Learning from our neighbours: a novel approach on sinogram completion using bin-sharing and deep learning to reconstruct high quality 4DCBCT

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ABSTRACT

Inspired by the success of deep learning applications on restoration of low-dose and sparse CT images, we propose a novel method to reconstruct high-quality 4D cone-beam CT (4DCBCT) images from sparse datasets. Our approach combines the idea of bin-sharing with a deep convolutional neural network (CNN) model. More specifically, for each respiratory bin, an initial estimate of the patient sinogram is obtained by taking projections from adjacent bins and performing linear interpolation. Subsequently, the estimated sinogram is propagated through a CNN that predicts a full, high-quality sinogram. Lastly, the predicted sinogram is reconstructed with an iterative CBCT algorithms such as the Conjugate Gradient (CG) method. The CNN model, which we referred to as the Sino-Net, was trained under different loss functions. We assessed the performance of the proposed method in terms of image quality metrics (mean square error, mean absolute error, peak signal-to-noise ratio and structural similarity) and tumor motion accuracy (tumor centroid deviation with respect to the ground truth). Lastly, we compared our approach against other state-of-the-art methods that compensate motion and reconstruct 4DCBCTs. Overall, the presented prototype model was able to substantially improve the quality of 4DCBCT images, removing most of the streak artifacts and decreasing the noise with respect to the standard CG reconstructions.

Keywords: 4DCBCT, Deep Learning, Sparse Data, Image Reconstruction, Respiratory Motion

1. INTRODUCTION AND RESEARCH GOAL

Cone beam computed tomography (CBCT) is a popular imaging modality in radiation therapy used for patient positioning, setup, and target localization directly preceding the delivery of radiation. When scanning areas of the thorax or abdomen, respiration can create motion artifacts that are represented as blurring in the final reconstructed image. To alleviate this problem, 4DCBCT is used to temporally bin the projections acquired using a respiratory signal extracted from the patient’s breathing, and reconstructing a volume for each phase.\textsuperscript{1} Typical CBCTs are performed in 1 minute and scanned under low dose settings keeping the number of projections low resulting in 4DCBCT images containing heavy streaking artifacts and of little use clinically.

In this work, we propose for the first time a novel approach to reconstruct high-quality, geometrically accurate 4DCBCT images from sparse projection datasets and we assess its performance on a prototype dataset as well as on the SPARE challenge dataset.\textsuperscript{2} Our method introduces the idea of sinogram bin-sharing, and combines it with a deep convolutional neural network (CNN) model to enhance the image quality and tumor location accuracy in 4DCBCT.

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2. METHODS

2.1 The bin-sharing method
In order to reconstruct a 4DCBCT dataset using the bin-sharing method, the following steps were applied. Firstly, the patient’s respiratory signal was used to divide the measured projections (680 in total) into 10 bins, resulting in 50-85 projections per bin. Each subset of the projection data represents the so-called sparse sinograms (Figure 1A). Second, each sparse sinogram was enhanced by taking the projections from two adjacent bins (i.e., the bin-sharing step). This approximation was made under the assumption that the patient respiratory motion between two consecutive bins is small. Third, the remaining missing projections in the sinogram of each bin were filled by linearly interpolated projections (Figure 1B). Subsequently, the shared + interpolated sinogram was propagated through a trained deep convolutional neural network (CNN) to enhance its quality (Figure 1C). Finally, each predicted high-quality sinogram was reconstructed using the standard Conjugate Gradient CBCT algorithm.3 The CNN was trained using pairs of input shared + interpolated sinogram images (as those shown in Figure 1B) and target full sinogram images (Figure 1D). The network model, training parameters and performance assessment are described in the following sub-sections.

2.2 Patient Data
Cone beam CT sinogram data used to train and validate the neural network, as well as to assess the overall performance of the proposed method, were generated from 4DCT datasets. Each 4D dataset consisted of 10 CT images of patients with lung tumors (respiratory phases) and their corresponding respiratory signal. More specifically, each CT image was forward projected under the CBCT geometry onto a set of 680 projections covering 360 degrees around the patient using the Reconstruction Toolkit Software.4 Each projection image was 512 x 384 pixels in size. These complete sinograms (of size 680 x 512 x 384) were considered as the ground truth and the corresponding low-quality sinograms were created following the bin-sharing + interpolation method. In total, 4DCT datasets of 16 different patients were included in this work. These data, in addition to the respiratory signals and the CBCT scanning geometries, were facilitated by the organizers of the SPARE Challenge.2,5

2.3 Network Architecture and Training
The architecture of our CNN (which we refer to as ‘Sino-Net’) is based on the popular ‘U-Net’ model proposed by Ronneberger et al 20156 but with minor modifications. In particular, we replaced the max-pooling and the de-convolution layers by 2D-convolutions to prevent checkerboard artifacts.7 Additionally, we added a residual connection between the inputs and the output to facilitate learning.8 The details of Sino-Net architecture, including the number and size of feature maps, activations, and convolutional layers are shown in Fig. 2. The U-Net architecture has shown success in sparse CT reconstruction9,10 and restoration of Low-Dose CT images.8

Following the philosophy of Zhao et al. 2015,11 we explored the performance of the Sino-Net under three different loss-functions: the mean absolute error (or $L_1$), the perceptually motivated multi-scale similarity index12 (MS-SSIM) and a weighted sum of $L_1$ and MS-SSIM (with weights equal to 0.16 and 0.84, respectively, as determined by Zhao et al.). Each Sino-Net model was trained with sinogram data from 12 patients. In order to allow for remainderless downsampling of feature maps by a factor of 2, the initial image height was cropped from 680 down to 672. To minimize aliasing effects when predicted sinograms are stacked back together,13 each input image consisted of 3-consecutive 672 x 384 low-quality sinogram slices (Figure 1B), whereas the target output was the high-quality sinogram slice corresponding to the central slice of the input (Figure 1D). Each patient full sinogram was normalized to [0,1] and no additional preprocessing was applied. In total, 30720 sinogram slices were used for training corresponding to 512 slices x 12 patients x 5 bins. Note that in order to minimize computational cost, only 5 out of the 10 sinogram bins (namely bins #1, #3, #5, #7 and #9) of each patient were used during training. The training data was augmented by randomly flipping the sinograms horizontally.

The network model was implemented in Keras14 (with Tensorflow backend15) and trained using the Adam optimizer algorithm with an initial learning rate of $10^{-4}$. All training runs were carried out on Google Cloud using a Nvidia Tesla P100 GPU. In this hardware, the time to run one epoch was approximately 2050 seconds. Due to the large size of the input images, the mini-batch size was set to 2 in order to fit into the GPU memory. The validation loss was monitored during training and when reaching a plateau the initial learning for the
following epoch was decreased by a factor of 10. When the loss no longer decreased the training was halted, resulting in a total of 6 training epochs.

2.4 Performance assessment

In order to evaluate our proposed model, we carried-out three different studies. First, we assessed the image-quality of the 4DCBCT images reconstructed using the Sino-Net-derived projections from models trained under each of the investigated loss functions. This preliminary study was useful to determine the optimal choice of loss-function for subsequent experiments. Second, using 4DCBCT images reconstructed from projections obtained with the optimal Sino-Net model, we evaluated the geometric accuracy of tumor motion under different tumor-contrast conditions. This experiment was valuable to explore the limitations of our proposed model under different imaging conditions. Finally, we applied Sino-Net to the test dataset of the SPARE challenge and submitted the results to the challenge organizers for evaluation. Although our results were submitted after the challenge deadline and therefore not included in the competition, this exercise allowed us to compare our model against other state-of-the-art methods that participated in the challenge. The details of each one of these three studies are described in the next sub-sections.

2.4.1 Effect of the loss function on the image quality of reconstructed 4DCBCT

We assessed the performance of the Sino-Net models (trained under each investigated loss function) in terms of the image quality of 4DCBCT images reconstructed from the estimated high-quality sinograms on a validation and a test set. The validation and test sets contained two patient datasets each.

The image quality was evaluated using the following metrics: the mean-square error (MSE), the mean-absolute error (MAE), the peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM) between the Sino-Net-derived and the ground truths 4DCBCTs.
2.4.2 Accuracy of tumor motion vs tumor contrast

In order to understand the conditions under which the proposed model fails at accurately tracking tumor motion, we placed 2 cm diameter spheres (representing tumors) with different tissue intensity (i.e., HU values) on six 4DCT patient datasets which were not used during training. More specifically, in each of the patient images, three spheres of HU values equal to 0 (high contrast), -250 (medium contrast) and -500 (low contrast), respectively, were placed at random locations within the lungs. A sinusoidal motion along the Superior-Inferior (SI), and Anterior-Posterior (AP) axes, was applied to each sphere to simulate tumor motion due to patient breathing. A total three levels of SI motion were applied through the six patients: 1 cm in amplitude (2 patients), 2 cm in amplitude (2 patients) and 3 cm in amplitude (2 patients). The AP motion amplitude was the same and equal to 1 cm across all six patients. As a result, we generated a dataset of six patients containing synthetic tumors with three levels of contrast and three levels of motion. Fig. 3 shows two CT coronal views of a sample patient containing the synthetic spheres.

These 4DCT data were forward projected to generate sparse and full sinograms of each of the 10 respiratory bins. The sparse sinograms were reconstructed using the CG method (referred to as sparse 4DCBCT) or they were passed through the optimal Sino-Net model and subsequently reconstructed using the CG method (Sino-Net 4DCBCT). Additionally, the 4DCBCT ground truth images were obtained by reconstructing the full sinograms.

The tumor motion accuracy was assessed in terms of the mean absolute deviation of the tumor centroid position with respect to the ground truth along the SI, SP and LR axes in the reconstructed images. To determine the tumor centroid, tumors were automatically segmented by thresholding a 4 cm diameter sphere around the tumor region with a threshold such that the recovered tumor volume was equal to the true volume.

2.4.3 Comparison of Sino-Net against other state-of-the-art methods

The Sino-Net model was applied to a projection dataset provided by the SPARE challenge organizers. These data consisted of a series of sparse projections from 1-minute 4DCBCT acquisitions of a total of 9 patients. The acquisitions were not from real patient studies but were simulated from prior 4DCT studies using accurate Monte-Carlo methods. Such choice allowed the challenge organizers to generate projections under different conditions of scatter and noise, corresponding to a total of 32 4DCBCTs. Details of the challenge dataset, as well as the data itself, can be found in the challenge website. The high-quality projections generated by Sino-Net were reconstructed using the CG method (30 iterations) and submitted to the challenge organizers for assessment.
Although our data was submitted after the challenge submission deadline, the organizers provided us with the performance results of our model and a comparison against the other participants for reference.

For comparison, we provide here a short summary of the fundamental ideas behind each of the 5 participants models that were submitted to the challenge. For a detailed description of these models we refer to the challenge publication as well as each of the model’s references:

- MC-FDK: A motion-compensated Feldkamp-Davis-Kress model developed by Rit et al.\textsuperscript{16}
- MA-ROOSTER: A reconstruction method based on motion-aware spatial and temporal regularization by Mory et al.\textsuperscript{17}
- MoCo: A data-driven motion-compensated method developed by Riblett et al.\textsuperscript{18}
- MC-PICCS: A motion-compensated prior image constrained compressed sensing reconstruction implemented by Shieh et al.\textsuperscript{19}
- Prior deforming: A method that deforms the pre-treatment 4DCT data to obtained projections registered to the CBCT projections.\textsuperscript{20}

The challenge organizers carried-out a very detailed performance evaluation of the submitted reconstructions. First, the image similarity of each reconstruction was assessed in terms of the root-mean squared error and the structural similarity index (on four regions-of-interest: patient body, lungs, planned tumor volume and bony anatomy) with respect to the ground truth. In addition, the geometric accuracy of the tumor motion was evaluated by registering the planned tumor volume on each respiratory bin image of the submitted 4DCBCTs with the ground truth. The translation and rotation components of this registration were considered the translation and rotation errors. A more detailed description of the performance metrics can be found in the SPARE challenge publication.\textsuperscript{5}

### 3. RESULTS AND DISCUSSION

#### 3.1 Effect of loss function on the image quality of reconstructed 4DCBCTs

Table. 1 presents the summary of the image quality assessment results for each investigated loss function on both the validation and test set. To allow for comparisons, the MSE and MAE were normalized to the dynamic range of each patient image. The model using the loss function defined by Zhao et al. in Ref. 11 had the best performance for three out of the four image-quality metrics evaluated and was deemed the most suitable for further reconstructions of the test set. Overall, the selected model generalized relatively well to the test dataset although metrics were slightly worse than in the validation data.
Table 1. Image quality assessment of the three models investigated in our study. The Mean-Squared-Error (MSE) and Mean-Absolute-Error (MAE) are normalized to the dynamic range of the tested patient images. Quantities in bracket represent the standard deviations of each evaluated metric across all patient images. Metrics in bold represent those that achieved the highest performance across our selected loss functions.

|        | MSE ($10^{-4}$) | MAE ($10^{-2}$) | PSNR [dB] | SSIM   |
|--------|-----------------|-----------------|-----------|--------|
| **Validation** |                 |                 |           |        |
| L1     | 2.45 (0.40)     | 1.15 (0.08)     | 36.2 (0.7) | 0.869 (0.015) |
| MS-SSIM | 2.31 (0.37)     | 1.11 (0.09)     | 36.4 (0.6) | **0.911 (0.018)** |
| Zhao et al. | **2.25 (0.37)** | **1.09 (0.09)** | **36.5 (0.7)** | 0.873 (0.011) |
| Sparse | 311.5 (80.4)    | 16.1 (2.8)      | 15.2 (1.1) | 0.070 (0.026) |
| **Test** |                 |                 |           |        |
| Zhao et al. | 4.66 (1.58)     | 1.55 (0.28)     | 33.6 (1.5) | 0.849 (0.017) |
| Sparse  | 439 (191)       | 17.2 (4.5)      | 14.0 (2.0) | 0.063 (0.011) |

The results of Table 1 shows that the choice of loss function had some impact on the image-quality of the reconstructed images. However, the differences among the investigated losses were not very large. However, in all cases there was a substantial increase in quality, with respect to the sparse CBCTs, demonstrating the potential of deep-learning methods to enhance the quality of medical images.

An example of the CBCTs reconstructed from the Sino-Net predictions on the test dataset, along with the sparse, and ground truth CBCTs are shown in Fig. 4 and Fig. 5. It is worth noting the severity of the artifacts present in the CBCT images reconstructed from sparse sinograms, mostly due to the low number of projections and the non-uniform distribution of these projections around the patient. Most of these artifacts were removed, or they decreased in severity, when CBCTs were created from Sino-Net-derived projection data.

Figure 6 shows the CBCT reconstructions (from sparse, Sino-Net-derived and ground truth projections) of 5 different respiratory bins of a patient to illustrate the breathing motion and the effect of the number of available projections on the quality of the image. In respiratory bins where the number of projects were low (e.g., bin 7 or bin 9), the sparse CBCTs exhibit severe loss of quality. In this particular example, we observe that a region on the center of the chest is almost faded. Such non-uniformities make unfeasible the use of these images to visualize tumors or adjust treatment planning volumes prior to radiation therapy. CBCTs reconstructed from Sino-Net data, however, showed a consistent quality across different respiratory bins, restoring some details of the patient anatomy that are not clearly visible on the sparse dataset such as the respiratory tracks (see Fig. 6).

### 3.2 Accuracy of tumor motion vs tumor contrast

The tumor centroid position as a function of the 4DCBCT respiratory bin for six different spherical tumors is depicted in Fig. 7. In general, the centroids of tumors on the Sino-Net-derived spheres have better agreement with the ground truth than those of the sparse data, especially on the AP axis and around the bins where the tumor motion amplitude is maximum.

The distribution of tumor centroid deviations with respect to the ground truth, for each tumor-contrast level, are shown in Fig. 8. Tumor-deviations tend to be lower (on average), and more consistent, for artificial tumors on the Sino-Net-derived 4DCBCTs.

Although the results shown in Fig. 7 and Fig. 8 suggest that Sino-Net-derived reconstructions yield better tumor-motion accuracy than that from sparse data, these differences are not as high as expected based on the visual assessment and the image quality analysis. We believe this might be due to two reasons. First, we are using rather ideal tumors, with relatively sharp boundaries, regular shapes and uniform tissue density. Second, the tumors were segmented using a fixed threshold approach, which allowed us to determine semi-automatically the tumor centroids, but it does not reflect the accuracy of tumor boundaries and shape. Nonetheless, this analysis is useful to illustrate some of the advantages and limitations of Sino-Net. For instance, in these semi-ideal conditions, tumor-geometric accuracy of Sino-Net showed the largest improvement in medium-contrast tumors. Low contrast tumors (HU = -500) were hardly visible in both the sparse and the Sino-Net reconstructions.
Figure 4. Axial slices from CBCT CG reconstructions generated from sparse (left), Sino-Net prediction (middle), and ground truth (right) sinograms for 3 different patient scans used in the contrast sphere analysis. The red arrows indicate the artificial tumor.

Figure 5. Coronal slices from CBCT CG reconstructions generated from sparse (left), Sino-Net prediction (middle), and ground truth (right) sinograms for 3 different patient scans used in the contrast sphere analysis. The red arrows indicate the artificial tumor.
Figure 6. CBCT reconstructions of Bins 1 (far left), 3, 5, 7, 9 (far right), of sparse, Sino-Net prediction, and ground truth sinograms. The number of projections in each sparse bin is shown above each column. A red dotted line is used as a visual aid to depict motion, the line marks the right diaphragm location at max inspiration (far left image).

Figure 7. Tumor centroid position in different respiratory bins for 6 different spherical tumors. The tumor was segmented for Sparse (blue), SinoNet (red), and Ground Truth CBCT images (green).
Figure 8. Distribution of tumor centroid deviations with respect to the ground truth along SI, AP and LR axes for high, medium and low tumor contrast levels on Sino-Net-derived 4DCBCT and sparse 4DCBCT reconstructions.
3.3 Comparison of Sino-Net against other state-of-the-art methods

Table 2 summarizes the PTV geometric accuracy assessment of Sino-Net compared against the 5 state-of-the-art algorithms successfully submitted to the SPARE challenge. The tabled values are the root-mean-square of the translation and rotation error over the complete challenge dataset. Overall, the errors for Sino-Net show its performance is either comparable or better than the listed models. In particular, the translation error in LR, SI, and AP for 4DCBCTs produced by Sino-Net is 0.57mm, 1.02mm, and 1.19mm, respectively. The combined 3D error is 1.67mm. Rotation error about LR, SI, and AP is 1.18°, 0.99°, and 0.63°, respectively.

The positional accuracy of the PTV in reconstructed 4DCBCT images is clinically important as it specifies the degree of confirmation that the target volume remains inside the high dose volume intended for treatment. As such, the PTV geometric accuracy metric along with image quality mark two of the more important metrics in 4DCBCT reconstruction algorithms. These results suggest that the bin-sharing method combined with Sino-Net provide one way to deal with sparse data in the image reconstruction of 4DCBCTs.

4. CONCLUSIONS AND FUTURE WORK

The proposed 4DCBCT reconstruction method, which combines sinogram bin-sharing and a deep learning approach, allows us to obtain high-quality and geometrically accurate 4DCBCT images reconstructed from sparse datasets.

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REFERENCES

[1] Sonke, J.-J., Zijp, L., Remeijer, P., and van Herk, M., “Respiratory correlated cone beam CT,” Medical Physics 32, 1176–1186 (mar 2005).

[2] Shieh, C.-C., Gonzalez, Y., Li, B., Rit, S., Hugo, G., and Keall, P., “Dataset for the spare challenge: Spare-view reconstruction challenge for 4d cone-beam ct from a one-minute scan.” http://sydney.edu.au/medicine/image-x/research/SPARE-Challenge.php/ (2018).

[3] Jia, X., Dong, B., Lou, Y., and Jiang, S. B., “GPU-based iterative cone-beam CT reconstruction using tight frame regularization,” Physics in Medicine and Biology 56, 3787–3807 (jul 2011).

[4] Rit, S., Vila Oliva, M., Brousniche, S., Labarbe, R., Sarrut, D., and Sharp, G. C., “The Reconstruction Toolkit (RTK), an open-source cone-beam CT reconstruction toolkit based on the Insight Toolkit (ITK),” Journal of Physics: Conference Series 489, 012079 (mar 2014).

[5] Shieh, C.-C., Gonzalez, Y., Li, B., Rit, S., Hugo, G., and Keall, P., “AAPM Grand Challenges Symposium: Image Reconstruction for 4D-CBCT,” American Association of Physicists in Medicine Annual Meeting 2018. (2018).
[6] Ronneberger, O., Fischer, P., and Brox, T., “U-Net: Convolutional Networks for Biomedical Image Segmentation,” 1–8 (2015).

[7] Odena, A., Dumoulin, V., and Olah, C., “Deconvolution and Checkerboard Artifacts,” Distill (2016).

[8] Li, H. and Mueller, K., “Low-Dose CT Streak Artifacts Removal using Deep Residual Neural Network,” (June), 3–6 (2017).

[9] Lee, H., Lee, J., Kim, H., Cho, B., and Cho, S., “Deep-neural-network based sinogram synthesis for sparse-view CT image reconstruction,” (2018).

[10] Han, Y. S., Yoo, J., and Ye, J. C., “Deep Residual Learning for Compressed Sensing CT Reconstruction via Persistent Homology Analysis,” (2016).

[11] Zhao, H., Gallo, O., Frosio, I., and Kautz, J., “Loss Functions for Neural Networks for Image Processing,” (2015).

[12] Wang, Z., Simoncelli, E. P., and Bovik, A. C., “Multi-scale structural similarity for image quality assessment,” IEEE Asilomar Conference on Signals, Systems and Computers 2, 9–13 (2003).

[13] Gong, K., Guan, J., Kim, K., Zhang, X., Fakhri, G. E., Qi, J., and Li, Q., “Iterative PET Image Reconstruction Using Convolutional Neural Network Representation,” (Oct 2017).

[14] Chollet, F. et al., “Keras,” (2015).

[15] Abadi, M. et al., “TensorFlow: Large-scale machine learning on heterogeneous systems,” (2015). Software available from tensorflow.org.

[16] Rit, S., Wolthaus, J. W. H., van Herk, M., and Sonke, J.-J., “On-the-fly motion-compensated cone-beam CT using an a priori model of the respiratory motion,” Medical Physics 36, 2283–2296 (May 2009).

[17] Mory, C., Janssens, G., and Rit, S., “Motion-aware temporal regularization for improved 4D cone-beam computed tomography,” Physics in Medicine and Biology 61, 6856–6877 (Sep 2016).

[18] Riblett, M. J., Christensen, G. E., Weiss, E., and Hugo, G. D., “Data-driven respiratory motion compensation for four-dimensional cone-beam computed tomography (4D-CBCT) using groupwise deformable registration,” Medical Physics 45, 4471–4482 (Oct 2018).

[19] Shieh, C.-C., Caillet, V., Booth, J., Hardcastle, N., Haddad, C., Eade, T., and Keall, P., “4D-CBCT reconstruction from a one minute scan, in Engineering and Physical Sciences in Medicine Conference,” in Australasian Physical & Engineering Sciences in Medicine, 41, 245–355, Springer Netherlands (Mar 2018).

[20] Ren, L., Zhang, J., Thongphiew, D., Godfrey, D. J., Wu, Q. J., Zhou, S.-M., and Yin, F.-F., “A novel digital tomosynthesis (DTS) reconstruction method using a deformation field map.,” Medical Physics 35, 3110–5 (Jul 2008).