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An Inter-Projection Interpolation (IPI) Approach with Geometric Model Restriction to Reduce Image Dose in Cone Beam CT (CBCT)

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Abstract

Cone beam computed tomography (CBCT) imaging is a key step in image guided radiation therapy (IGRT) to improve tumor targeting. The quality and imaging dose of CBCT are two important factors. However, X-ray scatter in the large cone beam field usually induces image artifacts and degrades the image quality for CBCT. A synchronized moving grid (SMOG) approach has recently been proposed to resolve this issue and shows great promise. However, the SMOG technique requires two projections in the same gantry angle to obtain full information due to signal blockage by the grid. This study aims to develop an inter-projection interpolation (IPI) method to estimate the blocked image information. This approach will require only one projection in each gantry angle, thus reducing the scan time and patient dose. IPI is also potentially suitable for sparse-view CBCT reconstruction to reduce the imaging dose. To be compared with other state-of-the-art spatial interpolation (called inpainting) methods in terms of signal-to-noise ratio (SNR) on a Catphan and head phantoms, IPI increases SNR from 15.3dB and 12.7dB to 29.0dB and 28.1dB, respectively. The SNR of IPI on sparse-view CBCT reconstruction can achieve from 28dB to 17dB for undersample projection sets with gantry angle interval varying from 1 to 3 degrees for both phantoms.

Keywords

Scatter correction; Dose reduction; CBCT; SMOG; Moving grids; Interpolation; Geometric model

1 Introduction

In recent years, on board cone beam computed tomography (CBCT) has been developed as an important imaging modality in image guided radiation therapy (IGRT) [1]. In IGRT, CBCT is performed before radiation delivery with a patient holding a treatment position similar to the position when the simulation/planning computed tomography (CT) was taken

[2]. The CBCT image is then registered with the simulation CT, and the patient's treatment position is adjusted and aligned according to the registration to ensure a precise radiation dose delivery [3]. The image quality of CBCT is critical, especially for cancer treatments requiring high accurate dose delivery. Also, the imaging dose is another important factor due to the frequent CBCT scans because radiation therapy usually requires 30–40 fractions of treatments.

Unfortunately, CBCT image quality is largely degraded by scatter artifacts because a large volume of the imaging object is irradiated for each projection [4]. Many approaches have been proposed to reduce the scatter artifacts and improve the CBCT image quality. Among them, the synchronized moving grid (SMOG) [5,6] is one of the most promising techniques. The SMOG approach utilizes a grid to divide the large cone beam field into multiple small narrow strips, and thus reduce the amount of scatter. In addition, the remaining scatter can be measured and thus be corrected by the shadow regions blocked by the grid. However, the imaging information in these shadow regions is also blocked by the grid (Fig. 1(b) and Fig. 2(b)). The SMOG approach resolves this issue by acquiring two complementary projections at each gantry angle (a linear accelerator is mounted on the gantry and the gantry angle is the rotation angle of the gantry) to obtain full information by shifting the grid a proper distance before taking the second projection. The SMOG approach may also potentially reduce the image lag-induced artifacts [5]. However, the SMOG approach is technically challenging since it requires a fast moving grid, especially for fast gantry rotation. More importantly, the CBCT control system needs to be redesigned completely with a capacity of taking at least two projections at the same gantry angle. This may increase the scan time and dose due to the limitation of the frame rate of the flat panel imager.

This study aims to derive the blocked information without taking an additional projection; thus, it may also reduce the imaging dose by half. Approaches based on total variance (TV) [7] have been proposed, but usually these TV-based methods are time-consuming due to iteratively repeated projection calculations. An efficient method would be interpolation. The interpolation process is called image inpainting which is used in the field of computer vision for old picture repairing. The inpainting technique could be roughly classified into several groups: 1) texture synthesis-based [8], 2) partial differential equation (PDE)-based [9], 3) exemplar-based [10] and 4) hybrid [11]. Texture synthesis-based inpainting uses similar unblocked neighbourhoods of the blocked pixels to synthesize the missing texture in blocked regions. PDE-based inpainting iteratively perfuses and propagates the information of unblocked pixels at the border of blocked regions in the direction of minimal change using 'isophote lines'. Exemplar-based inpainting selects the most similar patches from unblocked regions and pastes them back to blocked regions. Hybrid-based inpainting is a combination of the above methods. Although the inpainting starts to be used in fan-beam CT reconstruction [12], most of the above methods lack CBCT imaging geometric model restrictions. Thus, these inpainting results are very hard to validate and some artifacts are generated, as shown in the Results section. Generally, it is impossible to recover complete information in the blocked regions with inpainting.

In this study, we propose an inter-projection interpolation (IPI) method, which utilizes two adjacent projections as references and extracts groups of paired corresponding pixels on the

two projections based on the CBCT geometric model. The method uses a similar SMOG approach. Instead of moving the grid and taking two projections at each gantry angle, the new approach takes only one projection at each gantry angle and moves the grid at the same distance for the next gantry angle. Thus, the blocked regions in each projection correspond to open regions in the two adjacent projections. The missing pixels are finally estimated from the paired pixels with the highest similarity. We compared the reconstruction result of IPI and exemplar-based inpainting method in terms of signal-to-noise ratio (SNR) on two phantoms (Catphan phantom and head phantom). The proposed method increased SNR significantly. In addition, we applied IPI on sparse view CBCT reconstruction and found that SNR was kept in a reasonable range with increase of the interval.

The paper is organized as follows. The IPI framework, including the geometric model, cost function and optimization method, is described in Section 2. The results are presented and discussed in Section 3. Finally, the conclusion is given in Section 4.

2 Materials and Methods

2.1 Inter-projection Interpolation

The value of each pixel on each projection could be viewed as the line integral of attenuation of all points along the ray connecting the source and the pixel. Due to the continuity of a patient's anatomy, if the gantry angle interval between two consecutive projections is sufficiently small, the values of the corresponding pixel in three consecutive projections are usually similar, unless there is an 'abrupt' point, such as an edge of a bone, along the ray corresponding to the pixel. A geometric model was developed to approximately determine the location as well as the density change of this 'abrupt' point from two sets of corresponding pixels in the two nearest neighboring projections. Along the artificial ray, we sampled some equidistant points, and the paired projection pixels of each point onto the two nearest neighboring projections were identified via the geometric model. In this way, a group of paired projection pixels were detected and the two pixels corresponding to the 'abrupt' point are expected to have the smallest similarity cost. Thus, the location and corresponding pixel value of this 'abrupt' point was identified by picking up a pair of the 'closest' pixels. The pipeline of the process is shown in pseudocode:

Algorithm 1.1

Estimate the intensity of blocked scanline $PS_g^{scanline}(v_g)$

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- 1 Locate the paired projection pixels on two unblocked neighboring projections based on geometric model
 - 2 Along $\overrightarrow{S_g E_{g,j}(u_g, v_g)}$, sample equidistantly with different depths
 - 3 After minimizing the energy along the scanline with dynamic programming, 'abrupt' points are searched
 - 4 Based on the depths of 'abrupt' points, the estimation of the intensity is the mean of paired projection pixels
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2.2 Paired Projection Pixels Localization

The proposed geometric model is shown in Fig. 3 and the nomenclature is listed. Based on the geometric model, we first need to calculate the local coordinate of $PS_{g-1}(E_{g,j}(u_g, v_g))$

and $PS_{g+1}(E_{g,j}(u_g, v_g))$. Since the rotation orbit is perpendicular to the Z axis, $PS_g(u_g, v_g)$, $PS_{g-1}(E_{g,j}(u_g, v_g))$ and $PS_{g+1}(E_{g,j}(u_g, v_g))$ have the same known Z coordinate v_g (i.e., local V coordinate), and we just need to calculate the local U coordinate. Taking $PS_{g-1}(E_{g,j}(u_g, v_g))$ as an example, the U coordinate can be derived from θ between $\overrightarrow{S_{g-1}O}$ and $\overrightarrow{S_{g-1}E_{g,j}(u_g, v_g)}$. The θ is calculated as:

$$\theta = \arccos\left(\frac{\overrightarrow{S_{g-1}E_{g,j}(u_g, v_g)}}{\|\overrightarrow{S_{g-1}E_{g,j}(u_g, v_g)}\|} \cdot \frac{\overrightarrow{S_{g-1}O}}{\|\overrightarrow{S_{g-1}O}\|}\right) \quad (1)$$

and the distance between $PS_{g-1}(E_{g,j}(u_g, v_g))$ and $PS_{g-1}(O)$ is derived as:

$$\|\overrightarrow{PS_{g-1}(E_{g,j}(u_g, v_g))PS_{g-1}(O)}\| = SDD * \tan(\theta). \quad (2)$$

Finally, the local U coordinate is

$$|PS_{g-1}(E_{g,j}(u_g, v_g))_U| = \sqrt{(SDD * \tan(\theta))^2 - v_g^2} \quad (3)$$

where $PS_{g-1}(E_{g,j}(u_g, v_g))_U$ is the local U coordinate. The sign of the U coordinate is the same as the Z coordinate of $\overrightarrow{S_{g-1}E_{g,j}(u_g, v_g)} \times \overrightarrow{S_{g-1}O}$. In the same way, the local coordinate of $PS_{g+1}(E_{g,j}(u_g, v_g))$ can be calculated.

Therefore, a pair of projection pixels, $PS_{g-1}(E_{g,j}(u_g, v_g))$ and $PS_{g+1}(E_{g,j}(u_g, v_g))$, can be localized analytically for any sample point $E_{g,j}(u_g, v_g)$ under the geometric restriction.

2.3 'Abrupt' Point Searching

After locating the paired projection pixels, we can sample along the ray $\overrightarrow{S_gE_{g,j}(u_g, v_g)}$ equidistantly and find the 'abrupt' point defined as the depth of blocked pixel $PS_g(u_g, v_g)$ (i.e., $D(PS_g(u_g, v_g))$) based on the similarity of the corresponding paired projection unblocked pixels. The problem is called the 'stereo matching' [13] problem in computer vision and roughly can be divided into two steps: cost calculation and optimization. For the first step, a lot of similarity cost measurements have been proposed, including the sum of absolute difference, the sum of squared difference, and the normalized cross correlation [14,15]. Some of them target at the occlusion and non-rigid transformation problems, which can be omitted in our case [16]. Thus, we used the sum of squared difference to balance the speed and accuracy. For the second step, a large number of optimization methods are also developed, including Markov Random Field [17], graph-cut [18] and dynamic programming [19]. Among them, scanline-based dynamic programming is the fastest and most suitable for our case, since the paired projection pixels of the same scanline parallel to the U axis on projections share the same Z axis as we mentioned before.

Similarity Cost—After rewriting the paired pixels of a sample point $E_{g,j}(u_g, v_g)$ in local coordinate format as $(PS_{g-1}(u_{g-1}, v_{g-1}), PS_{g+1}(u_{g+1}, v_{g+1}))$ to simplify the formula, we

sampled a 2D window with width w (5 is used in our case) centered at each pixel. The similarity cost is defined as:

$$\begin{aligned} Cost(E_{g,j}(u_g, v_g)) &= Similarity(PS_{g-1}(u_{g-1}, v_{g-1}), S_{g+1}(u_{g+1}, v_{g+1})) \\ &= \sum_{i=-(w-1)/2}^{i=(w-1)/2} (S_{g-1}(u_{g-1}+i, v_{g-1}) - S_{g+1}(u_{g+1}+i, v_{g+1}))^2. \end{aligned} \quad (4)$$

Optimization—If we simply used the cost for each sample point of a missing pixel $PS_g(u_g, v_g)$ to search the ‘abrupt’ pixel individually as below:

$$D(PS_g(u_g, v_g)) = \underset{j}{\operatorname{argmin}} Cost(E_{g,j}(u_g, v_g)), \quad (5)$$

the smoothness along the scanline (i.e., $PS_g^{scanline}(v_g) = PS_g(1 \dots width, v_g)$) where $width$ is the width of the detector in pixels) can not be guaranteed. Thus, we built up an energy function:

$$\begin{aligned} E(PS_g^{scanline}(v_g)) &= E_{data} + \lambda E_{smooth} \\ &= \sum_{i=1}^{i=width} Cost(E_{g,j}(i, v_g)) + \lambda \sum_{i=1}^{i=width-1} |D(PS_g(i, v_g)) - D(PS_g(i+1, v_g))| \end{aligned} \quad (6)$$

where E_{data} is the sum of the data cost from the whole scanline and E_{smooth} is the sum of the difference of depths between two adjacent pixels in the scanline while λ adjusts the weight between the data and smooth terms. This energy can be minimized by rewriting the energy in recursive format and applying dynamic programming [20]:

$$\begin{aligned} E(PS_g^{scanline}(v_g)) &= E(PS_g(1 \dots width, v_g)) \\ &= \min_j (Cost(E_{g,j}(1, v_g)) + \lambda |D(PS_g(1, v_g)) - D(PS_g(2, v_g))| + E(PS_g(2 \dots width, v_g))). \end{aligned} \quad (7)$$

In this way, the sum of energy along the scanline is split into three parts: the first part is the cost of the first pixel defined in formula 4; the second part is the difference of depths between the first and second pixel; the third part is the sum of energy along the scanline expected for the first pixel. Iteratively, the sum of the energy could be split into a group of the first part and a group of the second part. Starting from the last pixel, we could trace back the depths of all pixels along the scanline with minimized energy. After finding the corresponding pair based on the optimized depths, the missing pixel intensity is estimated as the mean of the intensity of the corresponding paired projection pixels.

2.4 SMOG Simulation and Evaluation of the IPI Technique

A Catphan phantom and a head phantom were scanned using the onboard CBCT system on a Varian[®] Trilog[™] machine using a half fan mode, with the X-ray tube voltage of 120 kVp. In each scan, approximately 650 projections were acquired and each projection’s dimensions were 1024×768 with resolutions of $0.388\text{mm} \times 0.388\text{mm}$. The reconstruction images contain $384 \times 384 \times 64$ voxels with resolutions of $0.651\text{mm} \times 0.651\text{mm} \times 2.5\text{mm}$.

The SMOG was simulated by erasing the information (filling with '0') of the areas in each projection corresponding to the grid, which is designed as 1:1 space ratio and 21 pixels width. The artificial grid moves back and forth on each projection at the step of the grid width. In this way, a blocked projection pixel in one gantry angle is guaranteed to be 'seen' in the two adjacent gantry angles. The blocked image information was derived from the information in the two neighboring projections immediately before and after the projection using the IPI algorithm. A complete projection was derived, and the CBCT image was reconstructed using the FDK [21] reconstruction algorithm. SNR was calculated by comparing the CBCT images with the original unblocked CBCT image. The IPI method was also compared with an exemplar-based inpainting interpolation method in terms of the SNR [22].

The gantry angle step effect was also studied in the IPI technique. For the original 650 projections with an gantry angle step of ≈ 0.5 degree, we undersampled the projections by deleting 1/2, 2/3, 3/4, 4/5 and 5/6 of the projections evenly so that the gantry angle step was around 1, 1.5, 2, 2.5 and 3 degrees, respectively. The IPI technique was then used to recover the deleted projections, and CBCT images were reconstructed after that. The image quality of the IPI-recovered CBCT images with various gantry angle steps was evaluated by comparing with the original CBCT images and calculating the SNR.

3 Results and Discussion

3.1 IPI Technique to Recover Blocked Information for the SMOG-Based CBCT

Fig. 1 shows the result for the Catphan phantom. We noted that the CBCT image from the IPI-recovered projection had a SNR of 29dB in comparison to a SNR of 15.3dB for the inpainting-based interpolation.

Similarly, Fig. 2 shows the result for the head phantom. We noted that the CBCT image from the IPI-recovered projection had a SNR of 28.1dB in comparison to a SNR of 12.7dB for the inpainting-based interpolation.

These results demonstrate that the IPI technique can provide superior results to the inpainting-based interpolation. The SNR values of 29.0dB and 28.1dB are quite high, suggesting that the IPI technique is reliable. The IPI technique may allow us to directly add the SMOG system in the current clinical on-board CBCT system without significantly modifying the CBCT control system.

3.2 Gantry Angle Interval Effect in IPI Technique

The undersampled projection sets with various gantry angle intervals (1, 1.5, 2, 2.5 and 3 degrees) were used to study the gantry angle interval effect for the IPI technique. Fig. 4 shows the comparison of an axial cut of the CBCT images of the Catphan phantom with the missing projections recovered by the IPI technique for these undersampled projections. We noted that the SNRs were 28.3, 28.3, 21.8, 19.3 and 17.3dB for the gantry angle intervals of 1, 1.5, 2, 2.5, and 3 degrees, respectively.

Similarly, Fig. 5 shows the comparison of an axial cut of the CBCT images of the head phantom with the missing projections recovered by the IPI technique for the undersampled projections. We noted that the SNRs were 27.4, 23.5, 21.5, 20.2 and 19.0dB for the gantry angle intervals of 1, 1.5, 2, 2.5, and 3 degrees, respectively.

The SNR was reduced with the increasing gantry angle interval. The Catphan tended to have a better SNR than the head phantom when the gantry angle interval was very small (less than 2 degrees). The head phantom tended to have a better SNR for relatively large gantry angle intervals.

The IPI may also be used on sparse-view CBCT reconstruction to reduce the imaging dose (*i.e.*, reconstruction based on partial projections in sparse gantry view). When the gantry angle interval is less than 2 degrees, the SNR is still larger than 20dB and thus the image deviation due to the IPI estimation may still be acceptable.

4 Conclusion

The IPI technique is a new interpolation method utilizing neighboring projections to estimate the blocked projection following a geometric model. It shows a much higher accuracy level than the inpainting algorithm to recover the blocked information. The technique may allow us to directly add a SMOG system in the current clinical on-board CBCT system without significantly modifying the CBCT control program. In combination with SMOG, it may reduce the scatter artifacts and reduce the image dose. It may also be used for sparse-view CBCT reconstruction to further reduce the imaging dose.

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Fig. 1.
Comparison between inpainting and IPI of Catphan phantom

Fig. 2.
Comparison between inpainting and IPI of head phantom

Fig. 3.

The geometric model

Nomenclature for Fig. 3

S_{g-1}, S_g, S_{g+1} : the locations of source in continued gantry angle.

SAD: source-to-axis distance.

SDD: source-to-detector distance.

O: origin of global coordinate.

$PS_g(u_g, v_g)$: a blocked pixel on the detector projection plane of source S_g with local coordinate of (u_g, v_g) .

$E_{g,j}(u_g, v_g)$: a sampling point on the ray between S_g and $PS_g(u_g, v_g)$.

$D(PS_g(u_g, v_g))$: the depth of 'abrupt' point of $PS_g(u_g, v_g)$.

$PS_{g-1}(E_{g,j}(u_g, v_g)), PS_{g+1}(E_{g,j}(u_g, v_g))$: the unblocked projection pixel of $E_{g,j}(u_g, v_g)$ under source S_{g-1} and S_{g+1} on the detector, respectively.

$PS_{g-1}(O)$: the projection global coordinate origin under source S_{g-1} on the detector.

U,V(Z): local coordinate of the detector projection plane and the global axis; Z is the same as axis V.

X,Y,Z: global coordinate.

Fig. 4. Undersampled reconstruction after IPI results at different intervals of Catphan phantom

Fig. 5.

Undersampled reconstruction after IPI results at different intervals of head phantom