InDuDoNet+: A Model-Driven Interpretable Dual Domain Network for Metal Artifact Reduction in CT Images

Hong Wang\textsuperscript{a,b}, Yuexiang Li\textsuperscript{b,*}, Haimiao Zhang\textsuperscript{c}, Deyu Meng\textsuperscript{a,*}, Yefeng Zheng\textsuperscript{b}, Fellow, IEEE

\textsuperscript{a}Xi'an Jiaotong University, Xi'an, China
\textsuperscript{b}Tencent Jarvis Lab, Shenzhen, China
\textsuperscript{c}Beijing Information Science and Technology University, Beijing, China

Abstract

During the computed tomography (CT) imaging process, metallic implants within patients always cause harmful artifacts, which adversely degrade the visual quality of reconstructed CT images and negatively affect the subsequent clinical diagnosis. For the metal artifact reduction (MAR) task, current deep learning based methods have achieved promising performance. However, most of them share two main common limitations: 1) the CT physical imaging geometry constraint is not comprehensively incorporated into deep network structures; 2) the entire framework has weak interpretability for the specific MAR task; hence, the role of every network module is difficult to be evaluated. To alleviate these issues, in the paper, we construct a novel interpretable dual domain network, termed InDuDoNet+, into which CT imaging process is finely embedded. Concretely, we derive a joint spatial and Radon domain reconstruction model and propose an optimization algorithm with only simple operators for solving it. By unfolding the iterative steps involved in the proposed algorithm into the corresponding network modules, we easily build the InDuDoNet+ with clear interpretability. Furthermore, we analyze the CT values among different tissues, and merge the prior observations into a prior network for our InDuDoNet+, which significantly improve its generalization performance. Comprehensive experiments on synthesized data and clinical data substantiate the superiority of the proposed methods as well as the superior generalization performance beyond the current state-of-the-art (SOTA) MAR methods. Code is available at \url{https://github.com/hongwang01/InDuDoNet_plus}.

Keywords: CT Imaging geometry, Metal artifact reduction, Physical interpretability, Generalization ability

1. Introduction

Computed tomography (CT) images reconstructed from X-ray projections have been extensively adopted in clinical diagnosis and treatment planning. Unfortunately, metallic implants within patients always lead to the missing projection data and the captured CT images present streaky and shading artifacts, which negatively affect the clinical diagnosis \cite{DeMan1999, Park2018}. Hence, it is worthwhile to develop effective metal artifact reduction (MAR) methods for CT image reconstruction.

In recent years, many traditional methods \cite{Mehranian2013, Chang2018, Jin2015, Lemmens2008, Kalender1987, Meyer2010, Wang2013} have been proposed for the MAR task, which can be mainly divided into three categories, i.e., iterative reconstruction, sinogram domain MAR, and image domain MAR. Particularly, iterative algorithms aim at designing some hand-crafted regularizers, such as total variation \cite{Schiffer2014, Zhang2016} and sparsity constraints in the wavelet domain \cite{Zhang2018}, and formulating them into the algorithm optimization to constrain the solution space. Due to the subjective prior assumptions, these approaches cannot finely represent complicated and diverse metal artifacts in clinical applications. The sinogram domain based methods regard metal-affected regions (i.e., metal trace in sinogram) as missing data and fill them via linear interpolation (LI) \cite{Kalender1987} or forward projection (FP) of a prior image \cite{Meyer2013}.

\textsuperscript{*}Corresponding author

Email addresses: vicyxli@tencent.com (Yuexiang Li), dymeng@mail.xjtu.edu.cn (Deyu Meng)
Yet, these surrogate data in the metal trace often do not properly meet the CT imaging geometry constraint, which always bring secondary artifacts tangent to the metallic implants in the reconstructed CT images. The image domain based methods directly utilize some image processing technologies to overcome the adverse artifacts, which often have some limitations for the MAR performance improvement (Karimi et al., 2015; Soltanian-Zadeh et al., 1996).

Driven by the tremendous success of deep learning (DL) in medical image reconstruction and analysis (Ronneberger et al., 2015; Wang et al., 2018a), researchers began to apply the convolutional neural network (CNN) for MAR (Zhang and Yu, 2018; Lin et al., 2019; Liao et al., 2019b; Yu et al., 2020; Lyu et al., 2020). The existing DL-based MAR methods can be roughly grouped into three research lines, i.e., sinogram domain enhancement, image domain enhancement, and dual domain (joint sinogram and CT image) enhancement. Specifically, the sinogram-domain-based approaches utilize deep learning networks to directly recover metal-affect ed sinogram data (Park et al., 2018; Ghani and Karl, 2019; Liao et al., 2019a) or adopt the forward projection (FP) of a prior image recovered by CNNs to refine the sinogram (Gjesteby et al., 2017; Zhang and Yu, 2018). The image-domain-based approaches exploit deep CNNs to directly learn the mapping function from metal-corrupted CT images to the clean ones based on residual learning (Huang et al., 2018) or adversarial learning (Wang et al., 2018b; Liao et al., 2019b). For the research line of dual domain, recent studies (Lin et al., 2019; Yu et al., 2020; Lyu et al., 2020) accomplish the mutual learning between sinogram and CT image by integrating the differentiate FP layer and filtered back-projection (FBP) layer into deep network frameworks, which further improves the MAR performance.

Attributed to the robust feature representations learned by CNN, the DL-based MAR techniques generally outperform the conventional methods based on hand-crafted features. However, the existing DL-based MAR techniques still share some limitations: 1) most of them regard MAR as the general image restoration problem, which put less emphasis on the full embedding of the inherent physical geometry constraints across the entire learning process. The constraints, however, should be potentially helpful to further boost the performance of MAR; 2) most of the existing approaches rely on the off-the-shelf DL toolkits to build different network architectures, which lack sufficient model interpretability for the specific MAR task. Hence, the intrinsic role of network modules for MAR is relatively difficult to be explicitly analyzed. Against the aforementioned issues, we propose a novel interpretable dual domain network framework, termed InDuDoNet+, for the MAR task. The proposed framework sufficiently embeds the intrinsic imaging geometry model constraints into the process of mutual learning between spatial (image) and Radon (sinogram) domains, which is flexibly integrated with the dual-domain-related prior learning. Our contribution can be mainly summarized as:

- For the MAR task, we specifically propose a concise dual domain reconstruction model and utilize the proximal gradient technique (Beck and Teboulle, 2009) to design an optimization algorithm. Different from traditional solvers (Zhang et al., 2018) containing heavy operations (e.g., matrix inversion), the proposed algorithm is composed of only simple computations (e.g., point-wise multiplication), largely facilitating its easy deep unfolding to a network architecture.
- By unfolding the iterative algorithm, we easily construct an interpretable dual domain network, called InDuDoNet+. The specificity of InDuDoNet+ lies in the corresponding relationship between its neural network modules and the algorithm operations, naturally resulting in its fine physical interpretability.
- To further improve the generalization performance, we embed the prior characteristics of metal-corrupted CT images into an elaborately designed Prior-net involved in InDuDoNet+. Besides, the network capacity is largely shrunk by a simple weight net, which finely benefits the computational efficiency and generalization ability.
- Comprehensive experiments are executed on synthetic and clinical data and they fully substantiate the effectiveness of our method as well as its superior generalization ability beyond the current state-of-the-art MAR methods. Besides, more analysis and verifications are given, which show the good potential of our methods for real applications.

An early version (Wang et al., 2021a) of this work was presented at a conference. This paper extends the previous work substantially with following improvements: 1) In previously proposed InDuDoNet (Wang et al., 2021a), the Prior-net (refer to Fig. 1) is almost a black-box. In contrast, in the work, the designed Prior-net (see Fig. 3) is finely
integrated with empirical prior observations with better interpretability; 2) Compared with the previous InDuDoNet, the network parameters of our InDuDoNet+ are largely shrunk by a simple WNet (see Table 4), which accordingly boosts its generalization performance (see Sec. 6.3 and Sec. 6.4); 3) Apart from the datasets adopted by Wang et al. (2021a), we further validate the effectiveness of the proposed InDuDoNet+ on two additional datasets. Moreover, we conduct more comprehensive experiments on model verification and module analysis in Sec. 4 and provide the detailed information on network implementation in Sec. 5.

The paper is organized as follows. Sec. 2 provides the dual domain reconstruction model and the corresponding optimization algorithm. Sec. 3 constructs the interpretable dual domain network where every network module has specific physical meanings, corresponding to the iterative step involved in the proposed optimization algorithm. Sec. 4 analyzes the role of Prior-net and designs a model-driven Prior-net which is integrated with the prior knowledge of metal-corrupted CT images. Sec. 5 describes the network details. Sec. 6 demonstrates the experimental evaluations to validate the superiority of the proposed network. The paper is finally concluded.

2. Joint Spatial and Radon Domain Reconstruction Model

In this section, we first derive the joint spatial and Radon domain reconstruction model for the metal artifact reduction (MAR) task and then propose the corresponding optimization algorithm.

2.1. Dual Domain Model Formulation

For an observed metal-affect sinogram Y ∈ R^N_s×N_r with N_s and N_r as the numbers of detector bins and projection views, respectively, conventional iterative optimization based MAR methods are generally formulated as:

\[
\min_X \| (I - Tr) \odot (P X - Y) \|_F^2 + \lambda g(X),
\]

(1)

where X ∈ R^H×W with H and W as the height and width of the CT image X, respectively, is the expected metal-free clean CT image (i.e., spatial domain); P represents the Radon transform (i.e., forward projection); Tr ∈ R^N_s×N_r is the binary metal trace (i.e., the metal-corrupted region in sinogram domain); I ∈ R^N_s×N_r is a matrix with all elements as 1; \( \odot \) denotes the point-wise multiplication; g(·) is the regularization term for delivering the prior knowledge about X; \( \lambda \) is a trade-off parameter.

For the spatial and Radon domain mutual learning, we further execute the joint regularization on the dual domain and transform problem (1) to:

\[
\min_{S,X} \| P X - S \|_F^2 + \alpha \| (I - Tr) \odot (S - Y) \|_F^2 + \lambda_1 g_1(S) + \lambda_2 g_2(X),
\]

(2)

where S ∈ R^N_s×N_r is the clean metal-free sinogram (i.e., Radon domain); \( \alpha \) is a weight factor to balance the data consistency between spatial domain and Radon domain; g_1(·) and g_2(·) are regularization functions which represent the prior information of the to-be-estimated S and X, respectively; \( \lambda_1 \) and \( \lambda_2 \) are both trade-off parameters.

Clearly, correcting the normalized metal-corrupted sinogram is easier than directly correcting the original metal-affect sinogram, since the profile of the former is more homogeneous [Meyer et al. 2010; Zhang et al. 2018]. Based on this understanding, we rewrite the clean sinogram S as:

\[
S = \tilde{Y} \odot \tilde{S},
\]

(3)

where \( \tilde{Y} \in R^N_s\timesN_r \) is the normalization coefficient, usually set as the forward projection (FP) of a prior image \( \tilde{X} \in R^H\timesW \), i.e., \( \tilde{Y} = P \tilde{X} \). \( \tilde{S} \in R^N_s\timesN_r \) is the normalized sinogram. By substituting Eq. (3) into Eq. (2), we can derive the final dual domain reconstruction problem as:

\[
\min_{\tilde{S},\tilde{X}} \| P \tilde{X} - \tilde{Y} \odot \tilde{S} \|_F^2 + \alpha \| (I - Tr) \odot (\tilde{Y} \odot \tilde{S} - Y) \|_F^2 + \lambda_1 g_1(\tilde{S}) + \lambda_2 g_2(X).
\]

(4)

1We utilize a simple model-driven CNN integrated with prior knowledge to flexibly learn \( \tilde{X} \) from training data as shown in Fig. 5

3
From Eq. (4), it is clear that our goal is to estimate the unknown \( \tilde{S} \) and \( X \) from the observed \( Y \). In traditional optimization-based MAR methods, to constrain the solution space, researchers manually designed the regularizers \( g_1(\cdot) \) and \( g_2(\cdot) \) and formulated them as explicit forms (Zhang et al., 2018). However, the pre-specified prior forms cannot always cover the complicated structures of CT images collected from real scenarios. Considering that CNN has powerful representation ability to flexibly fit the prior knowledge, we propose to adopt deep network modules to automatically learn the dual-domain-related prior information \( g_1(\cdot) \) and \( g_2(\cdot) \) from training data in a purely end-to-end manner. This strategy has been comprehensively validated to be effective in diverse vision tasks, such as spectral image fusion (Xie et al., 2019), dehazing (Yang and Sun, 2018), and deraining (Wang et al., 2020, 2021b). The details are described in Sec. 3.

2.2. Optimization Algorithm

Our goal is to build an interpretable deep unfolding network where every network module is possibly corresponding to the iterative steps involved in an optimization algorithm so that the learning process of the entire network is interpretable and controllable. Therefore, it is necessary to design an optimization algorithm for solving problem (4) efficiently, which contains possibly simple operators that can be easily unfolded into network modules. For the dual domain reconstruction problem (4), traditional solvers (Zhang et al., 2018) are always composed of complicated computations, such as matrix inversion, which makes it challenging to accomplish the transformation from iterative processes to network units. Hence, we prefer to design a new optimization algorithm only containing simple iterative computations for the problem (4). Specifically, we rely on a proximal gradient technique (Beck and Teboulle, 2009) to alternately update \( \tilde{S} \) and \( X \). The details are given in the following:

Updating \( \tilde{S} \): At the \( n \)-th iteration, the normalized sinogram \( \tilde{S} \) can be updated by solving the quadratic approximation (Beck and Teboulle, 2009) of problem (4) about \( \tilde{S} \), expressed as:

\[
\min_{\tilde{S}} \frac{1}{2} \left\| \tilde{S} - \left( \tilde{S}_{n-1} - \eta_1 \nabla f(\tilde{S}_{n-1}) \right) \right\|_F^2 + \lambda_1 \eta_1 g_1(\tilde{S}),
\]

where \( \tilde{S}_{n-1} \) is the updated result after \((n-1)\) iterations; \( \eta_1 \) is the stepsize parameter; \( f(\tilde{S}_{n-1}) = \| P X_{n-1} - \tilde{Y} \circ \tilde{S}_{n-1} \|_F^2 + \alpha \| (1 - Tr) \circ (\tilde{Y} \circ \tilde{S}_{n-1} - Y) \|_F^2 \). For general regularization terms (Donoho, 1995), the solution of Eq. (5) can be derived as:

\[
\tilde{S}_n = \text{prox}_{\lambda_1 \eta_1} \left( \tilde{S}_{n-1} - \eta_1 \nabla f(\tilde{S}_{n-1}) \right),
\]

where

\[
\nabla f(\tilde{S}_{n-1}) = \tilde{Y} \circ (\tilde{Y} \circ \tilde{S}_{n-1} - P X_{n-1}) + \alpha (1 - Tr) \circ \tilde{Y} \circ (\tilde{Y} \circ \tilde{S}_{n-1} - Y).
\]

By substituting Eq. (7) into Eq. (6), we can easily get the updating rule of \( \tilde{S} \) as:

\[
\tilde{S}_n = \text{prox}_{\lambda_1 \eta_1} \left( \tilde{S}_{n-1} - \eta_1 \left( \tilde{Y} \circ (\tilde{Y} \circ \tilde{S}_{n-1} - P X_{n-1}) + \alpha (1 - Tr) \circ \tilde{Y} \circ (\tilde{Y} \circ \tilde{S}_{n-1} - Y) \right) \right) \triangleq \text{prox}_{\lambda_1 \eta_1} \left( \tilde{S}_{n-1} \right),
\]

where \( \text{prox}_{\lambda_1 \eta_1}(\cdot) \) is the proximal operator dependent on the regularization function \( g_1(\cdot) \). Instead of adopting fixed hand-crafted image priors (Zhang et al., 2015, 2018), we adopt convolutional network modules to automatically learn the implicit prox \( \text{prox}_{\lambda_1 \eta_1}(\cdot) \) from training data (detailed in Sec. 3).

Updating \( X \): Similarly, the metal-free CT image \( X \) can be updated by solving the quadratic approximation of Eq. (4) with respect to \( X \), written as:

\[
\min_{X} \frac{1}{2} \left\| X - (X_{n-1} - \eta_2 \nabla h(X_{n-1})) \right\|_F^2 + \lambda_2 \eta_2 g_2(X),
\]

where \( \nabla h(X_{n-1}) = P^T (P X_{n-1} - \tilde{Y} \circ \tilde{S}_n) \). Thus, the updating formula of \( X \) is expressed as:

\[
X_n = \text{prox}_{\lambda_2 \eta_2} \left( X_{n-1} - \eta_2 \nabla h(X_{n-1}) \right) \triangleq \text{prox}_{\lambda_2 \eta_2} \left( X_{n-1} \right),
\]
where \(\text{prox}_{\eta S_n^\circ}(\cdot)\) is the proximal operator related to the prior form \(g_2(\cdot)\) about \(X\).

As seen, the entire iterative optimization algorithm is composed of Eqs. (8) and (10). Both alternative updating steps only contain simple operators, making it easy to execute the unfolding process and thus correspondingly construct the deep network framework. The details are presented in the following section.

3. Interpretable Dual Domain Network

In many recent studies (Yang et al., 2017; Yang and Sun, 2018; Wang et al., 2020), deep unfolding techniques have achieved great success and the fine interpretability of unfolding networks has been substantiated. Motivated by these, in this section, we aim to specifically construct a deep unfolding network, namely InDuDoNet+, for the MAR task.

Specifically, the pipeline of the proposed InDuDoNet+ is illustrated in Fig. 1(a). As seen, the entire network structure is composed of Prior-net with parameter \(\theta_{\text{prior}}\) for the prior image \(X\) estimation, \(N\)-stage \(S\)-net with parameter \(\theta_{S_n}^{(n)}\) for the \(S\) estimation, and \(N\)-stage \(X\)-net with parameter \(\theta_{X_n}^{(n)}\) for the \(X\) estimation. At every stage, as illustrated in Fig. 1(b), \(S\)-net and \(X\)-net are step-by-step constructed based on the updating rules as expressed in Eqs. (8) and (10). Clearly, the proposed network framework has specific physical interpretability and it is naturally constructed based on the derived optimization algorithm. All the involved parameters, including \(\theta_{\text{prior}}, \{\theta_{S_n}^{(n)}, \theta_{X_n}^{(n)}\}_{n=1}^N, \eta_1, \eta_2,\) and \(\alpha\), can be automatically learned from training data in an end-to-end manner.

**Prior-net.** As shown in Fig. 1(a), Prior-net is utilized to learn \(\tilde{Y}\) and the network input is composed of metal-affected image \(X_{ma}\) and linear interpolation (LI) corrected image \(X_{LI}\) (Kalender et al., 1987), where \(X_{ma}\) and \(X_{LI}\) are reconstructed from the original metal-corrupted sinogram \(Y\) and the linear interpolated sinogram \(Y_{LI}\) (Kalender et al., 1987), respectively. The architecture of Prior-net will be discussed in details in next section.

**\(\tilde{S}\)-net and \(X\)-net.** With the sequential updates of \(\tilde{S}\)-net and \(X\)-net, the framework accomplishes the reconstruction of the artifact-reduced sinogram \(\tilde{S}\) and the CT image \(X\), respectively. As shown in Fig. 1(a), the updating process consists of \(N\) stages, which correspond to \(N\) iterations of the algorithm for solving problem (4). Each stage shown in Fig. 1(b) is correspondingly built by unfolding the iterative rules in Eqs. (8) and (10), respectively. In specific, at the \(n\)-th stage, \(S_{n-1}\) is firstly computed based on Eq. (8) and then fed to a deep network \(\text{proxNet}_{\eta_1}^\circ(\cdot)\) so as to execute the proximal operator \(\text{prox}_{\eta S_n^\circ}(\cdot)\). Subsequently, we get the updated normalized sinogram as \(\tilde{S}_n = \text{proxNet}_{\eta_1}^\circ(S_{n-1})\). Similarly, for updating the CT image \(X\), \(X_{n-1}\) is firstly computed based on Eq. (10) and then fed to a network module.
proxNet_θ(·). Then we obtain the updated artifact-reduced CT image as \(X_n = \text{proxNet}_\theta(\hat{X}_{n-1})\). Here proxNet_θ(·) and proxNet_θ(·) have the same residual structure, and the details about network implementation are described in Sec. [5]. With the \(N\)-stage optimization, the proposed InDuDoNet+ can finely recover the normalized sinogram \(\tilde{S}_N\), and therefore yield the final sinogram \(S_N\) by \(\tilde{Y} \odot \tilde{S}_N\) (refer to Eq. [5]), and the artifact-reduced CT image \(X_N\), where \(\tilde{Y}\) is the predicted result of Prior-net.

**Remark:** Our network is expected to possess advantages of both model-driven and data-driven methodologies. Particularly, compared with traditional prior-based methods, our network can more flexibly learn sinogram-related and image-related priors through \(\text{proxNet}_\theta(·)\) and \(\text{proxNet}_\theta(·)\), respectively, from training data. Compared with deep MAR methods, our framework incorporates both CT imaging constraints and dual-domain-related priors into the network architecture. Besides, with such unfolding operations, the proposed network has better interpretability where every network module has its own physical meanings, corresponding to specific iterative steps.

### 4. Architecture of Prior-net

In Sec. [2.1] we propose to reconstruct the clean sinogram in a normalized manner as given in Eq. [4] and then correspondingly construct the InDuDoNet+ as shown in Fig. [1] where \(S\)-net and \(X\)-net are both built based on iterative rules. The whole pipeline of InDuDoNet+ is similar to the previous InDuDoNet (Wang et al., 2021a), except the design of Prior-net. Concretely, the Prior-net of InDuDoNet has a similar U-shape architecture (Ronneberger et al., 2015) to the PriorNet in (Yu et al., 2020) with the depth of four and a halved number of channels. Such a Prior-net is built based on the off-the-shelf U-shape network structure and has weak interpretability. In this regard, we first comprehensively verify the effectiveness of Prior-net (i.e., the normalization coefficient \(\tilde{Y}\)) and further propose a novel architecture for Prior-net with clearer interpretability and better generalization ability.

#### 4.1. Analysis on Prior-net

To validate the effectiveness of U-shape Prior-net adopted by InDuDoNet (Wang et al., 2021a), we omit \(\tilde{Y}\) and then the corresponding dual domain reconstruction problem is degraded to Eq. [2]. With the same solver (i.e., proximal gradient technique) for Eq. [4] derived in Sec. [2.2], we can easily obtain the iterative rules for Eq. [2] as:

\[
S_n = \text{prox}_{\lambda\eta_1}(S_{n-1} - \eta_1 ((S_{n-1} - PX_{n-1}) + \alpha (1 - Tr) \odot (S_{n-1} - Y))) \triangleq \text{prox}_{\lambda\eta_1}(\tilde{S}_{n-1}),
\]

\[
X_n = \text{prox}_{\lambda\eta_2}(X_{n-1} - \eta_2 P^T (PX_{n-1} - S_n)) \triangleq \text{prox}_{\lambda\eta_2}(\tilde{X}_{n-1}).
\]

(11)

---

Figure 2: Performance comparison on synthesized DeepLesion, where “InDuDoNet w/o Prior-net” denotes omitting the Prior-net in InDuDoNet (Wang et al., 2021a) and directly learning the sinogram \(S\). The red pixels stand for metallic implant.
Figure 3: Illustration about interpretable Prior-net of InDuDoNet, where ⊙ is the point-wise multiplication.

By unfolding the iterative process in Eq. (11) into network modules, we can easily construct the degraded deep network architecture (i.e., InDuDoNet w/o Prior-net). The difference between InDuDoNet w/o Prior-net and InDuDoNet is that the former has no Prior-net and the sinogram domain network directly updates the sinogram \( \tilde{S} \) instead of the normalized sinogram \( \tilde{\tilde{S}} \). Fig. 3 displays the visual comparison between InDuDoNet w/o Prior-net and InDuDoNet on different types of metallic implants, where the clean ground truth CT images are collected from DeepLesion [Yan et al., 2018] and the metal-corrupted input images are synthesized based on the existing simulation procedure (refer to Sec. 6 for details). From the areas marked by green and blue rectangles, it can be easily observed that the artifact-reduced CT images reconstructed by InDuDoNet w/o Prior-net lose lots of detailed information, especially around the metallic implants. This is mainly attributed to the lack of normalization operation, which makes it challenging to directly recover the non-homogeneous metallic region. In contrast, by using the Prior-net, the normalized profile would be more homogeneous and thus InDuDoNet achieves better reconstruction of details, which validates the effectiveness of normalization operation achieved by Prior-net.

4.2. Interpretable Prior-net

Although Prior-net is helpful for the MAR task, the previous InDuDoNet simply builds Prior-net upon the off-the-shelf U-shape network structure, which results in a relatively weak interpretability. Such a design leads to the difficulty for network module analysis and further performance improvement. Inspired by traditional MAR methods [Meyer et al., 2010], we propose a novel interpretable Prior-net. Concretely, the previous method [Meyer et al., 2010] adopted the thresholding-based hand-crafted design to segment the metal-corrupted CT image \( X_{ma} \) and then captured the prior image \( \tilde{\tilde{X}} \) for CT reconstruction. The captured prior image \( \tilde{\tilde{X}} \) benefits the metal artifact reduction, since it takes the prior-knowledge, i.e., CT values among different tissues (e.g., low-density tissues and bones) are obviously different, into consideration. However, the generation process has a limitation—the thresholding-based segmentation strategy is sensitive to CT values.

To deal with the drawback, the proposed Prior-net first utilizes the thresholding-based clustering operator [Meyer et al., 2010] to generate a coarse prior image \( \tilde{X}_c \), as shown in Fig. 3. Then, it refines \( \tilde{X}_c \) with a pixel-wise mask generated by a shallow WNet, only containing three convolutional layers, which results in a fine prior image \( \tilde{\tilde{X}} \) for the subsequent MAR task. Clearly, this design is easy to be understood: 1) the prior knowledge helps the coarse estimation; 2) the shallow CNNs executes a more flexible adjustment. Besides, the role of network module involved in the new Prior-net can be easily evaluated (see Sec. 6.5).

Specifically, for obtaining \( \tilde{X}_c \), we first execute the k-means clustering on the artifact-reduced CT image \( X_{LI} \) and then automatically get the segmentation thresholds. Following [Meyer et al., 2010], we smooth \( X_{LI} \) with a Gaussian filter for further artifact removal and then segment it into air, soft tissue, and bone via a simple thresholding. The air regions are then set to -1000 Hounsfield Units (HU), the soft tissue parts to 0HU. Bone pixels keep their values, as they vary too much to properly model them with one value. The value that is assigned to metal is arbitrary since
it does not affect the normalization and only the sinogram parts close to, but not inside, the metal trace contribute. Finally, we can obtain the prior image $X_n$. Please refer to [Meyer et al., 2010] for more details.

Compared with InDuDoNet (Wang et al., 2021a), the advantages of InDuDoNet+ are: 1) the physical prior characteristics of tissues are finely integrated into the new Prior-net via $\tilde{X}$, which makes the entire network structure more transparent; 2) the WNet has a simple architecture, which significantly decreases the network parameters of In-DuDoNet+ as well as improves its inference efficiency. The fewer network parameters have the potential to alleviate the overfitting problem and thereby improve the model generalization (see Sec. 6).

5. Network Implementation

In this section, we present the implementation details of the proposed InDuDoNet+, including channel-wise concatenation and detachment operations, residual structures of $\text{proxNet}_{q^0}(\cdot)$ and $\text{proxNet}_{q^s}(\cdot)$, variable initialization ($\tilde{S}_0$ and $X_0$), and training loss.

Channel-wise Concatenation and Detachment. As shown in Fig. 1 (b), the images sent to $\text{proxNet}_{q^s}(\cdot)$ in $\tilde{S}$-net and $\text{proxNet}_{q^s}(\cdot)$ in $X$-net are $\tilde{S}_{n-1}$ and $\tilde{X}_{n-1}$, respectively, which are both gray images with a single channel. Such a single-channel input may be insufficient for deep networks to convey previous updating information for the iterations of $\tilde{S}_n$ and $X_n$. For attaining possibly efficient information propagation, we impose the channel-wise concatenation and detachment operations (Wang et al., 2020) on the original $\tilde{S}$-net and $X$-net shown in Fig. 1 (b).

Taking $\tilde{S}$-net as an example, as shown in Fig. 4, we additionally introduce a sinogram domain based auxiliary variable $Q^s_{n-1} \in \mathbb{R}^{N_b \times N_p \times 1}$ for $\tilde{S}$-net and concatenate it with the original input $\tilde{S}_{n-1}$ along the channel-wise direction. The concatenated result is adopted as the new input for $\text{proxNet}_{q^s}(\cdot)$, whose input dimension has been expanded from $N_b \times N_p \times 1$ to $N_b \times N_p \times (1 + N_s)$. Correspondingly, the output of $\text{proxNet}_{q^s}(\cdot)$ is with the size of $N_b \times N_p \times (1 + N_s)$. We divide it into two components along the channel-wise direction, i.e., the first channel as the updated sinogram data $\tilde{S}_n$ and the remaining channels as the updated auxiliary variable $Q^s_n$. Similar operations are executed on $X$-net.

$\text{proxNet}_{q^s}(\cdot)$ and $\text{proxNet}_{q^s}(\cdot)$. The $\text{proxNet}_{q^s}(\cdot)$ and $\text{proxNet}_{q^s}(\cdot)$ in Fig. 4 have the same residual structure—four $[\text{Conv} + \text{BN} + \text{ReLU} + \text{Conv} + \text{BN} + \text{Skip Connection}]$ residual blocks (He et al., 2016) at every stage, to represent the proximal operators $\text{prox}_{1, q^s}(\cdot)$ and $\text{prox}_{2, q^s}(\cdot)$, respectively. The kernel size in every convolution layer is set to $3 \times 3$ with a stride of 1 and $N_s = N_x = 32$. Actually, the effectiveness of adopting ResNet to describe a proximal operator has been fully verified by many existing studies for other computer vision tasks, such as spectral image fusion (Xie et al., 2019) and deraining (Wang et al., 2020).

Variable Initialization. To execute the iterative process, the variables $\tilde{S}_0$, $X_0$, $Q^s_0$, and $Q^s_0$ first need to be initialized.
By adopting the channel-wise concatenation and detachment operators, we initialize these variables as:

\[
\begin{align*}
\tilde{S}_0 | Q_0^n &= \text{proxNet}_q^n (\text{concat} (Y_{LI}, K_r \otimes Y_{LI})), \\
X_0 | Q_0^n &= \text{proxNet}_p^n (\text{concat} (X_{LI}, K_r \otimes X_{LI})),
\end{align*}
\]

where ‘|’ and ‘concat(·)’ represent the aforementioned channel-wise detachment and concatenation operation, respectively; \( Y_{LI} \) and \( X_{LI} \) are the reconstructed sinogram and CT images based on the traditional linear interpolation (LI) based method [Kalender et al., 1987]. \( K_r \) and \( K_c \) are the learnable convolutional filters with the size as \( f_s \times f_s \times N_s \times 1 \) and \( f_s \times f_s \times N_s \times 1 \), respectively (in our experiments, \( f_s \times f_s \times N_s \times 1 = f_s \times f_s \times N_s \times 1 = 3 \times 3 \times 32 \times 1 \); \( \otimes \) is the convolutional operator, which can be easily achieved by the current popular deep learning (DL) toolbox, such as Tensorflow\(^5\) and PyTorch\(^6\)). \text{proxNet}_p^n(·) \) and \( \text{proxNet}_q^n(·) \) are both ResNets with the same structures to \( \text{proxNet}_q^n(·) \) and \( \text{proxNet}_p^n(·) \) in an end-to-end manner.

**Training Loss.** For network training, we adopt the mean squared error (MSE) for the extracted sinogram \( \tilde{Y} \otimes \tilde{S}_n \) and the estimated CT image \( X_n \) at every stage as the training objective function:

\[
L = \sum_{n=0}^{N} \beta_n \| X_n - Y_{sl} \|_F (1 - M) + \gamma \left( \sum_{n=1}^{N} \beta_n \| \tilde{Y} \otimes \tilde{S}_n - Y_{sl} \|_F^2 \right),
\]

where \( X_{sl} \) and \( Y_{sl} \) are the ground truth CT image and metal-free sinogram, respectively; \( M \) is the binary metal mask. We simply set \( \beta_N = 1 \) to make the outputs at the final stage play a dominant role, and \( \beta_n = 0.1 \) \( (n = 0, \cdots, N - 1) \) to supervise each middle stage. \( \gamma \) is a hyperparameter to balance the weight of different losses, which is empirically set to 0.1 in the experiments.

6. Experiments

In this section, we first provide the detailed description and then evaluate the performance of the proposed In-DuDoNet+ on three medical image datasets by comparing with the existing representative MAR methods.

6.1. Details Description

**Synthesized DeepLesion.** Following the simulation settings in [Yu et al., 2020], we randomly select a subset from the DeepLesion [Yan et al., 2018] to synthesize metal-corrupted CT images. The metal masks are from [Zhang and Yu, 2018], which contain 100 metallic implants with different shapes and sizes. We choose 1,000 clean CT images and 90 metal masks to synthesize the training samples, and pair the additional 200 CT images from 12 patients with the remaining 10 metal masks to generate 2,000 images for testing. The sizes of the 10 metallic implants for test data are: \([2061, 890, 881, 451, 254, 124, 118, 112, 53, 35]\) in pixels. Consistent to [Lin et al., 2019, Lyu et al., 2020], we simply put the adjacent sizes into one group for average MAR performance evaluation. We adopt the procedures widely used by existing studies [Zhang and Yu, 2018, Liao et al., 2019b, Lin et al., 2019, Yu et al., 2020, Lyu et al., 2020] to simulate \( Y \) and \( X_{sl} \). Various effects are considered during the simulation of metal artifacts, including polychromatic X-ray, partial volume effect, beam hardening, and Poisson noise. All the CT images are resized to \( 416 \times 416 \) pixels and 640 projection views are uniformly spaced in 360 degrees. The resulting sinograms are of the size \( N_s \times N_p \) as \( 641 \times 640 \).

**Synthesized Dental.** To evaluate the generalization performance under the cross-body-site setting, we additionally collect several dental CT images [Yu et al., 2020] and synthesize the corresponding metal-affected dental CT images according to the same simulation protocol executed on DeepLesion for performance evaluation.

\(^5\)https://tensorflow.google.cn/
\(^6\)https://pytorch.org/docs/stable/index.html
Table 1: PSNR/SSIM of different methods on synthesized DeepLesion. Bold and underline indicate the best and the second best results, respectively.

| Methods               | Large Metal | → | Small Metal | Average |
|-----------------------|-------------|---|-------------|---------|
| Input                 | 33.36/0.8804 | 37.08/0.9157 | 36.46/0.9332 | 34.52/0.8839 | 36.46/0.9282 | 27.06/0.7586 |
| LI [Kalender et al., 1987] | 27.21/0.8920 | 28.31/0.9185 | 29.86/0.9464 | 30.40/0.9555 | 30.57/0.9608 | 29.27/0.9347 |
| NMAR [Meyer et al., 2010] | 27.66/0.9114 | 28.81/0.9373 | 29.69/0.9465 | 30.44/0.9591 | 30.79/0.9669 | 29.48/0.9442 |
| CNNMAR [Zhang and Yu, 2018] | 28.92/0.9433 | 29.89/0.9588 | 30.84/0.9706 | 31.11/0.9743 | 31.14/0.9752 | 30.38/0.9644 |
| DuDoNet (Lin et al., 2019) | 29.87/0.9723 | 30.60/0.9786 | 31.46/0.9839 | 31.85/0.9858 | 31.91/0.9862 | 31.14/0.9814 |
| DSCMAR (Yu et al., 2020) | 34.04/0.9343 | 33.10/0.9362 | 33.37/0.9384 | 32.75/0.9393 | 32.77/0.9395 | 33.21/0.9375 |
| DuDoNet++ (Lyu et al., 2020) | 36.17/0.9784 | 38.34/0.9891 | 40.32/0.9913 | 41.56/0.9919 | 42.08/0.9921 | 39.69/0.9886 |
| InDuDoNet (Wang et al., 2021a) | **36.74/0.9801** | **39.32/0.9896** | **41.86/0.9931** | **44.47/0.9942** | **45.01/0.9948** | **41.48/0.9904** |
| InDuDoNet++ | 36.28/0.9736 | 39.23/0.9872 | 41.81/0.9937 | **45.03/0.9952** | **45.15/0.9959** | **41.50/0.9891** |

Clinical SpineWeb. Furthermore, we evaluate the clinical feasibility of the proposed InDuDoNet+ using a clinical dataset, i.e., SpineWeb[^1]. Similar to Liao et al. (2019b), we select the vertebrae localization and identification dataset from SpineWeb, which contains many CT images with metallic implants. Following the pre-processing protocol (Liao et al., 2019b), we get metal-corrupted CT images for testing. The clinical images are resized and processed by using the same protocol to the synthesized data. Consistent to (Liao et al., 2019b; Yu et al., 2020), the clinical metal masks are segmented with a thresholding of 2500 Hounsfield Units (HU).

Evaluation Metrics. For synthesized data, we adopt the peak signal-to-noise ratio (PSNR) and structured similarity index (SSIM) for quantitative evaluation. For clinical data, we only provide visual results due to the lack of ground truth CT images.

Training Details. We implement our networks (i.e., InDuDoNet and InDuDoNet+) with PyTorch (Paszke et al., 2019) and differential operations $\mathcal{P}$ and $\mathcal{P}^T$ in the ODL library[^2] on a NVIDIA Tesla V100-SMX2 GPU. The Adam optimizer with $(\beta_1, \beta_2) = (0.5, 0.999)$ is adopted for network optimization. The initial learning rate is $2 \times 10^{-4}$ and divided by 2 every 40 epochs. The total epoch is 100 with a batch size of 1. Similar to Yu et al. (2020), in each training iteration, we randomly select a clean CT image from the pool consisting of 1,000 images and a metal mask from the pool with 90 masks to synthesize a metal-augmented sample. Following the previous InDuDoNet (Wang et al., 2021a), we select the number of the total iterative stages $N$ as 10.

Comparison Methods. We compare the proposed InDuDoNet+ with current state-of-the-art (SOTA) MAR approaches, including traditional LI (Kalender et al., 1987) and NMAR (Meyer et al., 2010), deep learning (DL)-based CNNMAR (Zhang and Yu, 2018), DuDoNet (Lin et al., 2019), DSCMAR (Yu et al., 2020), DuDoNet++ (Lyu et al., 2020) and our previous InDuDoNet (Wang et al., 2021a). For LI, NMAR, CNNMAR, and InDuDoNet, we directly use the released code. While for DuDoNet, DSCMAR, and DuDoNet++, we re-implement them since there is no official code.

6.2. Experiments on Synthesized DeepLesion

Quantitative Comparison. Table 1 reports the quantitative comparison of different MAR methods on synthesized DeepLesion. We can observe that most of DL-based methods consistently outperform the conventional LI and NMAR, showing the superiority of data-driven deep CNN for MAR. The dual enhancement approaches (i.e., DuDoNet, DSCMAR, and DuDoNet++) achieve higher PSNR than the sinogram-enhancement-only CNNMAR. Compared with DuDoNet, DSCMAR, and DuDoNet++, our dual-domain methods (i.e., InDuDoNet and InDuDoNet++) explicitly embed the physical CT imaging geometry constraints into the mutual learning between spatial and Radon domains, i.e., jointly regularizing the sinogram and CT image recovered at each stage. Hence, our methods achieve the most competing PSNRs for all metal sizes as listed.

[^1]: [http://spineweb.digitalimaginggroup.ca/Index.php?n=Main.Datasets](http://spineweb.digitalimaginggroup.ca/Index.php?n=Main.Datasets)
[^2]: [https://github.com/odlgroup/odl](https://github.com/odlgroup/odl)
Figure 5: Comparison of different MAR methods on the synthesized DeepLesion dataset with metallic implants of various sizes. PSNR (dB)/SSIM below is for reference. The display window is [-175, 275] HU. The red pixels stand for metallic implants.

Table 2: Average PSNR (dB) and SSIM of different MAR methods on synthesized Dental shown in Fig. [6].

| Figure | Input | LI | NMAR | CNNMAR | DuDoNet | DSCMAR | DuDoNet++ | InDuDoNet | InDuDoNet+ |
|--------|-------|----|------|--------|---------|--------|-----------|-----------|-----------|
| (a)    | 35.08/0.9557 | 35.03/0.9569 | 36.65/0.9747 | 39.07/0.9753 | 37.14/0.9751 | 40.04/0.9900 | 43.33/0.9731 | 43.64/0.9922 |
| (b)    | 36.46/0.9332 | 32.83/0.9217 | 33.57/0.9384 | 36.33/0.9690 | 38.09/0.9741 | 37.17/0.9784 | 39.16/0.9881 | 42.61/0.9727 | 43.01/0.9924 |
| (c)    | 34.19/0.8733 | 33.62/0.9129 | 34.98/0.9523 | 36.61/0.9746 | 37.75/0.9747 | 37.15/0.9796 | 38.45/0.9883 | 41.66/0.9700 | 42.69/0.9894 |

Visual Comparison. The visual comparisons are shown in Fig. [5]. We find that although LI, NMAR, and CNNMAR can remove obvious streaky artifacts, they introduce secondary artifacts and lose useful image details to a certain extent, which is caused by the discontinuity in the corrected sinogram. DuDoNet and DuDoNet++ both produce over-smoothed artifact-removed image, which is mainly due to the lack of physical geometry constraint on the final output of image enhancement module. Although DSCMAR can generate a sharper image, the image intensity is not very accurate, for example, for the bone structures. This is possibly because that the prior image is not sufficiently accurate for sinogram completion. Comparatively, our methods not only evidently remove more artifacts but also better preserve the image details.
Figure 6: Performance comparison on the synthesized Dental with different numbers of dental fillings where all the DL-based MAR methods are trained on synthesized DeepLesion.

Figure 7: Performance comparison on the clinical SpineWeb dataset. All the DL-based MAR methods are trained on synthesized DeepLesion. For each method, the first row is the generalized result and the second row is the ROI result by zooming in the region marked with the green box for easy observation. The red pixels stand for metallic implants.

6.3. Generalization to Synthesized Dental

Fig. 6 displays the visual comparison of different MAR methods on synthesized dental CT images with different numbers of dental fillings, where all the DL-based MAR comparison methods are trained on synthesized DeepLesion data (focusing on abdomen and thorax). The corresponding quantitative results are reported in Table 2.

From the listed results, we have several observations: 1) Due to the domain gap between thorax CT and dental CT, almost all the benchmarking methods leave obvious artifacts in the reconstructed CT images to some extent. In contrast, the performances of our InDuDoNet+ and the previously proposed InDuDoNet are still competing, owning to the inherent incorporation of physical imaging constraints; 2) In the cross-body-site (from abdomen/thorax CT to dental CT) scenario, InDuDoNet+ is evidently superior to InDuDoNet, which substantiates the effectiveness of the proposed model-driven Prior-net.
Figure 8: (a) Ground truth and metal-corrupted CT images with different metallic implants selected from synthesized DeepLesion; (b) The artifact-reduced results recovered by “InDuDoNet+ w/o WNet”; (c) The images predicted by InDuDoNet+. The red pixels stand for metals.

Table 3: Effect of WNet in Fig. 3 on the performance of InDuDoNet+ on synthesized DeepLesion.

| Methods                | Large Metal | Small Metal | Average |
|------------------------|-------------|-------------|---------|
| Input                  | 33.36/0.8804| 37.08/0.9157| 36.46/0.9332| 34.52/0.8839| 36.46/0.9282| 27.06/0.7586|
| InDuDoNet+ w/o WNet   | 31.07/0.9511| 33.66/0.9682| 37.65/0.9823| 40.01/0.9864| 40.36/0.9881| 36.55/0.9752|
| InDuDoNet+             | 36.28/0.9736| 39.23/0.9872| 41.81/0.9937| 45.03/0.9952| 45.15/0.9959| 41.50/0.9891|

6.4. Generalization to Clinical SpineWeb

We further evaluate all MAR methods on the clinical SpineWeb dataset. The experimental results are shown in Fig. 7. Due to the inaccurate sinogram completion, LI and NMAR introduce obvious secondary artifacts. CNNMAR, DuDoNet, and DuDoNet++ evidently blur the image details. DSCMAR fails to remove obvious dark shadings and streaky artifacts. For the existing MAR approaches, the degradation of MAR performance is mainly caused by the large domain gap between the synthesized DeepLesion (abdomen and thorax CT) and SpineWeb (spine CT). Compared with the previous InDuDoNet, our InDuDoNet+ removes more artifacts and preserves the image details better. This finely verifies that the interpretable Prior-net tends to better regularize the network learning and thus improve its generalization performance.

6.5. Ablation Study

Fig. 8 shows the visual comparison between “InDuDoNet+ w/o WNet” and InDuDoNet+, where “InDuDoNet+ w/o WNet” means that we directly utilize the manually-segmented coarse prior image \( \tilde{X}_c \) as the final prior image \( \tilde{X} \), while omitting WNet in Fig. 3. Table 3 reports the quantitative evaluation. From these results, it is clear to find that WNet plays a significant role in boosting the MAR performance. This finely validates the analysis in Sec. 4.2 that the introduction of WNet is helpful for refining the thresholding-based prior segmentation result and such data-driven adjustment manner is more flexible.

6.6. Model Verification

Here, we utilize InDuDoNet+ to execute a model verification experiment in order to present the working mechanism underlying the network modules (\( \tilde{S} \)-net and \( X \)-net). Fig. 9 displays the reconstructed normalized sinogram \( \tilde{S}_n \), sinogram \( S_n \), and CT image \( X_n \) at different stages (\( n = 1, 4, 7, 10 \)). It can be easily observed that with the increasing of \( n \), the metal trace region in \( \tilde{S}_n \) is gradually flattened, which correspondingly ameliorates the sinogram \( S_n \). Thus, the metal artifacts contained in the CT image \( X_n \) are gradually removed. The results verify the design of our interpretable iterative learning framework—the mutual promotion of \( \tilde{S} \)-net and \( X \)-net enables the proposed InDuDoNet+ to achieve MAR along the direction specified by Eq. (4).
Figure 9: The normalization coefficient $\tilde{Y}$, normalized sinogram $\tilde{S}_n$, sinogram $S_n$, and CT image $X_n$ restored by InDuDoNet+ at different stages where the number $N$ of the total iterative stages is 10. The red pixels stand for metallic implant.

Table 4: Numbers of network parameters and average testing time (seconds) for different MAR methods.

| Methods          | # Network Parameters | Testing Time (Seconds) |
|------------------|----------------------|------------------------|
| DuDoNet          | 25,834,251           | 0.4225                 |
| DSCMAR           | 25,834,251           | 0.3638                 |
| DuDoNet++        | 25,983,627           | 0.8062                 |
| InDuDoNet        | 5,174,936            | 0.5116                 |
| InDuDoNet+       | 1,782,007            | 0.3782                 |

6.7. Network Parameters and Inference Time

For the competing MAR methods (i.e., DuDoNet, DSCMAR, DuDoNet++, InDuDoNet, and InDuDoNet+), Table 4 lists the number of network parameters and the average inference time computed on 2,000 images with size $416 \times 416$ pixels on an NVIDIA Tesla V100-SMX2 GPU. As compared with other SOTA methods, the previously designed InDuDoNet has evidently fewer parameters, while the proposed InDuDoNet+ further reduces the network capacity. For inference time, InDuDoNet+ is comparable to DSCMAR, while faster than others. It is clear that due to the simple design of Prior-net, InDuDoNet+ performs better than previous InDuDoNet on computational efficiency.

7. Conclusion and Future Work

In this paper, for this metal artifact reduction (MAR) task, we have proposed a novel joint spatial and Radon domain reconstruction model and designed an optimization algorithm for solving it. By unfolding every iterative step into the corresponding network module, we constructed an interpretable network architecture, namely InDuDoNet+.

Besides, we analyzed the characteristics of metal-corrupted CT images and embedded such prior observations into our framework, which has clear interpretability and fine generalization ability. Comprehensive experiments conducted on synthesized and clinical data have substantiated the effectiveness of our dual-domain MAR approaches as well as the superior interpretability beyond current SOTA deep MAR networks.

As stated in Sec. 6.1, following the current SOTA methods, we have adopted the hand-crafted thresholding to coarsely segment the metallic implants for clinical data, which is not very accurate and lacks flexibility. For performance improvement, in the future work, we will try to design an automatic metal localization algorithm and incorporate it into the proposed dual domain network framework. Besides, how to finely apply such model-driven dual domain framework in a semi-/un-supervised manner for better generalization performance would be an interesting research direction worthy of further exploration.
Yang, Y., Sun, J., Li, H., Xu, Z., 2017. ADMM-Net: A deep learning approach for compressive sensing MRI. arXiv preprint arXiv:1705.06869.

Yu, L., Zhang, Z., Li, X., Xing, L., 2020. Deep sinogram completion with image prior for metal artifact reduction in CT images. IEEE Transactions on Medical Imaging 40, 228–238.

Zhang, H., Dong, B., Liu, B., 2018. A reweighted joint spatial-Radon domain CT image reconstruction model for metal artifact reduction. SIAM Journal on Imaging Sciences 11, 707–733.

Zhang, H., Wang, L., Li, L., Cai, A., Hu, G., Yan, B., 2016. Iterative metal artifact reduction for X-ray computed tomography using unmatched projector/backprojector pairs. Medical Physics 43, 3019–3033.

Zhang, Y., Yu, H., 2018. Convolutional neural network based metal artifact reduction in X-ray computed tomography. IEEE Transactions on Medical Imaging 37, 1370–1381.