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Rollback Reconstruction for TDC Enhanced Perfusion Imaging*

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Tomographic perfusion imaging is a significant function imaging modality for stroke diagnosis. However, the low rotational speed of C-arm is a challenge for the application of perfusion imaging in C-arm CBCT (from 6 to 8 seconds per circle). The traditional reconstruction methods can not remove the artifacts caused by the slow rotational speed or can not acquire enough sample points to restore the time density curve (TDC). This paper presents a dynamic rollback reconstruction method for CBCT. The proposed method could improve the temporal resolution by increasing the sample points used for calculating the TDC. Combined with the existing research results, the algorithm allows the possibility of using slow rotating scanners for perfusion imaging purposes. In experiments, the proposed method is compared with other dynamic reconstruction algorithms which is based on standard reconstruction, temporal interpolation approach. The presented algorithm could improve the temporal resolution without increasing x-ray exposure time or contrast agent.

Keywords: Rollback reconstruction, CBCT, Time resolution, Time density curve

I. INTRODUCTION

As one of leading causes of death, stroke may bring serious long-term disability. According to the statistics, there are about 2.5 million new stroke cases in China every year, and about 1.7 million patients die from stroke. In acute stroke treatment, time is life. Perfusion CT is a well-accepted method for stroke diagnosis [1–3] whose aim is to assess the blood supply of the tissue which has already found its way into clinical routine. Together with perfusion MRI (magnetic resonance imaging), they represent the primary imaging techniques for patients with symptoms of stroke. After injecting the contrast agent, the tissue was scanned multiple times in succession to obtain the TDC [4–6] of each slice. The curve reflects the changes of contrast agent concentration in tissues [7–9], i.e. the changes of blood supply in tissues. Hence, perfusion CT can be used to identify tissue regions that can be salvageable and may contribute to stroke therapy. However, there are still some challenges for perfusion CT. One limitation is that perfusion CT could only produce functional maps of a limited number of slices. CBCT (Cone Beam CT) [10, 11] can be used to tackle the problem. The application of large-area detectors allows users to conduct perfusion CBCT studies on the three-dimensional regions of interest. However, there are two problems to be addressed.

The first is known as the temporal resolution problem [12]. In order to reconstruct an image at any time t , we need for each projection at projection angle α . However, the source

turns with a restricted rotational speed ω . When the speed ω is slow, it means the contrast agent attenuation during the scanning process cannot be ignored. The scanning time of traditional perfusion CT is limited to two seconds per circle. In such a short time, the attenuation of the contrast agent is negligible. So direct reconstruction will not influence the final result, i.e., the recovery of the time density curve. However, the scanning time of CBCT is from 6 to 8 seconds per circle, which is much longer than the traditional perfusion CT. The concentration of the contrast agent in blood has a great influence on reconstruction quality. For example, it may result in the artifacts or inaccurate values in the reconstructed images. This will directly influence the subsequent production of perfusion parameter maps. The second problem is called the time sampling problem. After injecting the contrast agent, the acquisition time of traditional perfusion CT and CBCT is almost equal. However, due to the different rotational speed ω , the total number of CBCT perfusion is much less than traditional perfusion CT. That leads to a lack of sampling points. When using the same interpolation method to fit the time density curve, fewer sample points will lead to inaccurate results. The degraded time density curve will mislead the assessment of the patient's condition.

Various strategies have been proposed to tackle the above problems. Grangeat et al. [13] proposed a more sophisticated approach for dynamic reconstruction compared to the traditional FDK algorithm [14, 15]. The dynamic reconstruction algorithm is based on short-scan reconstruction with the tent Feldkamp (T-FDK) algorithm [16]. First, the cone-beam projections, were rearranged into the fan-parallel beam projections. Second, the filtering operation was performed for the projection data. Then the back-projection calculation was divided into three parts, and each part covered 60 degrees. These incomplete back-projections were denoted as partial block backprojections (PBBs). As a consequence of the dynamic acquisition scheme, the values of each PBB were known every half-rotation. Hence, for every PBB, a time series of values observed every t_{π} . In order to obtain the re-

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construction result at a certain time point, Grangeat and co-workers performed linear regression on the closest k values of the time series. This method was called k -mode linear regression. K -mode linear regression effectively reduced the impact of the temporal resolution problem, but did not solve the time sampling problem: it limited the attenuation of the contrast agent during the scanning process from the original to the current, but the number of sample points could not be improved. Although a sample point could be obtained every t_π by the rearrangement method, it was still not enough. Under the CBCT scanning protocol, only a dozen sample points could be obtained. At present, there is no good way to solve the time sampling problem. From the perspective of data collection, Fieselmann[17] proposed a method: when collecting data, the patient was injected with the contrast agent twice. After the second injection of the contrast agent, a time offset was added and data acquisition was not performed immediately. This time offset should be half the time of a single scan. In this way, the time sample points obtained are doubled. However, this method has great drawbacks. First, it did not solve the temporal resolution problem. More importantly, the contrast agent is harmful to human body, especially the liver and kidneys, and some patients may also have allergic reactions. Therefore, multiple injections of the contrast agent is obviously not recommended. In addition, the author did not prove whether the first injection of contrast agent will be left in the patient's body and whether it could influence the results of the second injection of the contrast agent. Jie Tang[18] proposed a temporal recovery method to recover time density curves to enable C-arm CBCT perfusion studies. This method did not increase the number of sample points, but proposed a more excellent fitting method. In their method, two optimization methods (CG and Bregman) were used to solve the proposed temporal recovery problem. Yinsheng Li[19] introduced a new technique referred to as enhanced SMART-RECON(eSMART-RECON) to enhance the temporal performance in a multi-sweep CBCT data acquisition protocol. However, this method is an iterative reconstruction method, which consumes a significant amount of computing resources. In addition to the traditional methods, with the rise of deep learning and neural network, it has also been combined with perfusion. For example, Zhu[20] proposed an optional way to reduce CTP imaging radiation dose, that is downsampling 30-pass images to 15 passes in temporal domain and then restoring them to 30 passes with the deep residual CNN model. It was also a method of recovering sample points. However, deep learning and neural network need a lot of training data to ensure the accuracy of the results, and the anti-risk ability is poor. If a little interference is added, the result of the network may be wrong.

In this article, we address the problem of dynamic reconstruction within the context of perfusion CT and presented a dynamic rollback reconstruction approach for perfusion CBCT to improve the time density curve. And combining it with the existing reconstruction method, it retains the advantages of the original method. We took the contrast agent attenuation caused by its propagation into account and assume that there was no movement or deformation during the scan-

ning process. Then the temporal interpolation performed on the partial block back-projections was employed to increase the number of sampling points. Experiments demonstrated the promising performance of the proposed rollback reconstruction algorithm.

II. METHODS AND MATERIALS

A. The T-FDK method

3D reconstruction from 2D projections obtained along a single circular source trajectory is most commonly calculated using the FDK algorithm. However, the FDK algorithm can not well preserve the reconstruction accuracy when the cone angle is large. In 2000, Grass et al. proposed an alternative approach based on a cone-beam to parallel-beam rebinning step, a corresponding rebining step into a rectangular virtual detector plane and a filtered backprojection. The computational complexity was lower than in Feldkamp's original approach. As shown in Fig.1, the fan-beam data acquired along a circular source-detector trajectory can be rearranged into sets of fans of rays. Similar to the algorithm of rearranging fan-beam into parallel-beam, we can rearrange cone-beams X-ray emitted from different positions of the ray source's circular trajectory into parallel-beams with the same cone angle and parallel to each other in space. Although cone-beams X-ray and parallel-beams X-ray are not completely corresponding, they can be corresponded one by one by interpolation.

The X-ray source moves along a circular trajectory of radius R , and the cone-beam projection data $P_{cone}(\beta, m, n)$ at various angles β are collected on the flat panel detector. Then these projection data are rearranged into the parallel-beam projections, which are used to reconstruct the tomographic images of the object. As shown in Fig.2, the ray received by virtual detector 1 can be converted to a corresponding ray on virtual detector 2. The projection of the rearranged parallel-beam on the X-Y plane is perpendicular to the virtual detector 2. The projection value of the rearranged parallel-beam on the virtual detector 2 can be expressed by $P_{para}(\theta, g, s)$, where θ is the projection angle of the parallel beam, g and s are the horizontal and vertical coordinates of the rearranged parallel beam on the virtual detector 2, respectively. The specific process can be divided into three steps: data rearrangement, weighted filtering, and back-projection reconstruction.

(1)Data rearrangement

First, the cone-beam projections $P_{cone}(\beta, m, n)$ are rearranged into parallel-beam projection data $P_{para}(\theta, g, s)$. During transforming the (β, m, n) space to (θ, g, s) space, not every parallel-beam projection has the corresponding cone-beam projection as the detector collected data are discrete. Usually, the nearest interpolation or linear interpolation are employed to tackle the above problem. Different interpolation methods will influence the spatial resolution of the reconstructed volume.

(2)Weighted filtering

Then, the rearranged parallel-beam projection data $P_{para}(\theta, g, s)$ is weighted and filtered according to the fol-

Fig. 1. The fan beam can be rearranged into a parallel beam.

Fig. 2. Transform the (β, m, n) space to (θ, g, s) space.

Fig. 3. Partial block back-projection.

be tackled from the algorithm perspective. Pau et al. introduced the block reconstruction strategy and presented the TIA-TFDK(temporal interpolation approach, TIA) algorithm to address the temporal resolution problem. First, the cone-beam projections were rearranged into the parallel-beam projections: $P_{cone}(\beta, m, n) \rightarrow P_{para}(\theta, g, s)$. Then Pau et al. introduced the $k\pi$ -mode linear regression to reduce the impact of temporal resolution problem. As shown in Fig.3. The partial block back-projection operations were performed at angular intervals of $2\pi/N$:

$$PBB_j(X, t_{\frac{\pi}{N}(2j+1)}) = \frac{1}{2} \int_{j \cdot \frac{2\pi}{N}}^{(j+1) \cdot \frac{2\pi}{N}} \tilde{P}_{para}(\theta, g, s) d\theta \quad (3)$$

$j = 0, 1, \dots, N-1$

lowing formula to obtain $\tilde{P}_{para}(\theta, g, s)$:

$$\int \tilde{P}_{para}(\theta, g, s) d\theta = \left[\sqrt{\frac{R^2 - g^2}{R^2 - g^2 + s^2}} \cdot P_{para}(\theta, g, s) \right] * h(g) \quad (1)$$

where $\sqrt{\frac{R^2 - g^2}{R^2 - g^2 + s^2}}$ represents the cosine value of the beam cone angle κ and $h(g)$ is the filter function. It is necessary to multiply the projection data by the cosine weight since $\tilde{P}_{para}(\theta, g, s)$ are the parallel-beam projections.

(3) Back projection reconstruction

Finally, the voxel (x, y, z) is reconstructed using the corresponding filtered parallel-beam projections $\tilde{P}_{para}(\theta, g, s)$. The tomographic images can be obtained after all the voxels are reconstructed. This process can be formulated as follows:

$$F(x, y, z) = \int_0^{2\pi} \tilde{P}_{para}(\theta, g(x, y, z), s(x, y, z)) d\theta \quad (2)$$

B. TIA-TFDK algorithm

As mentioned above, the contrast agent attenuation will lead to the temporal resolution problem when the scanning program consumes too much time. The best solution is to reduce the scanning time, but when the hardware conditions can not fulfil the requirement, the problem needs to

Using the general time interpolation method[21], each block is calculated independently of other blocks. The interpolation process could be performed after filtering as well due to the linear nature. In the same way, the interpolation process also could be performed after the back-projection. The computational complexity could be reduced since the calculated values only need to be accumulated after back-projection. And if the interpolation was not performed for each projection but partial block back-projection, the computational complexity could be further reduced. Therefore, a full scan was equally divided into N parts. In this way, the values of the j th and the $(j + N/2)$ th partial block back-projections were combined to a unique time sequence and a continuous signal estimated by interpolation. In the experiment, hermite interpolation was used, and the interpolation process was as follows:

$$H_3(x) = \left[\left(1 + 2 \frac{x - x_0}{x_1 - x_0} \right) y_0 + (x - x_0) y'_0 \right] \left(\frac{x - x_1}{x_0 - x_1} \right)^2 + \left[\left(1 + 2 \frac{x - x_1}{x_0 - x_1} \right) y_1 + (x - x_1) y'_1 \right] \left(\frac{x - x_0}{x_1 - x_0} \right)^2 \quad (4)$$

Where x_0 and x_1 was the positions of two adjacent points of the point to be interpolated, y_0 and y_1 correspond to the dependent variables of x_0 and x_1 , and y'_0 and y'_1 was the corresponding derivatives. The steps of interpolation of PBBs

was summarized as follows:

$$PBB_j(X, t) = H_3(PBB_j(X, t_{\frac{\pi}{N}(2j+1)})) \quad (5)$$

$$j = 0, 1, \dots, N-1$$

The required results could be obtained by accumulating the partial block back-projections at the given time point. The FDK reconstructed results of a full scan could be got through adding all the PBBs:

$$F(x, y, z) = \sum_{j=0}^{N-1} PBB_j(X, t) \quad (6)$$

The partial block back-projection approach reduced the data inconsistency in the projection domain. Even though the projections in a block were acquired at different times, the problem of time resolution was mitigated since the time between angular intervals are shorter than the time of a short-scan reconstruction. The linear regression estimation had compensated for the temporal evolution. In the experiments, Pau et al. also proved that the data inconsistency would be significantly reduced as N increased. But the calculation cost would also increase synchronously. The TIA-TFDK algorithm is equivalent to the FDK algorithm at $N=1$. Furthermore, Pau et al. concluded that the reconstruction quality and time could be well balanced when $N=6$.

C. Rollback reconstruction

The purpose of perfusion CBCT is to obtain an image sequence based on projection data acquired in several full rotations. However, the time sampling problem may lead to severe degradation of the time density curve. We adopt the rollback reconstruction strategy to address this problem. The cone-beam projection P_t is indexed by the time t . The source rotates at a constant angular speed ω from time $t = 0$. The acquisition could be performed either in continuous mode (the x-ray source is always on) or in discontinuous mode (the x-ray source is switched off regularly). We assume that the region of interest is within the FOV (field of view) of the cylindrical detector. The projections at all angles are needed to reconstruct the image frame at any time t . However, the sampling points are discrete in practice. Thus, at the time t_α , we only could acquire the projection at the angular position α . The same projection can be acquired again at time $t_\alpha + T_{2\pi}$ after the source has finished a full rotation. Hence, at the angular position α , we could obtain a discrete sequence $P_{t_\alpha} = P_{t_\alpha + T_{2\pi}}$. This dynamic acquisition process can be interpreted as sampling the time-dependent projection P_t with a period of $T_s = T_{2\pi}$.

Since the cone-beam projections have been rearranged into parallel-beam projections, the 180° reconstruction condition is extended from the 2D to the 3D case. Hence, we can get two reconstruction results after a full scan process. The one is reconstructed using the projection data of $0 - \pi$ and the other is reconstructed with the projection data of $\pi - 2\pi$. Here we take the middle time as the reference time point, that is, $t_{\pi/2}$

represents the time point of the scanning of $0 - \pi$ and $t_{3\pi/2}$ represents the time point of the scanning of $\pi - 2\pi$. Therefore, after a single full scan, we can obtain the reconstructed images at two time points: $t_{\pi/2}$ and $t_{3\pi/2}$. This dynamic acquisition process can be interpreted as sampling the time-dependent projection P_t with a period of $T_s = T_\pi$. These sampling can be used to plot the density curve. Ideally, the time density curve will be closer to the reference dynamic curve as the number of sampling points increases. Therefore, we propose the rollback reconstruction method to increase the sampling points while not increasing the radiation dose. Specifically, we could achieve a fixed angle rollback by reusing the projection data have been used for reconstruction. The following steps have explained the rollback reconstruction method in detail.

Start: $j = 0$

(1) Starting from 0° , reconstruct the angle range from $0 + j \cdot \frac{\pi}{3}$ to $\pi + j \cdot \frac{\pi}{3}$, and record the result as $t_{\frac{\pi}{2} + j \cdot \frac{\pi}{3}}$

(2) Rollback $\frac{2\pi}{3}$, in other words, $j = j + 1$

(3) Repeat steps 1 and 2;

It can be expressed as:

$$F_{\frac{\pi}{2} + j \cdot \frac{\pi}{3}} = \int_{0 + j \cdot \frac{\pi}{3}}^{\pi + j \cdot \frac{\pi}{3}} \tilde{P}_{para}(\theta, g, s) d\theta \quad (7)$$

The number of reconstructed images will increase as the

Fig. 4. Rollback reconstruction.

rollback angle increases. Hence, the presented rollback reconstruction could better preserve the accuracy of the time density curve compared with the traditional reconstruction method. Of course, the rollback reconstruction will increase the computational cost because of the increasing of reconstruction operation. Rollback reconstruction increases the number of reconstruction sample points by reusing projection data, and solves the time sampling problem, but it can't solve the problem of time resolution.

D. Rollback reconstruction with TIA-TFDK

Combining the rollback reconstruction and TIA-TFDK algorithm, we propose an improved reconstruction method for the perfusion CBCT, as shown in Fig.5. This approach could

Fig. 5. Rollback reconstruction with TIA-TFDK.

Fig. 6. Phantom A.

improve the reconstruction quality because it is promising to tackle the temporal resolution problem and time sampling problem simultaneously. The following steps explain the improved rollback reconstruction method in detail.

(1)Rebinning cone-beam projections to parallel-beam projections:

$$P_{cone}(\beta, m, n) \rightarrow P_{para}(\theta, g, s) \quad (8)$$

(2)Take $N=6$, and the rollback angle is $\frac{\pi}{6}$, reconstruction of PBBs with T-FDK:

$$PBB_j = \int_{0+j \cdot \frac{\pi}{6}}^{\frac{\pi}{3}+j \cdot \frac{\pi}{6}} \tilde{P}_{para}(\theta, g, s) d\theta \quad (9)$$

$$j = 0, 1, \dots$$

(3)Combination of the samples of the j th and the $(j+6)$ th PBBs;

$$PBB_j(X) = \{PBB_j, PBB_{j+6}, PBB_{j+12}, \dots\} \quad (10)$$

$$j = 0, 1, \dots, 5$$

(4)Interpolation of PBBs values;

$$PBB_j(X, t) = H_3(PBB_j(X)) \quad (11)$$

$$j = 0, 1, \dots, 5$$

(5)Accumulation:

$$F_1(x, y, z) = \sum_{j=0,2,4} PBB_j(X, t) \quad (12)$$

$$\text{and } F_2(x, y, z) = \sum_{j=1,3,5} PBB_j(X, t)$$

(6)Interpolation of F_1 and F_2 ;

After the cone-beam projections were rearranged into parallel-beam projections, the sampling time of the original TIA-TFDK algorithm was t_π . That is, each scan could obtain two reconstruction results. Furthermore, the number of sampling points doubled after introducing the rollback method, the optimization effect of TIA-TFDK algorithm on the time resolution problem is retained. Thus, the accuracy of the time density curve obtained by interpolation would be well-preserved.

E. Data preparation

In this study, the CTP images were collected from eight eligible slice locations of acute stroke patients. The scan protocol is detailed as follows: tube voltage, 80 kV; tube current, 250 mA; slice thickness, 5 mm. Each slice location has 30 CTP images with 512×512 pixels corresponding to 30 passes in time sequence. Based on CTP, we refer to the scanning protocol of CBCT, which reduces the number of samples obtained in time sequence under the same scanning time. This is due to the slower scanning speed of CBCT. We simulate the scanning process of 8 seconds acquisition cycle, that is, the time to obtain a reconstruction sample point is 8 seconds. The original $512 \times 512 \times 30$ data volume for each slice location was downsampled to the dataset of size $512 \times 512 \times 7$. The detailed steps was as follows:

(1)Through interpolation, expand the data $512 \times 512 \times 30$ with a sampling period of 2 seconds into $512 \times 512 \times 300$ with a sampling period of 0.2 seconds;

(2) Perform projection calculations. Since the experiment simulates the CBCT scanning process with a sampling period of 8 seconds, during the projection process, it is necessary to switch the next frame for projection every 0.2 seconds, that is, each frame of data only contributes 9° of projection data, in other words, 40 pieces of data will provide a complete set of projection data;

III. RESULT ANALYSIS

A. Rollback reconstruction for phantom

Firstly, we make use of a digital model to simulate the attenuation of contrast agent in the process of perfusion image acquisition. A circular trajectory scanner was simulated with a detector to focus distance of 1250 mm and a source to origin distance of 750 mm. A 648×474 pixel cylindrical detector was used with a maximum fan-angle of $\gamma_{max} = 0.25rd$. The image matrix was 512×512 with pixels of $0.5 \times 0.5mm^2$ size. The numerical phantom A illustrated in Fig.6 was used for simulation. Phantom A is a sphere of 8 cm radius, which

Fig. 7. The time density curves of simulated results. (a): $v_i = 0.133$, (b): $v_i = 0.267$, (c): $v_i = 0.4$, (d): $v_i = 0.534$, (e): $v_i = 0.667$, (f): $v_i = 0.8$.

Fig. 8. (a) is the result of FDK, (b) is the error between the FDK result and the original image, (c) is the result of RBTFDK, and the result of TIA-TFDDK is the same, (d) is the error between the RBTFDK result and the original image, (e) is the original image.

has six spherical inserts of 0.5 cm radius. The center of the inserts is 5.5 cm away from the center of the big sphere. The HU values of the big sphere are 50 HU and the HU values of the inserts are as follows:

$$\mu_i(t) = (50 + 50\sin(2\pi v_i t))HU \quad (13)$$

In this case, μ is the HU value, and v is the frequency. The frequencies of the inserts are in the range $v_i \in [0, 0.8]$. Specifically, $v_i \in \{0.133, 0.267, 0.4, 0.534, 0.667, 0.8\}$. The time density curves of simulated results are presented in Fig. 7. They demonstrate that with the increase of frequency v , the traditional sampling strategy is not enough to recover

Fig. 9. Time density curves of different methods.

Fig. 10. Perfusion maps. From top to bottom are the results from FDK, TIA-TFDK, RBTFDK and ground truth, respectively. (a): CBF, (b): CBV, (c): MTT, (d): TTP

B. Rollback reconstruction with TIA-TFDK(RBTFDK)

The previous section has demonstrated that the rollback reconstruction could reduce the impact of time sampling problem. The rollback reconstruction is promising to tackle the temporal resolution problem as well after introducing the TIA-TFDK algorithm. The pre-clinical dataset was utilized to validate the proposed rollback reconstruction algorithm. Fig.8 presents the results of RBTFDK method and traditional FDK reconstruction algorithm. The experiments demonstrate that TIA-TFDK can effectively improve the reconstruction accuracy and it could be used to enhance the rollback reconstruction. From Fig.9, we can observe that the rollback reconstruction based on TIA-TFDK not only could preserve the reconstruction accuracy but also could improve the time density curve.

C. Perfusion parameter results

The perfusion maps have great significance for the diagnosis and treatment of stroke. Some software may overestimate or underestimate ischemic core. This is probably due to differences in tracer delay sensitivity and postprocessing algorithms. The common perfusion postprocessing algorithms can be classified into two categories: maximum slope and deconvolution. Since the maximum slope method can only be used to calculate CBF, it is necessary to make further assumptions on perfusion model when calculating CBV and other perfusion parameters, so deconvolution method is often used now. Kudo et al. assessed the accuracy and reliability using a digital phantom with 13 perfusion postprocessing algorithms. Experiment results illustrated that the single value decomposition(SVD) of PMA can achieve the closest CBF, CBV and MTT values to the truth. Hence, PMA was employed to calculate CBF and other perfusion maps in this study. The results in Fig.10 demonstrate that the perfusion maps obtained from the RBTFDK reconstructed images match the reference perfusion maps best. The RBTFDK method combined with TIA-TFDK is closer to the real perfusion results in terms of the details and overall appearance of perfusion images.

The quantitative analysis also was performed for validation. Table 1 listed the mean perfusion values of different methods. The results demonstrate that the perfusion values in the RBTFDK reconstructed images are well-preserved. Table 2 and Table 3 listed the root mean square error (RMSE) and mean absolute percentage error (MAPE) of different methods. Both the RMSE and MAPE show the promising performance of the proposed RBTFDK algorithm in reconstruction accuracy preservation.

IV. COMPARISON OF ALGORITHMS

As mentioned above, The original $512 \times 512 \times 30$ data volume for each slice location was downsampled to the dataset of size $512 \times 512 \times 7$. Compared with the traditional FDK algorithm, TIA-TFDK adds the following calculation steps:

Table 1. The perfusion parameters of different methods(mean).

	Ground truth	FDK	TIA-FDK	RBTFDK
CBF	29.19	32.64	32.26	33.01
CBV	1.67	3.83	2.10	2.09
MTT	3.50	7.21	3.70	3.46
TTP	4.81	9.58	5.97	5.60

Table 2. The RMSE of perfusion parameters from different methods.

	FDK	TIA-FDK	RBTFDK
CBF	36.60	29.18	26.35
CBV	34.54	25.94	20.04
MTT	42.53	46.98	42.38
TTP	47.00	41.80	34.50

Table 3. The MAPE of perfusion parameters from different methods.

	FDK(%)	TIA-FDK(%)	RBTFDK(%)
CBF	39.23	32.48	27.65
CBV	46.50	29.76	21.99
MTT	40.22	32.95	28.64
TTP	146.60	76.79	66.67

Table 4. Reconstruction times for the three algorithms.

Algorithm	time
FDK	183s
TIA-FDK	211s
RBTFDK	385s

V. CONCLUSION

In this paper, we proposed a rollback reconstruction method based on TIA-TFDK algorithm for perfusion CBCT. In the TIA-TFDK algorithm, cone-beam projections are rebinned to parallel-beam ones. Subsequently, the backprojection is divided in N partial block backprojections. At this point, we incorporate the idea of the rollback reconstruction. The rollback reconstruction could tackle the time sampling problem by increasing the number of sampling points. By reusing the projection data that has been used for reconstruction, the number of reconstruction samples is increased without additional scanning time and contrast agent dose. Then, temporal interpolation is performed on the PBBs to estimate the values at the desired frame times. Finally, accumulate those values separately and interpolate again. In our experiment, we take the partial block angle $\pi/6$ and take the rollback angle half of the partial block back-projection. In fact, this is the balance result between the experimental results and the calculation time.

The algorithm was compared to the standard reconstruction and temporal interpolation approach. The experimental results demonstrated that the proposed RBTFDK algorithm could well preserve the accuracy of reconstructed images and perfusion maps as well as improve the time density curve, and show that with the decrease of partial block angle and rollback angle, the reconstruction results are closer to the real results. However, even from the same source data, different infusion tools will get different results. This may be caused by differences in contrast agent delay sensitivity and post-processing algorithms.

In the future, we will focus on reducing the acquisition time and radiation dose in perfusion CBCT imaging while preserving the image quality.

data rearrangement, partial block back-projection and the interpolation step. After combining rollback reconstruction, the computational complexity increases. Table 4 shows the reconstruction times of the three algorithms with a PC with a Intel Core i5 processor at 3.0 GHz. Indeed, the computational complexity of the partial block back-projection in the TIA-TFDK algorithm is almost negligible. The increased computation time is mainly due to the interpolation step. With the combination of rollback reconstruction, the computational complexity increases differently according to the angle of rollback. In our experiment, we take the rollback angle half of the partial block back-projection. The increased time is within the acceptable range.

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