Sparse-View Spectral CT Reconstruction Using Deep Learning

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Abstract—Spectral CT is an emerging technology capable of providing high chemical specificity, which is crucial for many applications such as detecting threats in luggage. Such applications often require both fast and high-quality image reconstruction based on sparse-view (few) projections. The conventional FBP method is fast but it produces low-quality images dominated by noise and artifacts when few projections are available. Iterative methods with, e.g., TV regularizers can circumvent that but they are computationally expensive, with the computational load proportionally increasing with the number of spectral channels. Instead, we propose an approach for fast reconstruction of sparse-view spectral CT data using U-Net with multi-channel input and output. The network is trained to output high-quality images from input images reconstructed by FBP. The network is fast at run-time and because the internal convolutions are shared between the channels, the computation load increases only at the first and last layers, making it an efficient approach to process spectral data with a large number of channels. We validated our approach using real CT scans. The results show qualitatively and quantitatively that our approach is able to outperform the state-of-the-art iterative methods. Furthermore, the results indicate that the network is able to exploit the coupling of the channels to enhance the overall quality and robustness.

Index Terms—Computed tomography, tomographic reconstruction, spectral CT, multi-channel CT, multi-spectral CT, few-view CT, sparse-view CT, photon-counting, spectral detectors, deep learning, U-Net.

I. INTRODUCTION

Spectral computed tomography (CT) has recently emerged following the advancement in the photon-counting X-ray detection technology [1], [2], [3], [4], [5]. The photon-counting detectors are able to resolve the energy of the received photons and, thereby, distribute the photons into discrete channels according to their energies. The CT reconstruction of such data allows us to obtain the X-ray attenuation coefficients as multi-channel energy profiles, providing higher chemical specificity when compared with the energy-integrating detectors used for the conventional single-energy and dual-energy CT [6], [7]. Some research suggest that the accuracy is improved with spectral detectors using just two energy channels [8].

The high specificity offered by spectral CT leads to improved performance in common tasks such as image segmentation [9], [10]. More importantly, high specificity is crucial in applications that require the identification of materials (e.g., detection of threats in luggage [9], [11], [12], [13]), which we pay special attention to in this work. Furthermore, resolving the full spectral shape with the spectral detectors makes it easier to tackle well known reconstruction artifacts, namely metal streaks and beam hardening [14], [15], [16].

Certain requirements such as a reduced scanning time and a simplified mechanical setup often restrict the design of CT scanners to have a limited number of viewpoints from which X-rays are projected into the scanned object. CT reconstruction from few projections is referred to as sparse-view CT (also as few-view or compressed-sensing CT), which is an active field of research [17], [18], [19], [20].

In sparse-view CT, the conventional filtered back projection (FBP) reconstruction method is computationally fast but it produces severe noise and structural artifacts in the reconstructed images [21]. Reconstruction methods and extensions have
been introduced for solving these ill-posed inverse problems by employing different types of optimization routines and regularizations \[22, 23\] or replacing the high pass filter with iteratively calculated filters unique to the specific acquisition geometry \[24\]. Nowadays, iterative methods such as ART-TV \[25\] are the standard approaches for sparse-view CT. In this paper, we introduce an alternative approach to spectral CT reconstruction employing convolutional neural networks (CNN) (Fig. 1).

One major drawback of the iterative methods is that they are computationally expensive even for single-energy reconstruction. For spectral CT, the computation time grows proportionally to the number of channels. If we reconstruct the channels independently with, e.g., ART-TV, the computation time would grow linearly. Using total nuclear variation (TNV) \[26\], which is a state-of-the-art method for joint spectral reconstruction, the computation time would grow super-linearly. It is worth noting that commercially available spectral detectors usually provide a high number of spectral channels (e.g. 128 channels by \[27\] and 6400 channels by \[28\]. Using iterative methods for spectral CT then becomes largely impractical, particularly so for time-critical applications such as luggage scanning. Another issue with the iterative methods is the need to manually tune hyper-parameters, which often set a trade-off between speed and quality.

One way to reduce the time spent on reconstruction is to apply data reduction techniques such as principal component analysis (PCA) \[29\] prior to reconstruction to reduce the number of channels. However, previous work suggests that even with data reduction, a high number of channels are still needed for material identification \[30, 31\]. Moreover, previous work also suggests that post-reconstruction data reduction causes less information loss \[31\]; it is preferable to reconstruct all the raw channels first and reduce them afterwards if necessary.

In spectral reconstruction, we obtain significantly lower signal-to-noise-ratio (SNR) per channel as compared to single-energy reconstruction with a similar acquisition setup (Fig. 2). This is because the spectral detectors distribute the received photons, which influence the reconstruction SNR, into the channels whereas single-energy detectors integrate the photons in one channel. The SNR becomes even lower in sparse-view spectral reconstruction. Imposing image priors such total variation (TV) by iterative reconstruction mitigates the lower SNR. This issue can be further mitigated by joint spectral reconstruction that exploits inter-channel correlations to maintain chemical properties such as spectral smoothness.

In this paper, we present a model for spectral CT reconstruction using CNN. The model employs the U-Net architecture \[32\] adapted to multi-channel images. The model takes as input the spectral image reconstructed by FBP on a channel-by-channel basis and processes the channels jointly with shared convolutional layers. The proposed approach improves the reconstruction quality, seen as piece-wise smoothness with clearly preserved edges in both the spatial and spectral domains. This outcome shows similar properties to e.g., methods regularized by TV \[25\]. In addition to that, structural artifacts are removed and contours become smooth. Such properties are difficult if not impossible to obtain with iterative methods but can be learned by a neural network. A major advantage of using neural networks is that the model parameters are learned off-line. At run-time the model only executes a fast forward pass through the network. Furthermore, since convolutions are shared between the channels the runtime does not significantly increase with the number of channels.

To train the model, we use a dataset of real spectral CT \[33\] supplemented with a synthetic dataset and with data augmentation during training. The model is trained with sparse-view data of only 9 projections reconstructed using FBP. To provide a training reference for the real data, each FBP image is paired with an image reconstructed with a high number of projections (dense-view). (b) shows how the received photons are distributed in the channels. The variance of the empty area inside the circle (which relates to the SNR) is shown in (c). Note that the variance increases as the photon count decreases (most visible in FBP (9)). In single-energy reconstruction, all photons are involved and thus we get significantly lower variance. FBP is fast but it produces noisy images and artifacts. ART-TV circumvents better the low SNR but it is computationally expensive.

![Fig. 2: Spectral CT vs single-energy CT.](image)

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**II. Related work**

Conventional CT systems are based primarily on single-channel X-ray detectors. The reconstruction methods developed for such systems follow two approaches: direct (analytical) methods and iterative methods. The direct methods \[35\] are essentially discretized versions of the inverse of the Radon
transform [36] that models tomographic scanning. The most common direct method is the FBP [35], which first applies a high-pass filter and then employs the Fourier slice theorem to obtain the inverse. In this work, the FBP is applied as an initial step to reconstruct each channel separately.

On the other hand, the iterative methods are generally optimization routines for solving the ill-posed inverse problem of CT reconstruction. The optimization typically minimizes a data fidelity term (i.e., the back-projection error) with potentially extra regularizing terms. Based on different optimization frameworks, researchers have developed a variety of reconstruction methods, most notably algebraic reconstruction technique (ART) [37], [38], simultaneous algebraic reconstruction technique (SART) [39], and simultaneous iterative reconstruction technique (SIRT) [40]. The most common regularizer is TV minimization [41], [42], which represents the state-of-the-art approach for sparse-view reconstruction addressed in this article. A number of methods incorporating TV have been developed such as ART-TV [25], SART-TV [43] and CP-TV [44].

With respect to spectral CT, recent iterative methods have been developed following the emergence of photon-counting detectors. The spectral CT methods solve the inverse problem for all channels jointly through some form of spectral coupling. In [45], the authors developed a method based on the primal-dual algorithm with fast convergence but it reconstructs the spectral data into a base map of few and distinct materials, e.g., bone and brain, limiting its applicability to, e.g., medical imaging. In [46], the authors also used a known basis of 5 materials to reconstruct 4 energy channels of the data jointly. Their method also incorporates a model of the detector response and the noise. In addition to limiting the reconstruction to certain materials, the robustness of these methods for sparse-view reconstruction was not demonstrated. In this respect, other methods have been developed for sparse-view spectral reconstruction. Zhang et al. proposed in [47] an algorithm with regularizers combining image-domain (intra-image) sparsity measures (i.e., total variation) with spectral-domain (inter-image) similarity measure (i.e. spectral mean). Also [48] used joint reconstruction of the energy channels by letting structures in favoured channels propagate throughout the spectral domain.

Other methods incorporate the spectrum with a single TV metric. This metric extends the conventional scalar TV formula applied in images with some kind of channel coupling. In [49], the authors performed the channel coupling by global pooling of TV across channels. This form of TV is referred to as color TV. In [50], the authors proposed local pooling instead using the nuclear norm of the image Jacobian and hence the method is referred to as TNV. The authors showed theoretically and experimentally the superiority of their approach in most aspects of performance. The TNV was later incorporated for spectral CT in [28]. While the recent spectral CT approaches satisfy the requirement of spectral reconstruction that exploits the spectral dimensions, the major limitation is the computational cost. Our approach provides an alternative that is faster and with superior quality. Another limitation of the current iterative methods is their robustness to metal artifacts, which show that it can be handled naturally by our approach even in extreme cases.

Inspired by the breakthroughs that deep learning achieved in numerous tasks [51], [52], [53], [54], [55], researchers have attempted to employ deep learning for CT reconstruction. Their work can be divided into two approaches. The first approach involves building an end-to-end network that reconstructs images from sinograms. An early work employing fully-connected neural networks to model the mapping from the sinogram domain to the image domain was presented in [56]. In their work, the authors designed two specific networks for the parallel-beam and the fan-beam scanning geometries by hard-wiring certain scanning configuration. Recently, CNN have been used instead of fully-connected layers as in [57], [58], [59]. Because training generic architectures would involve learning geometry mapping, the proposed architectures are built for specific geometries, hindering their use in customized geometries.

The second approach for CT reconstruction with deep learning is to apply neural networks in the image domain after an initial reconstruction with FBP [60], [61]. In sparse-view reconstruction, the FBP image would be noisy and convoluted with artifacts, making the problem resemble image denoising [62], [63], [64], [65]. In [66], Jin et al. introduced FBPConvNet, which is an architecture based on U-Net [32]. In their paper, the authors argued that iterative methods in certain forms in fact repetitively apply convolutions and point-wise nonlinearities. Therefore CNN can offer a data-driven alternative. Based on that more architectures have been proposed [67], [68], [69], [70]. In [71], other variants of the U-Net were compared. In [72], the authors employed the generative adversarial network (GAN) to train the U-Net as a generator. Similarly in [73], GAN was used but with an autoencoder as a generator. Note that the neural network approaches so far has been addressing single-energy CT. Our work can be viewed as an extension of the FBPConvNet model for spectral CT with multi-channel input and output.

### III. Architecture

Fig. 5 shows the architecture presented in this paper. This architecture is similar to the FBPConvNet model [60] with the extension to multi-channel input and output and with other modifications. Both models are variants of the U-Net [32], originally developed for image segmentation. The general U-Net scheme is composed of two parts: an encoder and a decoder. The encoder gradually compresses the spatial space of the input image using pooling while increasing the feature space through convolutions. This scheme allows for the derivation of higher-level features as we go down the levels in the encoder while suppressing the noise. After that, the decoder gradually restores the spatial space of the image using up-sampling while reducing the feature space through convolutions.

In this paper, our architecture is defined with 32 input and output channels, corresponding to the energy bins of the CT data. The multi-channel input and output convolutions provide a joint spectral processing mechanism for our spectral CT
images. To accommodate for the memory demands caused by increasing the number of channels, the spatial resolutions throughout the layers is reduced. Specifically, the spatial resolution in our model starts with 96x96 at the input layer whereas in [32] and [66], the resolution starts with 572x572 and 512x512, respectively. Lower spatial resolution also allows us to build a network that is shallower than the ones in [32] and [66]. More concretely, our network contains three encoding/decoding levels as opposed to four levels in the other networks, resulting in seven instead of nine convolutional blocks.

Similar to the FBPConvNet, we apply zero-padding convolutions to obtain an output image of the same spatial resolution as of the input. In the original U-Net, only valid convolutions are performed, i.e., edge pixels are discarded and the resulting segmentation map has a lower resolution (388x388). To produce a full segmentation map for an image of any resolution, the original U-Net adopts the "overlap-tile" strategy in which the input image is processed in patches. Each patch is cropped having the output resolution (388x388) and then padded by mirroring to match the input resolution (572x572) [32]. While such an approach is suitable for segmenting large images, the lower resolution of our data would yield very small tiles if we use the overlap-tile strategy. Because we use small convolution kernels of 3x3, only a 1x1 border of zeros is padded, minimizing any potential side effects. Furthermore, a recent evaluation of the overlap-tile strategy suggests that tiling may lead to undesirable errors that can be avoided by zero-padding [74].

Fig. 3: The architecture of the proposed network. The network is based on the U-Net [32] architecture. This architecture extends and modifies the one introduced in [66] with multi-channel input and output (32 channels). For better memory management, this architecture is shallower and comes with lower spatial resolution than the architectures in [32] and [66]. Our implementation is available at https://github.com/wailmu/spectral-ct.

Dropout regularization is applied to the last layer of each block with a dropout rate of 2%. We also utilize the skip connections, which is a key element in U-Net. The skip connections concatenates the features maps from the downstream layers to their corresponding layer in the decoder. Opposite to the FBPConvNet and like in the U-Net, batch normalization [75] is not applied between layers in the proposed architecture. Batch normalization acts as a regularizer and can be beneficial in very deep networks, e.g. the Inception architecture on which the method was first applied, [76]. The network was optimized with the RMSprop optimizer [77] with an initial learning rate of $10^{-4}$ and a decay of $10^{-6}$ over each update. The mean absolute error (MAE) loss was used to optimize the network outputs to predict noise- and artifact-corrected version of the spectral CT input images.

To prevent over-fitting and stabilize the training data augmentation is applied to the images before being fed to the network during training. The data augmentation types used here are additive white Gaussian noise (AWGN) and flipping of the images.

A. Data scaling

It is key that our model retains the actual X-ray attenuation coefficient profiles, as they are required by subsequent methods for material identification [31], [11]. This requirement makes our learning problem different from other common learning tasks such as, for example, object classification or semantic segmentation where the output is a class or segment ID. Maintaining attenuation coefficient profiles is challenging as the dynamic range is wide and the maximum value is unbounded—materials can have arbitrarily high attenuation coefficients. In contrast, the data in most learning tasks (e.g., rgb or gray-scale images) is bounded, making it straightforward to rescale the data to a certain range (typically between 0 and 1). Data scaling is common practise in machine learning for better numerical stability.

In order to address the above requirements, we propose to first scale the data with respect to an absolute maximum value.

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Then, the output obtained from the network is rescaled back to the original range. By doing so, we provide the network with a scaled data while retaining the actual attenuation values. We choose the absolute maximum value to be 7.66 cm\(^{-1}\), which is the highest attenuation coefficient of Cadmium (Cd) (i.e., at 26 Kev). Although this sets a cut-off value for the attenuation coefficients, Cadmium is a highly attenuating material and all materials of interest to Airport security have lower attenuation coefficients.

### B. Computational complexity

To analyze the computational complexity of our model, we need to look at the computational complexity of the FBP part and the CNN part. The FBP computations are dominated by the back projection, which computes the sum of all line integrals passing through each of the reconstructed pixels. To reconstruct an \( N \times N \) image from \( V \) projections, the FBP operations amounts to \( O(N^2V) \) when a fixed-size discretization kernel is used (as in our case) \(^7\), \(^6\). To reconstruct \( S \) spectral channels, the operations grow linearly, resulting in \( O(SN^2V) \) operations.

There are several operations in the CNN such as additions, upsampling, downsampling, activation functions but the computations are dominated by the convolutions. With \( L \) layers, \( R \) filters per layer and a \( K \times K \) kernel size, the run-time evaluation of a standard CNN requires \( O(R^2N^2K^2L) \) operations \(^7\). For the U-Net, this complexity estimation represents an upper bound since the number of pixels are gradually reduced in the lower levels. In our network, we process the spectral channels with input and output filters similar to the internal filters. To accommodate for the spectral channels, we only add filters at the first and last layer; the number of internal filters is unchanged. Therefore, the added operations are still within the upper bound defined above. Furthermore, since our approach is composed of a FBP step followed by a CNN step, the overall complexity of our approach can be described by the operations of the step with higher complexity, i.e., the CNN.

For the iterative methods, the computations are dominated by the back projections, which scale linearly with the number of projections and the iterations (\( I \)), leading to \( O(SN^2VT) \) operations. The TV adds additional complexity amounting to \( O(N^2T) \) operations for one channel and \( O(N^2TS) \) for \( S \) channels, where \( T \) is the TV iterations. In the ART-TV method, we get \( O(N^2VIT) \) operations with single channel and \( O(SN^2VIT) \) for \( S \) channels. For TNV, we get \( S^2N^2VIT \).

The computational complexity analysis discussed above is summarized in Table I (a). When comparing methods with some parameters being method-specific, we should take into account the typical values of the parameters (Table I (b)). More specifically, note that the number of iterations (\( I \) and \( T \)) in ART-TV are usually much higher than \( K \) and \( L \) in the CNN (in our case, \( I = 200 \) and \( T = 30 \) whereas \( K = 3 \) and \( L = 17 \)). This complexity analysis highlights the computational advantage of the CNN step and thereby our model despite being an upper bound estimation. In addition to that, a key practical feature of CNN is that we can easily speed up the computation by exploiting the existing tools for parallel computing and hardware acceleration (e.g. using GPUs).

The computation advantage in run-time comes with higher memory complexity. With the CNN, we need to store the pre-trained convolutions in all layers and the intermediate feature maps produced within a forward pass. These memory demands amounts to an upper bound of \( O(S^2N^2K^2L) \) \(^8\), \(^1\). With the current hardware technology, accepting such memory demands in exchange for fast run-time is considered a good trade-off. In the training phase however, the memory complexity increases with the batch size, i.e., the number of spectral images passed together in a single training step. This issue may limit the batch size or impose other design constraints. In our work, we chose to lower the spatial resolution and, subsequently as well, reduce the number of layers as we discussed above.

### IV. Dataset

The CNN is trained with both real and synthetic data. The data are arranged as sets of 4D volumes, each of which is composed of stacked slices of 3D spectral images. Note that the model processes each spectral image separately. In Fig 2 example slices are presented, showing the diversity of materials and geometrical shapes the dataset contains. The real data used in this paper are composed of 22 volumes comprising in total 4350 spectral images. The data is a subset of MUSIC dataset \(^3\), which is provided by the 3D Imaging Center, DTU \(^1\). The data is acquired using the Multix Me-100 - V2 detector and a Hamamatsu micro-focus source operated at 150 kVp and 75 µA. Spectral detectors are subject to a number of physical effects causing deviations in the detector response. We correct the detector response using the method presented in \(^5\).

An example of the detected spectra after correction is shown in Fig 2 (b). At the higher end of the spectrum, a lower number of photons are emitted, which leads to higher statistical noise. The number of detected photons are reduced further by the decreased absorption efficiency of the detector at higher energies. At the lower end of the spectrum the sample

| parameter | typical range |
|-----------|---------------|
| \( N \)   | \( 10^3 \)    |
| \( I \)   | \( 10^3 \)    |
| \( T \)   | \( 10^2 \)    |
| \( R \)   | \( 10^2 \)    |
| \( S \)   | \( 10^2 \)    |
| \( L \)   | \( 10^2 \)    |
| \( V \)   | \( 10^1 \)    |
| \( K \)   | \( 10^1 \)    |

\(^1\)The 3D Imaging Center: [http://imaging.dtu.dk/](http://imaging.dtu.dk/)
\(^2\)The dataset is available at [http://easi-cil.compute.dtu.dk/index.php/datasets/music/](http://easi-cil.compute.dtu.dk/index.php/datasets/music/)
\(^3\)The new version 3 is now sold as Detection Technology X-card ME3
absorbs most of the photons, leading to the detection of very few photons and consequently to a high noise as well.

The MUSIC dataset comes with 128 spectral channels covering the range between 20 keV and 160 keV. In this work however, we use 32 channels evenly distributed between 20 keV and 108.2 keV. We chose to include the lower end of the spectrum because this range of energies carries distinctive characteristics, which are important for material identification. Due to the high levels of noise, the lower end of the spectrum thus poses a special challenge to the reconstruction methods.

Each sample in the MUSIC dataset is acquired with 74 projections evenly distributed over 360°. These dense-view projection data are reconstructed with ART-TV and used as reference images to train the CNN. To provide the input images to the CNN, we generate sparse-view projections from the original dense-view projections. The is performed by sampling 9 evenly spaced projections out of the 74 projections. Each of the sparse-view data is then reconstructed with FBP.

In addition to the real data, we generate synthetic data to add more geometrical variations. In this work, we generated 51 volumes containing 5100 spectral images. The synthetic volumetric objects are produced using randomly generated 3D containers. The containers are generated using TomoPhantom toolbox [83]. Each container is randomly assigned a material that is defined by a vector representing the spectral attenuation coefficients. The materials are selected from a database of 48 materials that were previously reconstructed and segmented from real dense-view data.

The synthetic images are used as ground-truth references for the CNN. To generate sparse-view synthetic data, we first produce dense-view projections through simulating the forward projection assuming the same CT acquisition geometry as the one used to generate the real data. We then, as for the real data, sample 9 projections and reconstruct them with FBP. The forward simulation and the FBP reconstruction were performed using Astra toolbox [84].

To train the model, the real and synthetic data are split into training and validation subsets. The training subset is composed of 13 real volumes (4350 images) and 40 synthetic volumes (4000 images), resulting in a total of 8350 spectral images. The validation subset is composed of 5 real volumes (1625 images) and 10 synthetic volumes (1000 images), resulting in a total of 2625 spectral images. Furthermore, to evaluate our approach, we keep out 4 real volumes and one synthetic volume.

V. RESULTS AND DISCUSSION

To evaluate the model, we perform a number of experiments and comparative tests on a dedicated test subset. The objective of the experiments is to validate several aspects of the model. First, the performance properties of the proposed model on sparse-view CT in terms of the reconstruction quality both spatially and spectrally as compared with the state-of-art approaches. Second, we would like to show that the joint spectral processing is not only faster but also enhances the reconstruction quality when compared with independent channel processing. Third, we would like to assess the robustness of joint spectral reconstruction when some channels are affected by variable noise levels. Fourth, we would like to assess the robustness to metal artifacts, a common issue in CT imaging.

In the following, we refer to the output of our approach as 'Ours', which is obtained after re-scaling the output of the CNN (Sec. III-A). We compare our approach with ART-TV [25] and TNV [26]. Moreover, we include the FBP in the comparison; it is a standard method and also the initial step in our approach. Note that both FBP and ART-TV reconstruct the channels independently whereas TNV imposes the TV regularization spectrally. When showing real samples, we also compare with ART-TV for reconstructions from 74 projections since that is the type of data we provide as reference to train the CNN.

For qualitative evaluation in the comparison below, we show images from eight spectral channels (out of 32 channels). This allows us to observe the reconstruction quality and the variation thereof across the spectrum. In addition to the images, we include four means of quantitative assessment:

- attenuation coefficient curves. The attenuation coefficient curves provides a comparative assessment indicator. We show the mean and the standard deviation of the attenuation coefficients in selected image patches belonging to different materials. The mean allows us to assess whether we can reconstruct the attenuation coefficients of materials. The mean also gives an indication for the spectral smoothness. The standard deviations allow us to compare the reconstruction quality along the spectrum. Because each patch belongs to one material, lower standard deviation indicates higher quality.
- TV. Iterative methods incorporating TV minimization represent the state of the art. We include TV as a measure of relative image quality. Lower TV indicates higher quality (i.e. piece-wise smoothness with edge preservation). It is worth noting that TV can be misleading in some cases. For instances, an undesirably over-smoothed image would have a low TV value. Therefore, we carry the comparison with TV in the presence of qualitative results (images) and other metrics.
- MAE and structural similarity index (SSIM), which are standard metrics for error quantification. [85], [86], [87].
Fig. 5: Our approach vs iterative methods. The comparison is carried out on a synthetic slice (left) and a real slice (right). The synthetic slice comes from the synthetic test volume where as the real slice comes from Volume I (renderings of the volumes are shown in Fig. 9). Reconstructions with other methods are compared with our approach in (a) and (b). The number between parentheses indicates the number of projections. Spectral profiles showing the mean of the attenuation coefficients and the standard deviation (std) at selected patches across 32 channels are presented in (c) and (d). In (e) and (f), we show the image TV as well as the SSIM and the MAE metrics across all channels.

We show the MAE because it is the loss function we use to train the CNN (Sec. III). The SSIM is widely used with images as it incorporates structural information. For the real data, these metrics are computed with respect to the images reconstructed using ART-TV with 9 projections, as no actual ground-truth images are available. Therefore, those metrics are not perfect in this case, as improvement in quality will be wrongly measured as error. Nevertheless, we use them to confirm significant improvement, which can clearly be observed qualitatively.

The evaluation aspects are presented and discussed in the following subsections:

A. Ours vs iterative methods

We start by examining a spectral slice from the synthetic test volume and a slice from a real test volume as shown in Fig. 5. The figure compares our approach with the iterative methods. The reconstructions in Fig. 5 (a) and Fig. 5 (b) show clearly the high-quality images produced by the CNN. In spite of the noise levels in the FBP being visibly high, particularly in the real sample, the CNN is able to overcome that. The CNN is also able to remove the reconstruction artifacts, which appear as lines in the FBP image.

Moreover, the CNN also removes other types of artifacts appearing in the real slice at the lower end of the spectrum (most visible in the images at 20.0 keV and 31.0 keV). Those artifacts are due to the presence of small pieces of metal (the container’s lids).

In general, the images produced by the CNN appears smoother and better at preserving the edges when compared to the other methods with 9 projections. When compared to the images obtained with 74 projections however, edges appear less sharp and fine shape details are lost (best viewed in Fig. 5 (b)). The loss of such details can be attributed to missing viewpoints, which the CNN is unable to compensate for. On
In (a), reconstructions obtained when our model is trained on single-channel images are compared to our standard model. Spectral profiles from the two yellow patches are shown in (b).

(a)

(b)

Fig. 6: Joint spectral (Ours) vs channel-by-channel reconstruction (Ours_sc). In (a), reconstructions obtained when our model is trained on single-channel images are compared to our standard model. Spectral profiles from the two yellow patches are shown in (b).

The importance of joint spectral reconstruction is demonstrated in Fig. 6 by comparing it to independent channel-by-channel reconstruction. The channel-by-channel model was realized by adapting our model to operate with single-channel input and output, i.e., similar to the model in [69] but we apply our approach to data scaling for the reasons discussed in Sec. III-A.

The figure shows that the single-channel model is able to suppress the noise and remove the artifacts at a level comparable to our model. However, the single-channel model reconstructs shapes poorly. This indicates higher sensitivity to the low per-channel SNR, causing inconsistent shape reconstruction in the individual channels. On the other hand, the joint convolutions appear to let our model recover the overall spectral SNR, leading to improved shape reconstruction.

C. Robustness to variable channel noise

Certain spectral channels may experience unexpected disturbances during scanning. To assess the robustness of our model to such disturbances, we introduce AWGN to the sinograms with a standard deviation (σ) of 0.5, 1.0 and 1.5. The noise is added to two channels: 42.0 keV and 76.2 keV. We evaluate the reconstruction quality of our model compared with TNV as shown in Fig. 7.

The figures show that our model is able to overcome a considerably high level of noise with σ = 0.5 cm⁻¹ whereas the reconstruction quality with TNV degrades at the affected channels. However, as the noise is further increased, the reconstruction quality of our model drops, resulting in distorted and over-smoothed shapes (Fig. 7(a)). This degradation is clearly visible by the drop in the SSIM (Fig. 7(b)).

The robustness to such disturbances further emphasizes the importance of joint reconstruction, as it yields a visible reconstruction quality improvement up to a certain noise level.

D. Robustness to metal artifacts

Fig. 8 shows a comparison similar to the one presented in Fig. 5 but with a slice containing a large object made of Aluminum. CT reconstruction of a sample containing a highly-absorbing material such as Aluminum is prone to streaks. In spectral data, the streaks appear predominantly at the lower end of the spectrum. The figure shows that the single-channel model is able to suppress the noise and remove the artifacts at a level comparable to our model. However, the single-channel model reconstructs shapes poorly. This indicates higher sensitivity to the low per-channel SNR, causing inconsistent shape reconstruction in the individual channels. On the other hand, the joint convolutions appear to let our model recover the overall spectral SNR, leading to improved shape reconstruction.

E. Test set quantification

In the above subsections, we have studied the reconstruction quality of our approach on individual slices selected from our dataset. In Table I, we present a quantification summary of the whole test set. The set is composed of 4 volumetric images...
Fig. 7: The effect of adding white noise to certain channels. The numbers between parentheses indicate the standard deviation ($\sigma$) of the noise added to the channels outlined in red.

(shown in Fig.), each containing between 300 and 500 slices and with a total of 10 slices. The table shows that our approach consistently performs the best.

**F. Computation time**

In this subsection, we present run-time comparison of our approach with respect to the other state-of-the-art methods we consider in this paper. This comparison supports the computational complexity analysis discussed in Sec. III-B. The main challenge in conducting such comparisons is that implementations vary significantly from one method to another. In order to provide fair comparison, we consider mainly the CPU implementations written in C++. Furthermore, we force the execution to utilize only one CPU core to limit parallelism. Moreover, for implementations with Python interface, we measure the execution time of the primitive function invoking a C++ function. Because we don’t have an optimized C++ implementation for the TNV method, we exclude it from this comparison.

Table III summarizes the execution time of the methods in comparison using both their CPU and GPU implementations. The evaluations are performed on a machine running a Linux system and equipped with an Intel Xeon (3.0 GHz) E5-2687W v4 x 48 CPU and an NVIDIA GeForce GTX 1080 GPU (20 streaming multiprocessors, each with 128 CUDA-cores at 1.6 GHz base clock).

The table shows that our approach is significantly faster than ART-TV in both the CPU and the GPU implementations. When comparing the speedup achieved with GPU implementation however, we find that we gain about 37 times speedup with ART-TV and about 7 times speedup with our approach. This disparity in speed boost can be attributed to the fact that for ART-TV, we use an implementation optimized for performance and data access patterns whereas for CNN, we use off-the-shelf packages made for generic prototyping.

One aspect to note is that the evaluation time for the CNN part of our approach (i.e., with 32 channels) is 6.4 ms while it is 4.32 ms for a single-channel version of the network (discussed in Sec. V-B). This highlights the speed advantage of using our spectral CNN, as the internal layers are shared between the channel. Furthermore, in our computational complexity analysis in III-B, we estimated that the complexity of our approach was dominated by the CNN part rather than the FBP. The table shows that with CPU implementations, the
We have shown here that one model can be used to reconstruct learning to tackle several problems with one end-to-end model. This opens up opportunities to take full advantage of machine learning to tackle several problems with one end-to-end model.

The network is trained to maintain. The coupling of channels also to metal artifacts, which affect primarily the low-energy detectors.

Our results strongly suggest that channel coupling enables the network to utilize the ‘healthy’ channels to compensate for disturbances affecting other channels. This was demonstrated by the robustness of network to channels with significantly higher noise levels and also to metal artifacts, which affect primarily the low-energy channels. This robustness is driven by the spectral consistency the network is trained to maintain. The coupling of channels in such a way allows us to maximize the gain of using spectral detectors.

When compared with the iterative methods, our approach provides a strong alternative that is faster and more effective for sparse-view reconstruction. Furthermore, The use of CNN opens up opportunities to take full advantage of machine learning to tackle several problems with one end-to-end model. We have shown here that one model can be used to reconstruct high-quality images and can simultaneously overcome metal artifacts. In the future, other features, e.g., super resolution, can be incorporated as well.

Applying CNN raises the question of generalization. Even though generalization is beyond the scope of this paper, we applied data augmentation to diversify our data and mitigate potential over-fitting. Moreover, we used a dedicated test set for validation and that makes it possible to detect signs of over-fitting. That said, the test set resembles the training set with respect to several aspects such as acquisition settings, object geometries, and materials. It is therefore difficult to draw final conclusion on the network generalization properties, especially regarding those aspects. Those aspect will be further explored in future work.

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| CPU    | 1 channel | 32 channels | 1 channel | 32 channels |
|--------|-----------|-------------|-----------|-------------|
| ART-TV (9) | 25.70     | 822.33      | 0.09      | 22.00       |
| FBP (9)    | 0.14      | 4.50        | 0.03      | 0.90        |
| CNN (9)    | 0.40      | 6.40        | 0.06      | 0.60        |
| Ours [FBP+CNN] | 0.34 | 10.99       | 0.05      | 1.50        |

| Volume I | Volume II | Volume III | Volume IV |
|----------|-----------|------------|-----------|
| TV       | SSIM      | MAE        | TV        | SSIM      | MAE        |
| 11.83    | 0.04      | 1.873      | 8.74      | 0.73      | 0.102      |
| 11.45    | 0.02      | 1.465      | 8.30      | 0.72      | 0.074      |
| 11.67    | 0.02      | 1.379      | 8.52      | 0.72      | 0.074      |
| 11.55    | 0.01      | 1.631      | 8.40      | 0.77      | 0.077      |

| Volume I | Volume II | Volume III | Volume IV | mean     |
|----------|-----------|------------|-----------|----------|
| TV       | SSIM      | MAE        | TV        | SSIM      | MAE        |
| 9.31     | 0.67      | 0.191      | 7.75      | 0.84      | 0.073      |
| 8.91     | 0.72      | 0.140      | 6.92      | 0.82      | 0.052      |
| 9.01     | 0.66      | 0.120      | 7.46      | 0.83      | 0.051      |
| 9.04     | 0.78      | 0.151      | 6.85      | 0.80      | 0.059      |
| 8.88     | 0.69      | 0.151      | 7.27      | 0.81      | 0.059      |

TABLE III: Comparison on the test set. The set contains four volumetric (multi-slice) images. The volume mean of each metric is shown. The overall mean is shown at the bottom.

TABLE II: Comparison of the evaluation time (ms). We show the time needed to process a single channel (1 channel) and to process the whole spectrum (32 channel). Italicized numbers are estimates (not actual measurements) computed to facilitate the comparison. CNN_sc is a single-channel version of our network (discussed in Sec. V-B).
Fig. 9: Renderings of the four volumes (channel 53.1 keV) composing the test set. Each volume is reconstructed slice by slice.
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image analysis, scientific data visualisation, and algorithms and data structures

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