scanning mode and less than 3 minutes for the case under the half-fan scanning mode. Specifically, the time spent on the FDK reconstruction, forward projection calculation, and TF reconstruction are shown in Table 1, and time on other steps are negligible. The computation time for the TF step depends on many factors. Some apparent factors are the projection number, projection resolution, and volumetric image resolution, as they directly impact the size of the optimization problem to be solved. For the cases reported here, the variance of time is mainly ascribed to the number of projections (60 for the HN case and 170 for the Catphan case). In addition, the required time is also affected by the regularization parameter. Inappropriate regularization parameters may give fast convergence but fine structures may be lost in the resulting images. Therefore, to ensure quality, the parameters for each case have been manually tuned and the computation time here corresponds to these manually tuned parameter values.

4. Discussion and Conclusions

In this paper, we have proposed a new CBCT imaging method, aiming at maximally reducing imaging dose yet meeting requirements for ART purposes. CBCT images with high quality inside a ROI and relatively low quality outside the ROI can be obtained. We have validated our method on a simulated HN patient case, a semi-real experiment conducted on a HN cancer patient case under a full-fan scan mode, as well as a Catphan phantom under a half-fan scan mode. RRMSEs of less than 3% for the entire image and ~1% within the ROI compared to the ground truth have been observed. These numbers demonstrate the ability of our proposed method to reconstruct high-quality images inside a ROI. As for the part outside the ROI, although the images are relatively noisy, it can still provide sufficient information for radiation dose calculations, as demonstrated in our studies. Compared with the standard clinical CBCT scheme, the imaging dose from our scheme is reduced greatly. An approximate 3–6 times dose reduction has been achieved inside the ROI and 8 times outside the ROI. Regarding computational efficiency, it takes 1–3 min to reconstruct the image depending on the number of projections used. These results indicate that the proposed method is suitable for applications in ART.

Due to hardware limitations, in the real experimental studies with the Catphan phantom, we conducted two scans to acquire the two groups of projection data. Recent advances in the developer mode of the Varian TrueBeam System (Varian Medical System, Palo Alto, CA) allow us to perform one scan to acquire all the projections needed. As such, we have actually designed an XML file to control the CBCT scan process, which acquires all projections in one gantry rotation. As such, projections in P1 are continuously taken as if in a standard CBCT scan. The gantry stops at a few beam angles to acquire projections in P2. The x-ray blades move to the designed positions before a projection in P2 is taken and move back to continue to the data acquisition for P1. Exposure levels at each projection are also programmed to the designed level. The data acquisition process is fully automatic, which demonstrates the feasibility of our method to a certain extent. However, due to the slow x-ray blade motion, there exists many time intervals in which the x-ray source is turned off

while waiting for the blades to move. Hence the scan time is prolonged to ~5 min, much longer than the current CBCT scan time of 1 min. In addition, since the lowest exposure level on the Varian TrueBeam system is 0.1 mAs per projection, we did not observe too much difference in terms of image quality inside the ROI and outside in our CBCT, or a gain in terms of dose reduction. Hence, we continued to use the data acquired by a Varian Trilogy machine under double scans in our experimental studies.

One limitation of our method is the required geometry accuracy. In fact, due to two scans involved in our method, geometry accuracy is extremely important for the success of our algorithm. In real experiments, we found that artifacts may be introduced by geometrical inaccuracy. For instance, our method relies on the gantry angle information when generating forward projections. There existed a slight inconsistency between the angle values recorded in the projections and the actual ones, possibly due to hardware gantry wobbling. Hence, the forward projections were calculated to slightly incorrect directions. As a consequence, the slice-thickness wire indicated by the arrow in Fig. 5(d) is tilted, which should actually be vertical as in Fig. 5(f). While the ultimate solution would be to improve CBCT hardware so that all the geometrical information used in the reconstruction is sufficiently accurate, there are also other possible solutions. For instance, we may perform a search for the actual gantry angle in the neighborhood of the recorded gantry angle by matching some obvious structure (e.g. edges) in the calculated DRR with those in the measured ones. However, that will inevitably increase the computational time. Alternatively, if the angle inconsistency is reproducible, another approach is to perform an accurate geometry calibration to obtain mapping between the recorded and the actual gantry angles.

As iterative reconstruction is involved in our scheme, there exists a practical challenge regarding parameter selection. For the TF algorithm, there is only one parameter that affects the image quality, namely the threshold for TF wavelet coefficient. We have manually selected this parameter in each case to yield the best image quality. Similar to other iterative algorithms, the parameter here is case-dependent. A potential solution to this problem could be incorporating a parameter adjustment in the iteration process, in which the algorithm assesses image quality repeatedly and makes adjustments on the parameter values to guide the reconstruction process.

Our method is actually a combination of multiple CBCT dose reduction methods in order to maximally reduce image dose while meeting the requirements of radiotherapy. The reconstruction of a noisy portion outside the ROI provides a simple way to overcome the truncation issue encountered in the interior tomography problem (Yu and Wang, 2009, 2010). It also offers anatomical information needed for dose calculations and patient setup. Inside the ROI, the reconstruction is achieved via our TF algorithm. It is expected that other types of iterative algorithms that can handle sparse-view reconstruction problems, e.g. TV-based ones, can also be used. We also noticed that there is current research on fluence field modulation in CBCT, which has the potential to yield a CBCT image of a prescribed spatially varying image quality while using only the minimally necessary amount of radiation exposure to the patient (Bartolac *et al.*, 2011; Szczykutowicz and Mistretta, 2014; Bartolac, 2014; Graham *et al.*, 2007). However, currently it is still challenging to achieve this in practice due to hardware limitations. Our proposed scheme can be regarded as a

special case of this approach, where high beam fluence is delivered for the ROI with a sparse set of beam angles. While this is a simplified version of the fluence modulation idea, it is practical as demonstrated by our studies. There are also other ways to achieve fluence modulation, e.g. using a nonuniform filter in front of the beam (Cho *et al.*, 2009; Chen *et al.*, 2008b) or using linearly combined projection measurements acquired in two scans (Kolditz *et al.*, 2010). Compared to these methods, our work utilizes sparsely acquired projections for the ROI, which further reduces imaging doses. Using an iterative reconstruction algorithm on a small ROI also makes the computation time acceptable. However, a method with a nonuniform filter (Cho *et al.*, 2009; Chen *et al.*, 2008b) allows data acquisition in a single scan and avoids issues such as the geometry mismatch encountered in our method.

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Figure 1.

Illustrations of x-ray projection acquisitions in our CBCT method. (a) P1: a projection with low mAs and uncollimated beam; (b) P2: a projection with high mAs and collimated beam; (c) Combination of the two groups of projections.

Figure 2.

Workflow of the proposed reconstruction method. Shaded boxes are data along the workflow.

Figure 3.

One transverse slice of the reconstructed images for the MC-simulated HN patient case. (a) ROI image reconstructed by our method. (b) ROI image reconstructed by FDK under SP1, and (c) the ROI reference image; (d) our complete CBCT image; (e) and (f) are the complete CBCT images reconstructed by the FDK algorithm under SP2 and SP1, respectively. Display window $[-162, 1234]$ HU.

Figure 4.

One transverse slice of the semi-real experiment conducted on a HN cancer patient case. (a) is our CBCT image; (b) and (c) are CBCT images reconstructed by FDK algorithm under SP2 and SP1, respectively. Display window $[-832, 1234]$ HU.

Figure 5.

Two transverse slices of the reconstructed images for the Catphan phantom. (a)-(c) are the resolution slice of our CBCT, CBCT image reconstructed by FDK under SP2, and the reference image under SP1, respectively. Display window $[-162, 955]$ HU. Profiles of 5 line pairs (marked) are also shown. (d)-(f) are the contrast slice. Display window $[173, 397]$ HU. The inserts show the zoom-in views around the ROI.

Figure 6.

The imaging dose results for the MC simulated HN patient case ((a)–(d)) and the experimental Catphan case ((e)–(h)). (a)(e) imaging dose for P1; (b)(f) imaging dose for P2; (c)(g) imaging dose for P1+P2; (d)(h) imaging dose for SP1. (i) and (j) are dose profiles comparison along a horizontal cut shown in the figure for the MC simulated HN patient case and the experimental Catphan case, respectively.

Figure 7. Radiation dose results on a HN cancer patient case. (a)–(c) are the dose distribution calculated on our CBCT images shown in a transverse view, a coronal view and a sagittal view, respectively. Color bar is in the unit of prescription dose. (d)–(f) are the difference between doses on our CBCT image and those on the CBCT image under a high-dose scan SP1. (g)–(i) are the difference between doses on our CBCT image and those on the CBCT image under a low-dose scan SP2. (j) shows the DVH curves of PTV, brain stem, spinal cord and brain corresponding to doses computed in the three CBCTs. The insert shows a zoom-in view.

Table 1

Computation time of the proposed method.

<i>Calculation Time (s)</i>	<i>FDK</i>	<i>DRR</i>	<i>TF</i>	<i>Total</i>
<i>Case</i>				
Simulated HN	3.8	1.0	44.2	50.8
Catphan	5.2	2.4	130.3	141.4