New method for correcting beam-hardening artifacts in CT images via deep learning

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Abstract Beam-hardening is the increase of the mean energy of an X-ray beam as it traverses a material. This effect produces two artifacts in the reconstructed image: cupping in homogeneous regions and dark bands among dense areas in heterogeneous regions. The correction methods proposed in the literature can be divided into post-processing and iterative methods. The former methods usually need a bone segmentation, which can fail in low-dose acquisitions, while the latter methods need several projections and reconstructions, increasing the computation time.

In this work, we propose a new method for correcting the beam-hardening artifacts in CT based on deep learning. A U-Net network was trained with rodent data for two scenarios: standard and low-dose. Results in an independent rodent study showed an optimum correction for both scenarios, similar to that of iterative approaches, but with a reduction of computational time of two orders of magnitude.

1 Introduction

The origin of the beam-hardening effect lies in the polychromatic nature of the X-ray sources. It is defined as the process whereby the mean energy increases its value when traversing a material. This energy shift is due to the fact that low-energy photons are more easily absorbed than high-energy photons. The beam-hardening effect produces two artifacts on the reconstructed image: cupping in homogeneous regions and dark bands among dense areas in heterogeneous regions [1].

We can find multiple correction schemes in the literature. It is common to pre-harden the beam by using a physical filter that eliminates most of the low-energy photons [1]. However, this is not enough to completely eliminate the artifacts, making it necessary to use image processing methods. The method implemented in most of the scanners is the water linearization. It assumes that the sample is homogeneous, correcting only the cupping artifacts [2]. To correct both cupping and dark bands, the beam-hardening effect can be modeled using the spectra knowledge and an estimation of the tissue thicknesses [3, 4]. The spectra knowledge was substituted with a beam-hardening model using information either from a calibration phantom [5] or the sample itself [6]. Other works avoid the characterization of the beam-hardening model by maximizing the flatness [7] or the entropy [8] of the reconstructed image. However, all the previous methods need a segmentation that can fail in low-dose acquisitions. In these scenarios, the use of iterative algorithms allows for the improvement of the segmented masks with successive iterations. The work proposed by Elbakri et al. [9] included a polychromatic model of the source, but required the spectra knowledge to incorporate the energy effect into the projection matrix. This requirement was eliminated in the method proposed by Abella et al. [10], called bhSIR, with a simplification of the polychromatic model based on two parameters and the same calibration step of the water-linearization method. However, the use of iterative methods leads to an increase in the execution time.

Over recent years, deep learning has been widely used in CT images for segmentation and classification [11, 12] or to improve the quality of low-dose acquisitions [13, 14]. U-net [15], originally used for image segmentation and one of the most known architectures, has already been used to reduce the sparse-view artifacts in CT images [16], metal artifacts [17] or ring artifacts [18]. To the best of our knowledge, there are no deep learning approaches to reduce the beam-hardening artifacts on CT images.

In this work, we proposed a new method to obtain images free of beam-hardening artifacts in CT. We compensate the artifacts by using deep-learning techniques based on a U-net architecture in low and standard-dose scenarios.

2 Materials and Methods

The proposed method uses a modification of the original U-net architecture [15], eliminating the sigmoid layer that normalizes the resulting image to allow the restoration of the monochromatic values. We use the mean squared error (MSE) as the cost function. Figure 1 shows the network architecture.

The training was performed during 100 epochs using the Adam optimizer [19] with axial slices of four rodent studies acquired with the micro-CT scanner ARGUS/CT (SEDECAL) [20]. Two scenarios, standard dose (360 projections covering 360 degrees) and low dose (180 projections covering 360 degrees), were acquired and reconstructed with the software FUX-SIM [21], obtaining projections of 512×375 pixels and 0.2×0.2 mm of pixel size. Reconstruction was performed with the FDK algorithm [22], resulting in volumes of 512×512×375 voxels and 0.121×0.121×0.121 mm of voxel size. In both scenarios, images obtained with bhSIR [10] from standard dose data were used as reference (Figure 2).

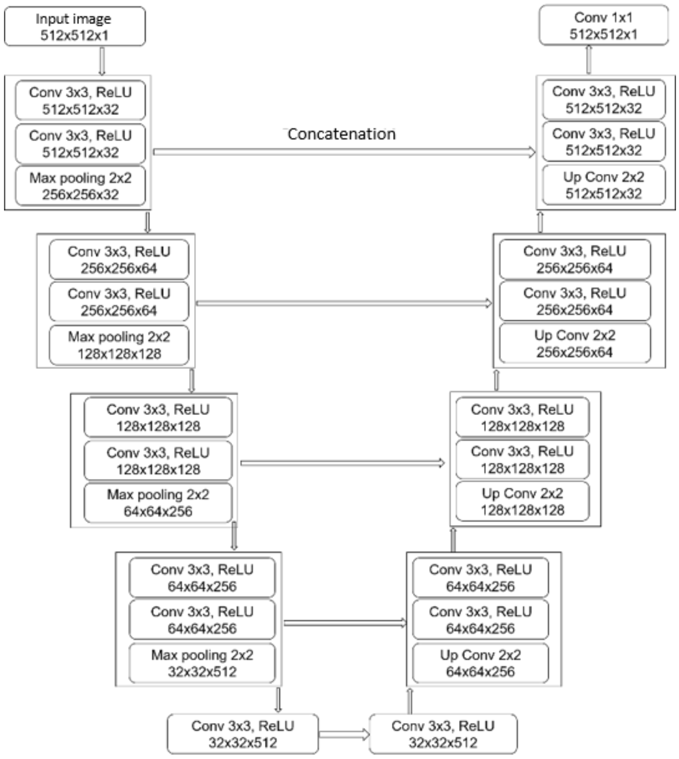

Figure 1: Modified Architecture of the U-net

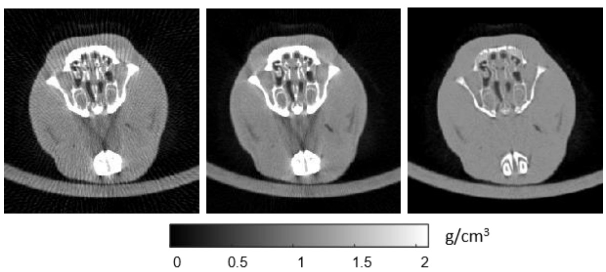

Figure 2: Axial slice of the rodent study for the low (left) and standard-dose (right) scenario and the reference obtained with the iterative method (right)

Images obtained with bhSIR [10] were used as reference. To select the appropriate learning rate, we used the Leslie N. Smith test [23], resulting in 10^{-5} (Figure 3).

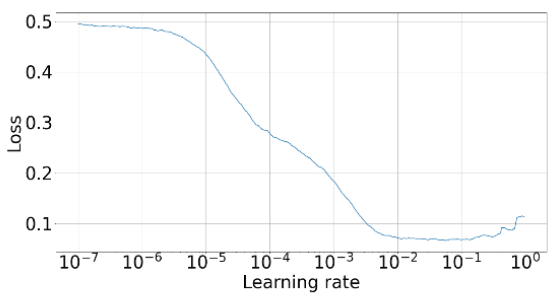

Figure 3: Results of the Leslie N. Smith test to determine the optimum learning rate.

3 Evaluation and results

The network was applied to a fifth rodent study, also acquired in standard- and low-dose scenarios. We compared the proposed method with the FDK, FDK+2DLinBH [5] and bhSIR [10] visually and in terms of execution time.

Figure 4 shows the two axial slices of the standard dose scenario obtained with the different methods. We can observe a reduction of the dark bands with all the methods but with a slight noise increase with the analytical approach FDK+2DLinBH. The image corrected with the proposed method is very similar to the one obtained with the iterative algorithm bhSIR, with higher SNR and a complete reduction of the beam-hardening artifacts.

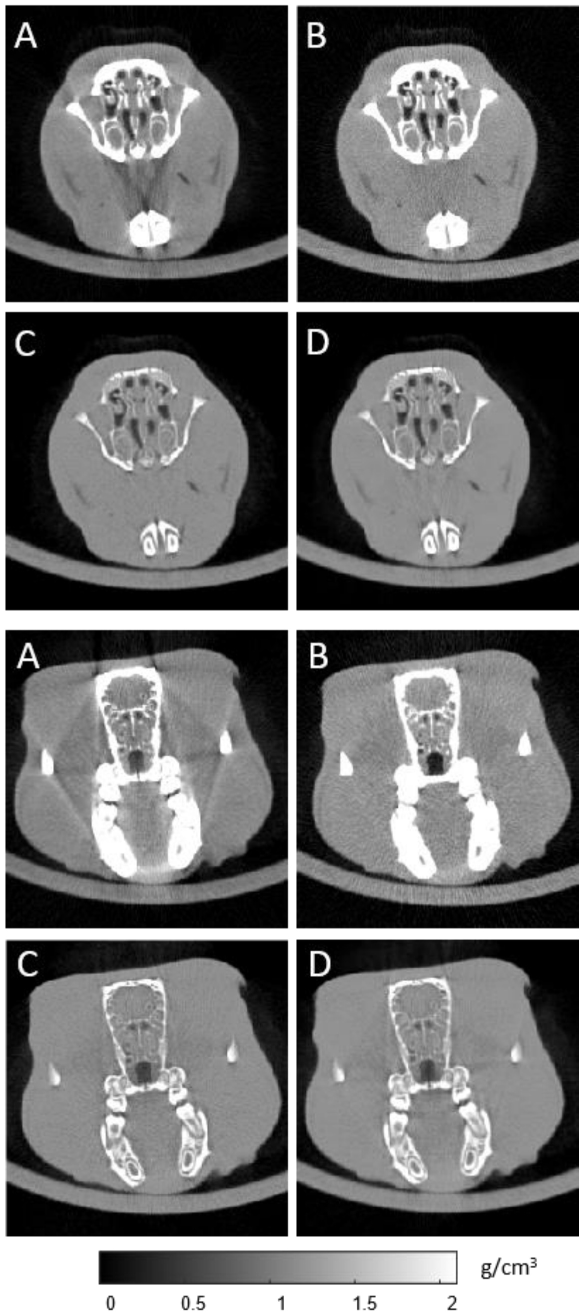

Figure 4: Standard-dose scenario for two different axial slices 1 (top) and 2 (bottom) obtained with the FDK (A), FDK+2DLinBH (B), bhSIR (C) and the proposed method (D)

Figure 5 shows the results for the low-dose scenario. FDK+2DLinBH shows streak artifacts because of the low angular sampling. The proposed method reduces these low-sampling artifacts and compensates the beam-hardening artifacts similar to that in the reference.

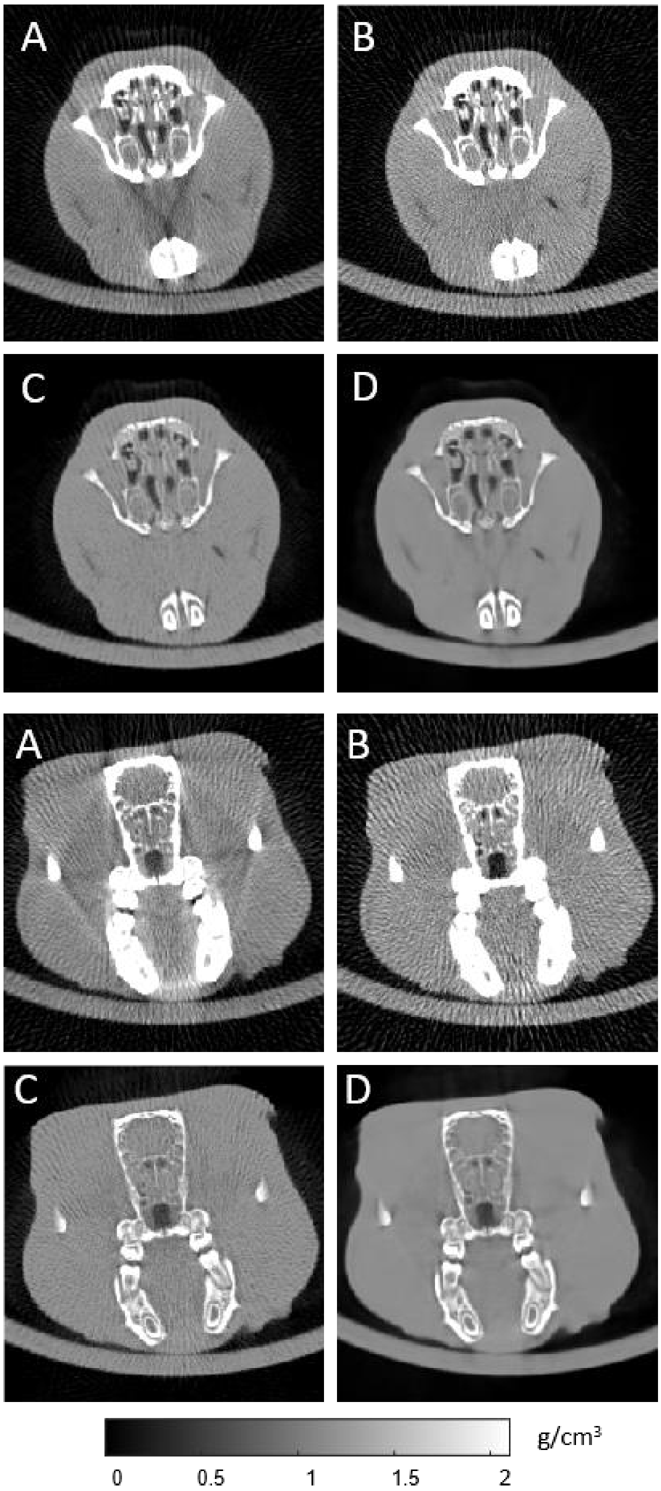

Figure 5: Low-dose scenario for the slices 1 (top) and 2 (bottom) obtained with FDK (A), FDK+2DLinBH (B), bhSIR (C) and the proposed method (D)

Table I shows the computational time of the complete volume for the different methods. We can observe that the lowest time corresponds to the proposed method.

TABLE I
EXECUTION TIME OF EACH METHOD (SECONDS)

	FDK	FDK+2DLinBH	bhSIR	FDK+DL
Standard dose	10.4	10.4+59.9	28800	10.4+28.7
Low dose	6.3	6.3+42.7	28080	6.3+28.7

4 Discussion

We have proposed a new method to compensate the beam-hardening artifacts on CT images based on the combination of conventional reconstruction and deep learning. Our method outperforms classical post-processing methods in low-dose data, showing a similar performance to a polychromatic iterative method (bhSIR) but with a considerable reduction of computational time.

Evaluation performed on real data showed a good correction of the beam-hardening artifact but a slight loss of spatial resolution. The selection of the simple cost function MSE for these preliminary results may be responsible for this loss of spatial resolution. Future work will evaluate the use of more sophisticated cost functions, such as SSIM or perceptual loss, or architectures like GAN (Generative Adversarial Networks).

Due to the impossibility of acquiring the rodent studies with a monochromatic source, an iterative method was used as the gold standard.

We focused on head studies, creating a different model depending on the number of projections. Further work will evaluate the performance of the method when other anatomical parts, such as the abdomen or thorax, are included in the dataset. We also expect that this increase in the amount of training data would enable a single model to work independently of the number of acquired projections.

5 Conclusion

The proposed method based on deep learning corrects the beam-hardening artifacts in CT images with a reduction of noise and low-sampling streaks similar to iterative methods but with a significant reduction of computational time. This reduction allows the method to be used in real-time applications like intraoperative imaging. The method can be easily implemented in real systems, since it involves only an extra processing step right after a conventional reconstruction.

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