Normalized Metal Artifact Reduction using Physics-based Deep Prior Images

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Introduction

Metallic objects in the scan field can introduce artifacts severe enough to compromise or preclude diagnosis based on CT images. Metal artifacts are caused by dense, high Z materials in the field of measurement that lead to a much higher X-ray attenuation than soft tissue or bones. This high attenuation results in scatter artifacs, beam hardening, photon starvation, and edge gradient effects.

Todays gold standard to mitigate metal artifacts is the normalized metal artifact reduction[1] (NMAR). It requires the generation of a prior image. This is typically obtained by thresholding the CT values of an initial reconstruction. The prior sinogram (the forward-projected prior image) is then used to normalize the measured rawdata. Those normalized rawdata are then interpolated along the metal regions, denormalized and reconstructed. However, the quality of the NMAR algorithm strongly depends on the correctness of the prior image.

Methods

Beam-Hardening Awareness

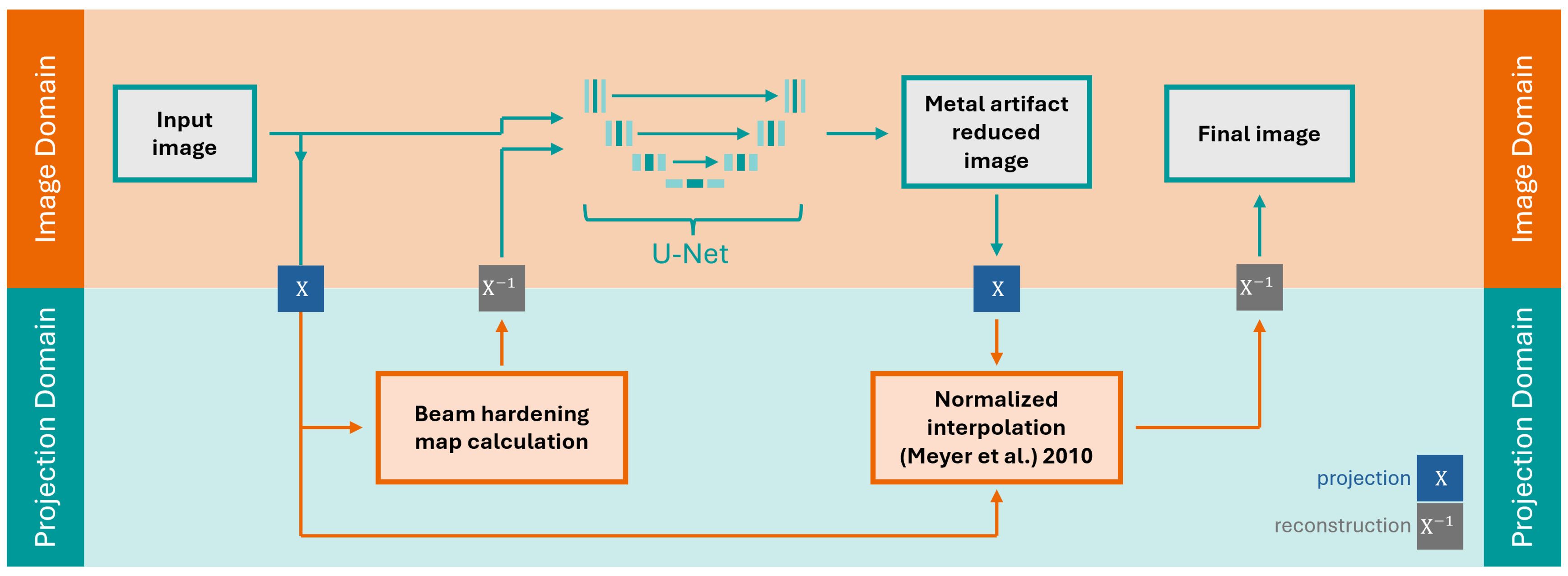

Figure 1: Flow chart of the proposed algorithm. The U-Net receives the metal-afflicted image as well as spatial information about the metal artifacts, inferred from beam hardening considerations (beam hardening map), resulting in two input channels.

The quality of the NMAR algorithm strongly depends on the correctness of the prior image. Consequently vendors use iterative versions of NMAR to improve the prior. We here extend NMAR by reformulating its heuristic prior image generation as a physics-consistent, data-driven estimation problem. We than use a residual U-Net to estimate the prior image. Input to the U-Net is a first reconstructed image, as well as physics-derived beam hardening maps[2]. These are based on an image-based material decomposition into metal and non-metal energy-dependent functions:

$$\mu(E,\mathbf{r}) \approx f_0(\mathbf{r})\,\psi_0(E) + f_2(\mathbf{r})\,\psi_2(E)$$

The forward projections p_0, p_2 from f_0, f_2 the series expansion:

$$\hat{p}_1 \approx p_0 + c_{01}\,p_2 + c_{11}\,p_0 p_2 + c_{02}\,p_2^2 + \cdots$$

After reconstructing (operator X^T), we receive the physics-derived beam hardening maps:

$$f_{02}(\mathbf{r}) = X^T(p_2^2)(\mathbf{r})$$
$$f_{11}(\mathbf{r}) = X^T(p_0\,p_2)(\mathbf{r})$$

These correlate strongly with regions most affected by metal artifacts as shown in Figure 2. We employ a custom loss function that also incorporates second order beam hardening maps to put more emphasis on artifact-contaminated voxels.

Dataset and Metal Artifact Simulation

For the simulation, the abdomen atlas was used[3]. It comprises 8,448 CT volumes with a total of 3.2 million CT slices. In addition, we used 100 binary implant masks whose shape resembles real metal implants such as hip replacements, rods or screws. Our simulation takes into account all relevant physical effects such as beam hardening, photon starvation, scatter radiation, and quantum noise.

Results

We evaluated our method on a clinical dataset, phantom scans and simulated data from our in-house simulation pipeline, showing substantial artifact reduction on all three. On simulated data, we quantitatively compared the proposed method with NMAR and the iterative NMAR implementation iMAR (using the prototype reconstruction software ReconCT, Siemens Healthineers). Physics-based deep prior NMAR outperformed both reference methods across all evaluated metrics. For clinical data, pronounced artifact reduction was observed, particularly in the presence of large metallic implants such as hip prostheses, as well as very narrow metal components (e.g., needles), where the proposed method demonstrated superior performance.

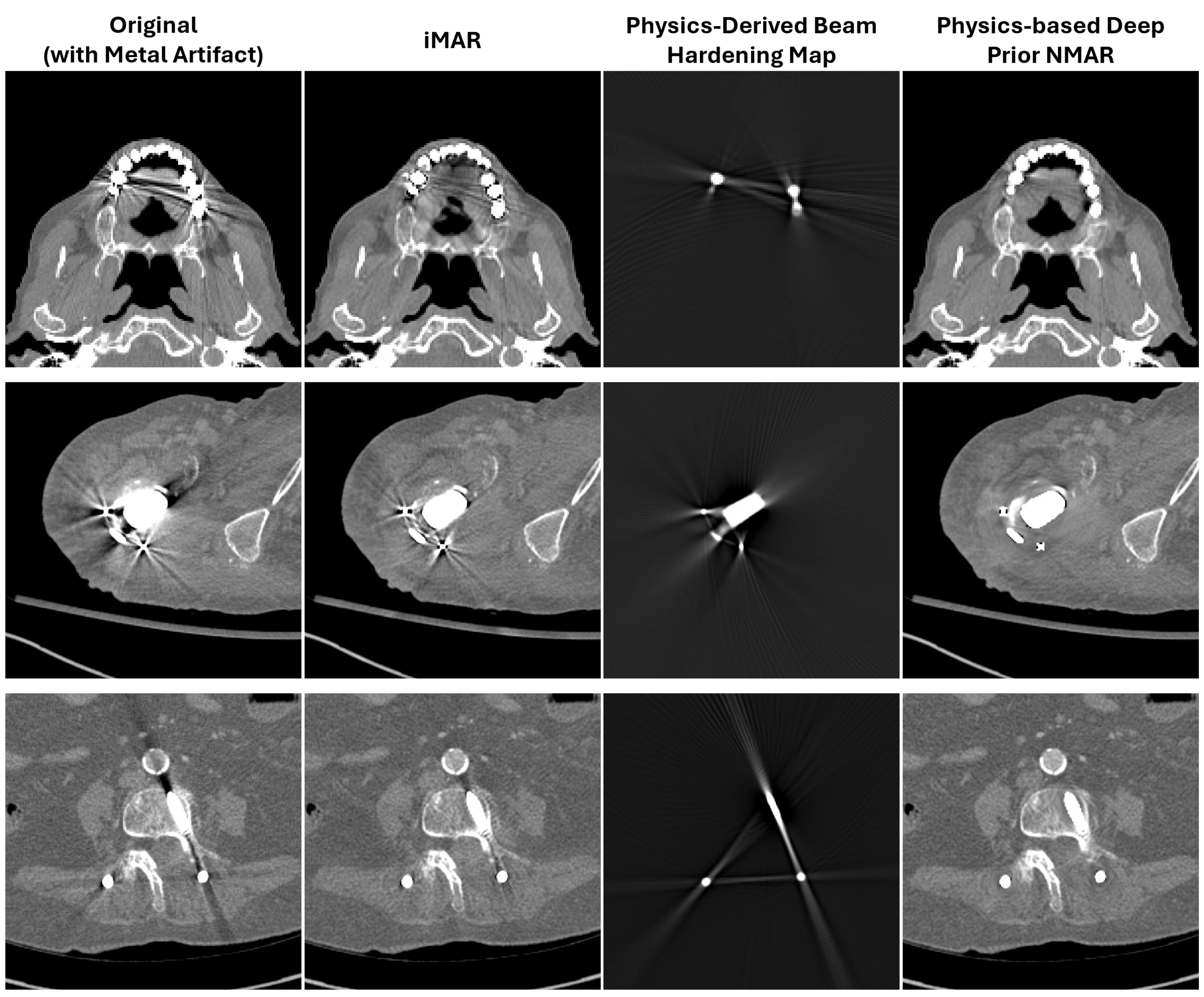

Figure 2: Metal artifact reduction applied to patient data acquired with a photon-counting CT scanner. From left to right: original images affected by metal artifacts; results obtained with the vendor-provided iMAR algorithm (iMAR reconstructions were performed using the prototype reconstruction software ReconCT, Siemens Healthineers, Germany); physics-derived beam hardening map; results of the proposed method. The beam hardening maps are displayed using an arbitrary window setting and do not represent values in Hounsfield units. For all CT images, *C* = 50 HU and *W* = 1200 HU.

Conclusion

Physics-based deep prior NMAR shows strong potential for metal artifact reductionreduction in both simulated and clinical applications. Compared to iMAR, it achieves comparable or superior performance while offering a reduced reconstruction time due to omitting the iterative step, supporting its suitability for clinical deployment.

[1]E. Meyer et al. "Normalized Metal Artifact Reduction (NMAR) in Computed Tomography". In: Med. Phys. 37.10 (Oct. 2010), pp. 5482–5493.
[2]Y. Kyriakou et al. "Empirical Beam Hardening Correction (EBHC) for CT". In: Med. Phys. 37.10 (Oct. 2010), pp. 5179–5187.3E.
[3]W. Li et al. "AbdomenAtlas: A Large-Scale, Detailed-Annotated, & Multi-Center Dataset for Efficient Transfer Learning and Open Algorithmic Benchmarking". In: Med Image Anal 97 (Oct. 2024), p. 103285.

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