SPIE Medical Imaging Conference, San Diego, CA, February 2016.

Metal Artifact Reduction in CT via Ray Profile Correction

Sungsoo Ha*[a] and Klaus Mueller*[a]

[a]Center of Visual Computing, Computer Science Department, Stony Brook University, Stony Brook, NY, USA 11790 and SUNY Korea, Incheon, South Korea

ABSTRACT

In computed tomography (CT), metal implants increase the inconsistencies between the measured data and the linear assumption made by the analytical CT reconstruction algorithm. The inconsistencies appear in the form of dark and bright bands and streaks in the reconstructed image, collectively called metal artifacts. The standard method for metal artifact reduction (MAR) replaces the inconsistent data with the interpolated data. However, sinogram interpolation not only introduces new artifacts but it also suffers from the loss of detail near the implanted metals. With the help of a prior image that is usually estimated from the metal artifact-degraded image via computer vision techniques, improvements are feasible but still no MAR method exists that is widely accepted and utilized. We propose a technique that utilizes a prior image from a CT scan taken of the patient before implanting the metal objects. Hence there is a sufficient amount of structural similarity to cover the loss of detail around the metal implants. Using the prior scan and a segmentation or model of the metal implant our method then replaces sinogram interpolation with ray profile matching and estimation which yields much more reliable data estimates for the affected sinogram regions. As preliminary work, we built a new MAR framework on fan-beam geometry and tested it to remove simulated metal artifacts on a thorax phantom. The comparison with two representative sinogram correction based MAR methods shows very promising results.

Keywords: MAR, data-driven, PSO, ray profile, prior, ray matching

1. INTRODUCTION

The presence of metal objects in X-ray computed tomography (CT) scan produces adverse artifacts such as bright and dark shadows and streaks. The high attenuation coefficients of metal objects dramatically decrease the photon numbers. This lowers the signal-to-noise ratio (SNR) and the noise in a sinogram causes streak artifacts in the reconstructed CT image. Moreover, beam hardening effects are getting severe as a ray passes through higher density objects with longer path length due to a polychromatic X-ray source. These artifacts obscure information about anatomical structures, making it difficult for radiologists to correctly interpret the CT images.

Many researchers have proposed various types of metal artifact reduction (MAR) algorithms to challenge this problem. Among them, the most popular approach is to make corrections in the sinogram with the idea that sinogram values are unreliable if the corresponding rays have intersected metal objects. One simple way to compute surrogate values is using an interpolation scheme in the sinogram space [1]. However, it often suffers from the loss of detail around metal objects as well as the introduction of new streak artifacts [2]. To compensate for the lack of structural information in simple interpolation-based MAR, researchers create (roughly segmented) prior images that contain important edge information by applying some computer vision techniques on the uncorrected CT image [3][4].

In our study scenario, the prior CT images are CT images that are taken before implanting metal objects. For example, pre-operative CT scans, which are typically taken to plan a spinal surgery, can serve as these prior images. Since such prior images have been acquired from the same patient, they will likely contain very similar internal structures, especially around metal implants that are often at least partly surrounded by bone, which is unlikely deformed by the surgery. Thus, to find surrogate values to replace unreliable data in the sinogram, we first search ray paths in the prior images that have the most similar density profile along the ray passing through the metal objects. Then, the best matched prior ray profiles are used to correct the ray paths profiles that are corrupted by metal artifacts. Finally, the unreliable data are replaced with the re-projections of corrected ray profiles.

In the following, section 2 describes the method and technical details of our new MAR scheme. Then, we will show some initial results in section 3 and conclude the paper in section 4.

*{sunha, mueller}@cs.sunysb.edu

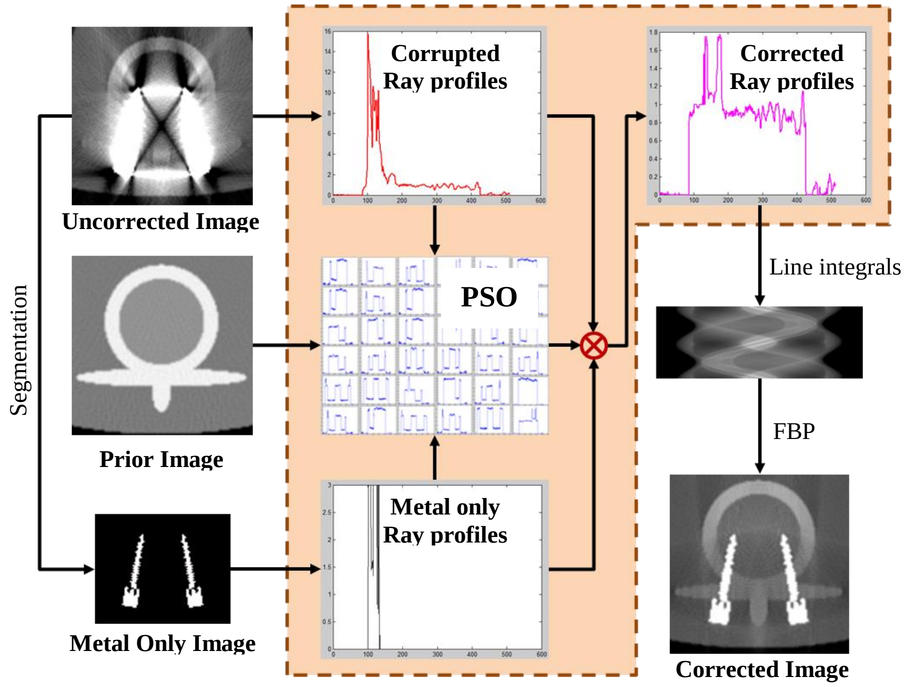

Figure 1. Flow chart of the proposed MAR algorithm. The colored region (or in the dotted box) will be executed for all rays that pass through metal objects. The proposed algorithm can be executed multiple times.

2. METHODS

The proposed MAR framework starts with segmenting implanted metal objects from the uncorrected image. In the sinogram, the regions where the corresponding rays have intersected metal objects are discovered by re-projecting the segmented metal objects. These regions are called *metal shadow*. As the sinogram values under the metal shadow are unreliable because of beam-hardening, photon starvation, and so on, we compute surrogate values using a prior CT image. For now, we restrict the set of candidate prior CT images to those 1) taken from the same patient without metal objects and 2) in different pose but without internal deformation. Here, we define a set of sample points along a ray as *ray profile*. A line integral is computed as the weighted sum of all sample points of a ray profile. Then, the proposed method first extracts (metal artifact corrupted) ray profiles corresponding to metal shadow region and searches the most similar ray profiles from a given prior CT image (See section 2.1). Our new metal artifact correction scheme is applied to the ray profiles as explained in section 2.2. Finally, the sinogram values under the metal shadow are replaced with line integrals of the corrected ray profiles. This ray profile-based metal artifact reduction scheme can be executed several times until the change in the metal artifact reduced CT image is minimal. The overall process is illustrated in Figure 1.

2.1 Ray profile matching

The similarity between the metal artifact corrupted and artifact-free ray profiles is measured using the weighted root mean square error (RMSE):

$$similarity(f^{noisy}, f^{clean}, w) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} w_i \cdot \left(f_i^{noisy} - f_i^{clean}\right)^2} \tag{1}$$

Here, f is a ray profile represented by N sampled values along a ray and the two superscripts, *noisy* and *clean*, indicate the metal artifact corrupted and artifact-free (prior) image, respectively. The weight factor, w_i, will be zero if f_i^{noisy} is sampled on metal. The weight factor then gradually increases with distance from the metal objects to lower the influence of ray samples suffering from beam hardening effects, which are usually observed nearby metal objects. Specifically, w is derived from a ray profile extracted from the metal only image such that $w = 1 - \exp(-dist(f^{metal})/h)$ where

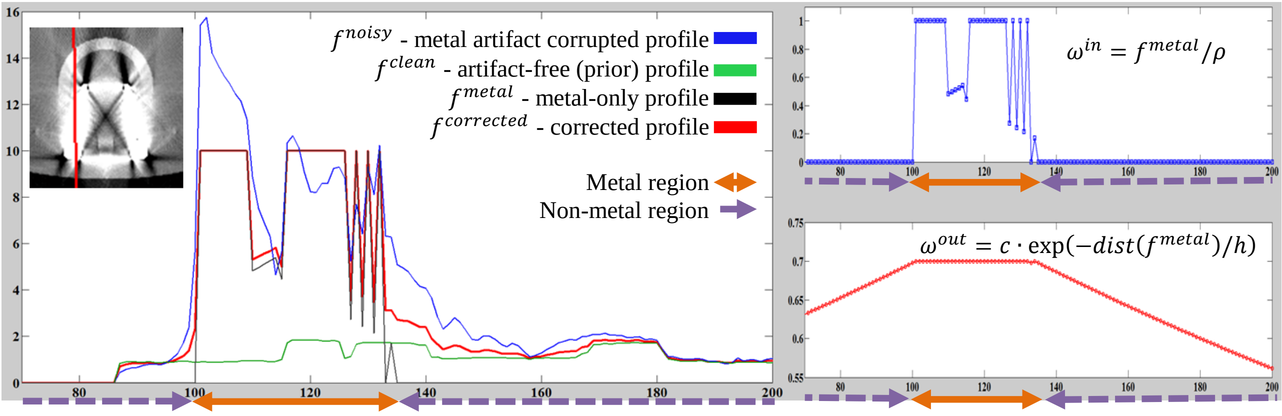

Figure 2. An example of ray profile correction

$dist(\cdot)$ is a function to compute the distance to the closest non-zero element [5] and h is a smoothness parameter, which is set to 300 in this study. Hence, the similarity measurement relies more on non-metal region less impacted by artifacts.

Since the prior CT image is usually not well aligned with the uncorrected CT image, the most similar ray profiles corresponding to all corrupted ray profiles in each view are found simultaneously by solving the object function using particle swarm optimization (PSO) [6]. This is not only computationally efficient but it also will make our ray profile matching scheme become more robust to internal deformations which, for e.g., can be observed in lung or heart regions.

$$\hat{\theta} = \arg\min_{\theta} \sum_{i=1}^{M} similarity\left(F_i^{noisy}, F_{i,\theta}^{clean}, W_i\right) \tag{2}$$

The term F^{noisy} is a $M \times N$ matrix where each row is a ray profile that is passing through metal objects and W is the corresponding weight matrix. The F_{θ}^{clean} are M ray profiles extracted from the prior image at a view, which is described by CT geometry parameter vector, θ. In this study, we used fan-beam CT geometry and all parameters remained the same for both prior and uncorrected CT images except the projection angles. Note that the subscript i is used as the index for a ray profile (or row of $M \times N$ matrix).

2.2 Ray profile based in-painting

The surrogate values in the metal shadow region are computed by line integrals of corrected ray profiles. The noisy ray profiles are corrected by linear interpolation between the attenuation coefficient of the metal objects and the clean ray profiles if the sample positions are within metal objects; otherwise it is corrected by linear interpolation between the noisy and the clean ray profiles. Note that the clean ray profiles are the most similar ray profiles extracted from the prior CT image as described in section 2.1 (see also Figure 2 for an illustration):

$$f^{corrected} = \begin{cases} \omega_i^{in} \cdot \rho + \left(1 - \omega_i^{in}\right) \cdot f_i^{clean} & , i \in R \\ \omega_i^{out} \cdot f_i^{clean} + \left(1 - \omega_i^{out}\right) \cdot f_i^{noisy} & , i \notin R \end{cases} \tag{3}$$

The interpolation weighting factor within the metal objects, ω^{in}, is computed by dividing the ray profile in the metal-only image by the (constant) linear attenuation coefficient value of the metal object, i.e. $\omega^{in} = f^{metal}/\rho$. Conversely, the interpolation weighting factor applied for the outside region of metal objects, ω^{out}, is determined such that close to metal objects more emphasis is given to the priors image, i.e. $\omega^{out} = c \cdot \exp(-dist(f^{metal})/h)$, but further away the current image is used. Here, c is a confidence factor on the prior CT image which can be a measurement of the overall similarity between prior and uncorrected images. In this study, the confidence factor is set to 0.7 throughout because we assume that there are less internal deformations (or changes) before and after metal implanting. Investigating this confidence parameter is subject of future research. Figure 2 shows an example of the ray profile correction operation. The final values that will be in-painted into the sinogram are computed as line integrals of the corrected ray profiles.

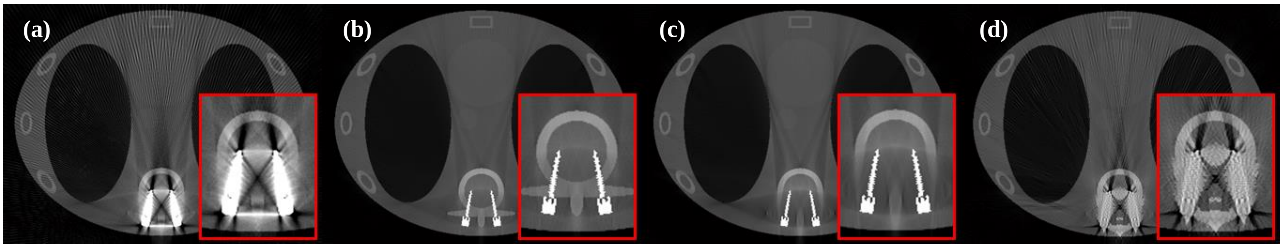

Figure 3. Method comparison for the simulated thorax phantom. (a) uncorrected image, (b) proposed method, (c) linear interpolation in-painting [1] and (d) normalized MAR [3].

3. RESULTS

The proposed method was tested with simulated thorax CT data. Two pedicle screws were implanted into a spine region and metal artifacts were simulated. Here, we do not consider scattering effects in the metal artifact simulation. The same thorax CT data were used as prior CT image but at a different orientation and without metals. All simulated data were generated and reconstructed using fan-beam geometry. We compare our method with linear interpolation-based MAR in-painting [1] and normalized MAR (NMAR) [3]. Figure 3 shows the results with an enlarged view on the spine region for better observation. In this experiment, only the proposed method can successfully remove streak artifacts and beam hardening effects while it well preserves bone structures around the implanted pedicle screws.

4. CONCLUSIONS

In this paper we presented a new method for metal artifact reduction (MAR). It assumes that a CT scan taken before implanting the metal objects into the patient is available. Using this prior scan and a segmentation or model of the metal implant, we employ a novel ray profile correction scheme that computes an accurate estimate of the rays in the sinogram regions affected by the metal artifacts. Our preliminary experiments achieved results that compare favorably with those obtained with recent methods that use simple sinogram interpolation to estimate these regions.

Future work will generalize this scheme. The current implementation was evaluated with simulated data under the somewhat limited condition that the internal structure of the prior CT image was equivalent to that of the uncorrected image as both were taken from the same patient with no deformation. Future work is needed to verify the proposed MAR method on clinical datasets where such ideal conditions do not generally hold. In addition, future work will also extend our framework to support cone-beam CT geometry and GPU acceleration.

REFERENCES

[1] Kalender, W. A., Hebel, R., and Ebersberger, J., “Reduction of CT artifacts caused by metallic implants,” Radiology, 164(2), 576-577 (1987)

[2] Müller, J. and Buzug, T. M., “Spurious structures created by interpolation-based CT metal artifact reduction,” SPIE Medical Imaging Proc., 7258(1), 1Y1-1Y8 (2009)

[3] Meyer, E., Raupach, R., Lell, M., Schmidt, B., and Kachelrieß, M., “Normalized metal artifact reduction (NMAR) in computed tomography,” Medical physics, 37(10), 5482-5493 (2010)

[4] Karimi, S., Cosman, P., Wald, C., and Martz, H., “Segmentation of artifacts and anatomy in CT metal artifact reduction,” Medical physics, 39(10), 5857-5868 (2012)

[5] Maurer Jr, C. R., Qi, R., and Raghavan, V., “A linear time algorithm for computing exact Euclidean distance transforms of binary images in arbitrary dimensions,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, 25(2), 265-270 (2003)

[6] Kennedy, J., “Particle swarm optimization,” In Encyclopedia of Machine Learning. Springer US, 760-766 (2010)