Simultaneous correction of motion and metal artifacts in head CT scanning

Tao Sun, Johan Nuyts, Roger Fulton

***Abstract*– Often patients are found to have metal implants or devices in a head CT scan. The high-density materials create severe artifacts because of beam hardening and scattering effects. Further complication happens when the patient moves at the time of the scan, even if only slightly. The compound artifacts in the reconstructed images are likely to degrade the accuracy of the diagnosis. In this study we propose an approach to correct these compound artifacts based on the knowledge of the measured projections and known x-ray spectrum. We did this in two steps: (1) in an iterative scheme, rigid motion was estimated and a preliminary reduction of the metal artifacts was performed; (2) the estimated motion was modeled in a full polychromatic reconstruction, in which the starting image was the preliminary corrected image from step 1. The polychromatic reconstruction has the capability to further reduce the compound artifacts. We demonstrate the proposed approach in a simulation study. The image was improved significantly after correction, compared with the one with no correction.**

I. INTRODUCTION

In a diagnostic CT scan, the presence of high density implants often induces artifacts, e.g. streaks in reconstructed images. Further problems arise if the patient moves during the scan - even a slight movement can induce additional artifacts. The compound effects of the motion and metal degrade the image quality, hence affect the diagnostic accuracy.

Efforts have been made to reduce either metal artifacts or motion artifacts individually. For example, some studies attempted to reduce the metal artifacts from implants [1-4]. Methods for reducing rigid motion artifacts have also been proposed by several groups [5-10]. In this work, we study an approach which corrects the compound artifacts from metal implants and motion. Results are presented for both simulations and a patient study.

II. METHODS

The proposed method in this work is based on [8], which corrects the motion artifacts in a CT scan only relying on the measured raw data. [8] assumes that the rigid pose of the object may be different for each projection view. Consequently, a rigid transform representing the object pose is estimated by a 3D-2D registration process for every view (motion update). Compensation for changes in pose during the scan is applied during reconstruction (image update). The motion-corrected image and the motion estimate are alternately updated to increase the likelihood (Fig. 1). A final image with full resolution can be obtained in a final reconstruction.

Manuscript received Nov. 10, 2017. This work was supported in part by the IWT MIRIAD SBO project. T. Sun and J. Nuyts are with the Medical Imaging Research Center, Department of Nuclear Medicine, Katholieke Universiteit Leuven, Belgium. R. Fulton is with the School of Physics, University of Sydney, and the Department of Medical Physics, Westmead Hospital, Westmead, Australia

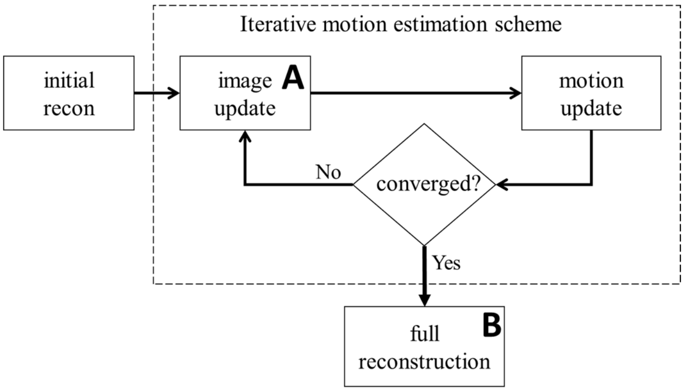

Fig. 1. Flowchart of proposed approach.

To enable the approach in [8] further capable of reducing the metal artifacts, we proposed two modifications A and B in Fig. 1, illustrated the details below.

A. *Image update with streaks reduction*

The image update can be performed with any reconstruction algorithm that can model the arbitrary rigid motion. We have been using iterative algorithms. In [8], MLEM (Maximum Likelihood Expectation Maximization) was used for image updates, but here we adopted another patch-based iterative reconstruction approach. The idea of this approach is that a reconstruction update can be divided into updates on metal and no-metal patches. In different patches, different resolution models can be defined.

Specifically for each image update, the previous image estimate was used to define small patches containing the metals and a large patch containing the rest of the image. The iterative reconstruction starts from that image, and all patches were updated sequentially (metal patches first, then the background patch). The update equation within a patch uses monochromatic patched MLTR (Maximum Likelihood Transmission Reconstruction) [4]:

$$\mu_j^{new} = \mu_j + \frac{a_j \sum_i c_{ij}(\bar{y}_i - y_i)}{\sum_i c_{ij}(\sum_k c_{ik} a_k)\bar{y}_i} \quad (1)$$

where

$$\begin{cases} a_j = 1 \text{ if } j \in \text{patch} \\ a_j = 0 \text{ if } j \notin \text{patch} \end{cases}$$

i is the index of the projection lines, y_i is the measured transmission scan, $\bar{y}_i$ is the estimated transmission scan, computed from the current reconstructed image $\mu = \{\mu_j\}$, with μ_j the linear attenuation coefficient in voxel *j*. c_{ij} is the intersection length of projection line *i* with voxel *j*

The denominator of Eq. 1 will be smaller when the area of the update patch is smaller. With this feature, patched MLTR has the capability to significantly reduce streaks artifacts by improving

978-1-5386-2282-7/17/$31.00 ©2017 IEEE

the convergence near the metals [4]. In addition, the improved reconstruction of the metals should result in improved motion estimation, since the metals contribute high contrast details to the projections which should benefit the 3D-2D registration.

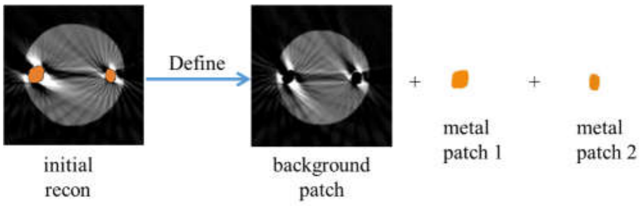

Fig. 2 Patch definition. Metal patches were identified by dilation after thresholding on an initial reconstruction which was performed from the measured projections. The pixel size in the metal patches (full resolution) was two times smaller than that of the non-metal patch (downsampled).

B. *Full reconstruction with estimated motion and spectrum*

The iterative motion estimation generates the motion estimate and the motion-corrected image with preliminary metal artifacts correction. Using these estimates, a polychromatic reconstruction algorithm performs simultaneous motion and metal artifacts reduction. The starting image is the last image update from the iterative motion estimation scheme.

Metal artifacts reduction were performed by modeling the energy model in the polychromatic reconstruction. We used the hybrid reconstruction approach proposed in [4]. In the metal patches, a full polychromatic model was used and the corresponding IMPACT (iterative maximum likelihood polychromatic algorithm for CT) reconstruction was performed. For the non-metal patch, a water polychromatic model was used and the corresponding MLTRC (MLTR water correction) reconstruction was performed. One IMPACT update requires 4 forward and 4 back projection operations, while one MLTRC update contains 1 forward and 2 back projection operations. Since IMPACT calculations are restricted to the small metal patches, the increase in processing time due to the polychromatic modeling is limited.

Motion correction was performed by incorporating the estimated motion into the system matrix [8,9], during every single forward and back projection operation in all reconstructions.

III. Experiments and Results

A. *Simulation setups*

A 3D software phantom representing a water cylinder containing two metal (Fe) implants was designed. A helical scan with a Siemens Definition AS scanner (peak voltage 120kVp, angles per rotation 300, pitch 1.0, collimation 32×1.2 mm) was simulated. During this simulated acquisition, the object moved rigidly. The simulation and reconstruction were done with the same voxel size. The simulated spectrum and the phantom are shown in Fig. 3.

The iterative motion estimation algorithm in Fig. 1 applied 11 iterations, each consisting of an image update and a motion update. For the image update the patched MLTR algorithm applied 1 iteration, 30 subsets alternate updates for metal and non-metal regions. The full hybrid reconstruction in II-B started from the last image update in the initial motion estimation scheme. This full reconstruction applied 2 iteration, 30 subsets for metal and non-metal regions.

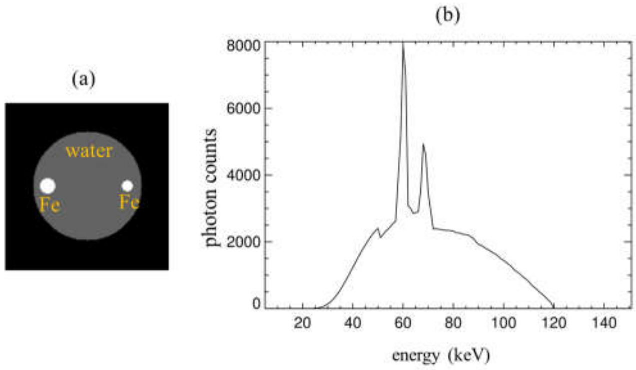

Fig. 3 (a) Digital phantom (image size $160\times160\times30$, voxel size $1\times1\times1$ mm^3); (b) simulated spectrum at 120kVp from Specktr [11].

B. *Reconstructions*

From the simulated corrupted projections, we computed five reconstructed images:

1) **REF:** A FDK (Feldkamp-Davis-Kriss [12]) reconstruction image from motion-free and metal-free projections, as a reference.
2) **FDK (no correction):** A FDK reconstruction was performed for the simulated projections, without motion and beam hardening correction.
3) **MC (only motion correction):** Only motion was estimated in an iterative scheme (II-A). After that, a monochromatic MLTR reconstruction was performed.
4) **POLY (only metal artifact correction):** Only polychromatic reconstruction was performed (II-B). No motion was estimated beforehand nor corrected in this reconstruction.
5) **MC + POLY (both corrections):** Motion was first estimated (II-A) and then corrected inside a polychromatic reconstruction (II-B).

C. *Simulation results*

To compare the results from different experiments, we selected a middle plane of all images to display in Fig. 4. The reconstruction that both modeled the estimated motion and energy spectrum has the least artifacts and is closest to the reference image in appearance. Selected parameters of the estimated motion from the reconstruction with both corrections are plotted in Fig. 5, together with the known simulated motion.

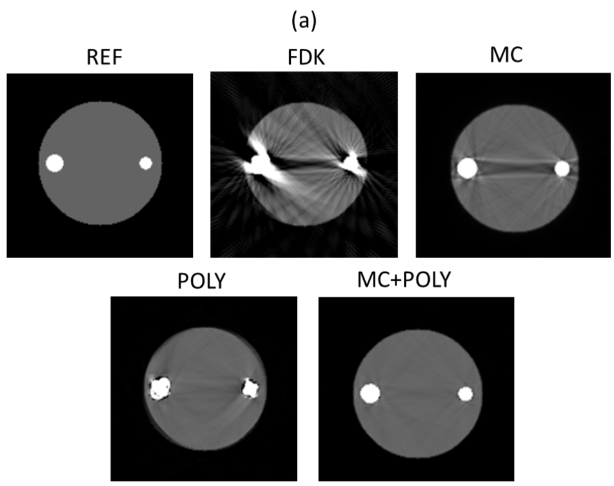

Fig. 4. Results from simulation study.

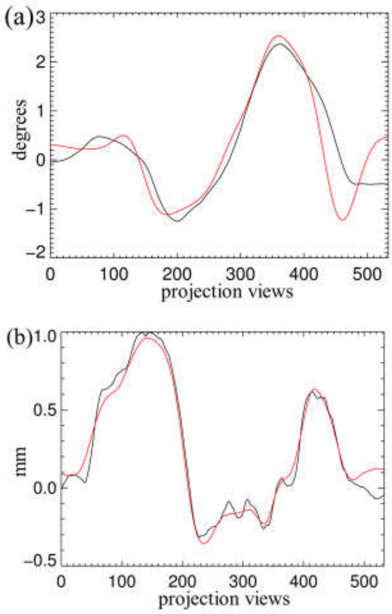

Fig. 5 Motion in two selected degrees of freedom of six as a function of the projection view number: (a) rotation around the rotation axis of the X-ray source; (b) translation along that rotation axis. Estimated motion is in red, and the true simulated motion is in black. The other four parameters are not shown here.

D. *Patient study*

A patient scan identified with motion and metal artifacts are chosen to validate the proposed approach. The scan was from a Siemens Definition Force scanner (120 kVp, both phiFFS and zFFS on, pitch 0.55, collimation 96×0.6 mm).

Several reconstructions were performed. Since ground truth is missing, a corrected image with NMAR [3] was used as the reference. Similar to simulation study, the corrected image has better visual quality than the uncorrected one (Fig.6).

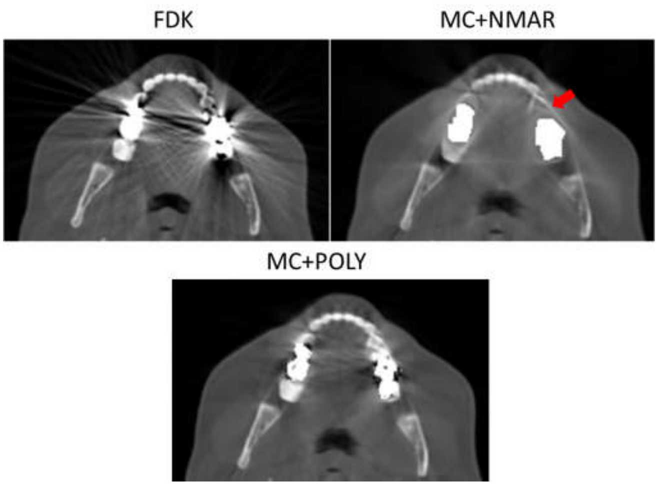

Fig. 6 Reconstructions from the patient study with motion (≤2 mm) and metal artifacts. The second image is after NMAR correction [3], with motion correction enabled. NMAR is known to be subjective to erase the regions close to the metal (red arrow), which is not observed in the image corrected with proposed method.

IV. Discussion and Conclusion

The combination of rigid head motion and the presence of metals can severely degrade the image quality in CT imaging, preventing accurate diagnosis. In this study, we investigated an approach to correct for artifacts due to the combined effects of both factors. Patch-based reconstruction was introduced to an iterative motion estimation scheme, which estimated the motion and removed the streaks at the same time. A subsequent polychromatic reconstruction was performed to account for both energy and motion models. The corrected image was superior to the reconstruction with motion correction only or with metal artifacts reduction only. The evaluation on both and patient study showed promising results. Future work involves tests on robustness of the proposed method and comparing it with other state-of-art methods.

References

[1] G. H. Glover, N. J. Pelc. An algorithm for the reduction of metal clip artifacts in CT reconstructions. Med Phys. 1981;8(6):799–807.
[2] I. A. Elbakri and J. A. Fessler, "Statistical image reconstruction for polyenergetic X-ray computed tomography," in IEEE Transactions on Medical Imaging, vol. 21, no. 2, pp. 89-99, Feb. 2002.
[3] E. Meyer, R. Raupach, M. Lell, B. Schmidt, and M. Kachelrieß, “Normalized metal artifact reduction (NMAR) in computed tomography,” *Med. Phys.*, vol. 37, no. 10, pp. 5482–5493, Oct. 2010.
[4] K. Van Slambrouck and J. Nuyts, “Metal artifact reduction in computed tomography using local models in an image block-iterative scheme.,” *Med. Phys.*, vol. 39, no. 11, pp. 7080–93, Nov. 2012.
[5] H. Yu and G. Wang, “Motion Artifact Reduction in Fan-Beam CT,” *IEEE Trans. Med. Imaging*, vol. 26, no. 2, pp. 249–260, 2007.
[6] Schretter, C., Rose, G. & Bertram, M., 2009. Image-based iterative compensation of motion artifacts in computed tomography. *Med. Phys.*, 36(11), pp.5323–5330.
[7] Clackdoyle, R. et al., 2016. Data Consistency Conditions for Cone-Beam Projections on a Circular Trajectory. *IEEE Signal Processing Letters*, 23(12), pp.1746–1750.
[8] T. Sun, J.-H. Kim, R. Fulton, and J. Nuyts, “An iterative projection-based motion estimation and compensation scheme for head X-ray CT,” *Med. Phys.*, vol. 43, no. 10, pp. 5705–5716, 2016.
[9] T. Sun, J. Nuyts, R. Fulton. “A motion compensation approach for dental cone-beam region-of-interest imaging”, In Conference Record of *International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine*, Xi’an, China, 2017.
[10] Sisniega, A. et al., 2017. Motion compensation in extremity cone-beam CT using a penalized image sharpness criterion. *Phys. Med. Biol.,* 62(9), pp.3712–3734.
[11] J. Punnoose, J. Xu, A. Sisniega, W. Zbijewski, and J. H. Siewerdsen, “Technical Note: spektr 3.0—A computational tool for x-ray spectrum modeling and analysis,” *Med. Phys.,* vol. 43, no. 8, pp. 4711–4717, Aug. 2016.
[12] L. A. Feldkamp, L. C. Davis, and J. W. Kress, “Practical cone-beam algorithm,” *J. Opt. Soc. Am. A*, vol. 1, no. 6, pp. 612–619, 1984.