A Deep-learning Method for Detruncation of Attenuation Maps

Akshay Thejaswi, Aditya Nivarthi, Daniel J. Beckwith, Karen L. Johnson, P. Hendrik Pretorius, Emmanuel O. Agu, Michael A. King, and Clifford Lindsay

***Abstract*– In hybrid imaging, such as with SPECT/CT, the use of CT-derived attenuation maps has the potential to improve image quality. However, the benefits of attenuation correction can be reduced when the patient CT (e.g. obese) is truncated. We investigate the use of Deep Learning to complete truncated regions within cone-beam CT-derived attenuation maps for attenuation correction in cardiac perfusion SPECT. Our technique is based on inpainting, which attempts to reconstruct missing parts of an image using a special type of Convolutional Neural Networks called a context encoder to learn the size and shape of the patient's body. For training, we used 1,169 non-truncated low-dose cone-beam CTs acquired with a SPECT/CT clinical imaging system from an existing cardiac perfusion study under an IRB approved protocol. Using our method, we were able to construct contours for the truncated images and fill them in with appropriate voxel values. Our method can be advantageous over other de-truncation methods due to being image-based and not requiring specialized reconstruction methods. We also show that utilizing the de-truncated CTs for attenuation correction is beneficial in improving the photon counts in cardiac perfusion studies.**

I. Introduction

In hybrid imaging, such as with SPECT/CT, the use of CT-derived attenuation maps has the potential to improve image quality [1]. However, the benefits of attenuation correction can be reduced when the patient CT (e.g. obese) is truncated. We investigate the use of Deep Learning to complete truncated regions within cone-beam CT-derived attenuation maps for attenuation correction in cardiac perfusion SPECT. Machine learning is a broad category of computational methods whose goal is to automatically learn how to solve problems using prior examples or experience. Of interest for this work is a class of methods called neural networks, which process data through layers of simplified functions called "neurons," inspired by structures in the brain. Convolutional Neural Networks (CNNs) apply learned convolution kernels at each layer to extract spatially invariant features and are well-suited for image processing tasks. In this work, we utilize CNNs to infer missing voxels of truncated CT images from un-truncated body shapes in order to synthesize a method for CT de-truncation.

In recent years, various methods have been developed to address truncation in attenuation maps and the CTs from which they are derived. These techniques fall into one of the following categories: 1) methods that utilize raw projection data [2] or 2) image-based methods that operate only on reconstructed CT images. The vast majority of the methods utilize the projection data and therefore require custom reconstruction software, which limits their clinical applicability. In contrast, our method is performed post-reconstruction and does not require projection data for de-truncation. A simple image-based method for addressing truncation is to mirror the CT or attenuation map [3] and replace truncated voxels using data from the opposite side of the CT. Other methods utilize previously acquired CTs to replace truncated voxels [4]. These methods rely on the existence of prior and non-truncated images. Our method assumes no previous CT acquisition and is therefore more generally applicable.

II. Methods

Our technique is based on inpainting [5], which attempts to reconstruct missing parts of an image using a special type of CNN called a context encoder [5]. Prior to training our model, we preprocess each cone-beam CT to remove the bed, artifacts, and extract a bounding contour of the patient's body (see Fig 1 – top). Our model uses a series of convolution layers in a context encoder configuration to learn the size and shape of the patient's body. Once fully trained, our method can be used to correct truncated contours and replace missing voxel data.

For training, we used 1,169 non-truncated low-dose cone-beam CTs acquired (FOV; 47cm, transaxial) with a Philips Healthcare Brightview SPECT/CT clinical imaging system from an existing cardiac perfusion study under an IRB approved protocol. CTs were acquired during free-breathing with 300 projections covering a 360-degree rotation over a 60s acquisition (5mA current at 120Kvp voltage), matrix size of 256×256×101, and voxel size of 4mm3. Truncation occurred in approximately 40% of the patients, ranging from negligible to severe. The truncation results from either positioning the patient partially outside the FOV or from an insufficient imaging

Manuscript received May 11, 2017. This work was supported in part by the National Heart, Lung, and Blood Institute of the National Institutes of Health under award number R01 HL122484 and the National of Biomedical Imaging and Bioengineering (NIBIB) of the National Institutes of Health award number K25EB019032. The contents are solely the responsibility of the authors and do not necessarily represent the official views of the National Institutes of Health.

Akshay Thejaswi, Aditya Nivarthi, and Daniel J. Beckwith are with Worcester Polytechnic Institute, Worcester, MA, 01609 USA (e-mail: athejaswi @wpi.edu).

E.O. Agu is with Computer Science Department, Worcester Polytechnic Institute, Worcester, MA, 01609 USA (e-mail: emmanuel @wpi.edu).

K.L. Johnson, P.H. Pretorius, M.A. King, and C. Lindsay are with the Radiology Department, University of Massachusetts Medical School, Worcester, MA, 01655 USA (e-mail: clifford.lindasy @umassmed.edu).

978-1-5386-2282-7/17/$31.00 ©2017 IEEE

volume to envelope the entire patient. For cardiac perfusion studies, left side truncation (heart side) has a greater impact due to a higher influence on the attenuation correction. For training our CNN, we chose CTs not truncated during acquisition and expanded our set to 5,845 CTs by generating 5 different artificially-truncated CTs for each non-truncated CT. Artificial truncation was randomly chosen as 85-95% (5-15% truncation) of original volume and we utilized 70% of the artificially-truncated CTs for training and 30% for validation. Since CNNs are a supervised learning method, having non-truncated and artificially-truncated CTs provides ground truth for the truncated CTs. The ground truth CTs are used during training to aid the CNN in learning optimal parameters. After testing different sets of parameters, we determined the best performance (i.e., MSE/computation time) used a kernel size of 5 and a depth of 128 over 583 epochs. Our implementation uses Python and the Tensorflow library.

Our method works in three phases to recover an approximate CT. First, a contour of the truncated CT (fig 1 – top row, center column) is processed by our fully trained CNN to recover the approximate shape of the non-truncated patient body contour (fig 1 – top row, right column). Next, the recovered contour is superimposed over the original unprocessed truncated CT. Empty voxels outside the original truncated CT but within the recovered 3D contour are filled-in with voxel values consistent with the tissue values in that region of the patient's body which are previously determined as part of the preprocessing stage described above. The tissue profile is generated by marching inward toward the center at contour point of non-truncated scans and sampling values at different depths at each slice and averaging the values across all non-truncated CTs. Since truncation within our dataset occurs primarily in the thoracic regions composed of mainly adipose and epidermis tissue, the range of potential voxel values needed is reduced, thus creating a concise tissue profile.

III. Results and Discussion

We evaluated the performance of our method in two stages: 1) validation of our de-truncation with artificially-truncated CTs and subsequently 2) determining the improvement in photon counts for CTs truncated during CT acquisition. For validation of our training method, we reserved 30% of the artificially-truncated CT images left out of the training set (1,753 CTs of 5,845) and performed de-truncation on them. Using the Structural Similarity Index Measurement [6], our ability to reconstruct the artificially truncated regions was on average 0.2% with a standard deviation of 0.1% of the original non-truncated volume from which the artificially truncated CTs were derived. This result shows that we were not only successful in recovering the lost portions of the original un-truncated CTs, but that our method did not adversely affect the volume of the recovered CTs.

Our second-stage validation involved generating polar map results for 5 artificially-truncated and 3 originally-truncated patients (see Fig 2) by incorporating our method into a previously established SPECT/CT reconstruction pipeline [7] with the goal of improving photon counts in the lateral regions of the heart. For the 5 artificially truncated CTs, our assessment was based on photon count preservation using our method when compared to the original reconstruction using non-truncated CTs. We were able to show that the 5 artificially-truncated CTs, when de-truncated with our method, retained 99.77% of the counts with a standard deviation of 1.22% compared to the original CTs. For the 3 CTs truncated during acquisition, we show that we were able to positively increase the photon counts.

IV. Conclusions

Using our method, we were able to construct contours for the truncated images and fill them in with appropriate voxel values. Our method can be advantageous over other de-truncation methods due to being image-based and not requiring specialized reconstruction methods. We also show that utilizing the de-truncated CTs for attenuation correction is beneficial in improving the photon counts in cardiac perfusion studies.

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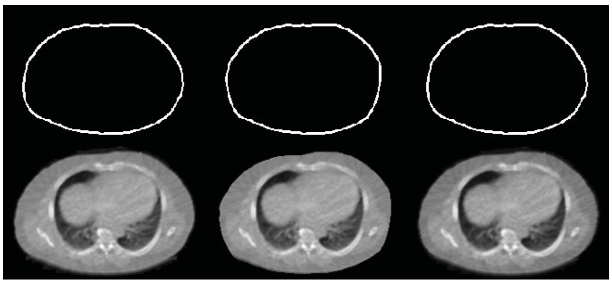

Fig 1. Contours (top) & CT slices (bot) showing ground truth (col. 1), truncated CT (col. 2), & de-truncated CT (col. 3)

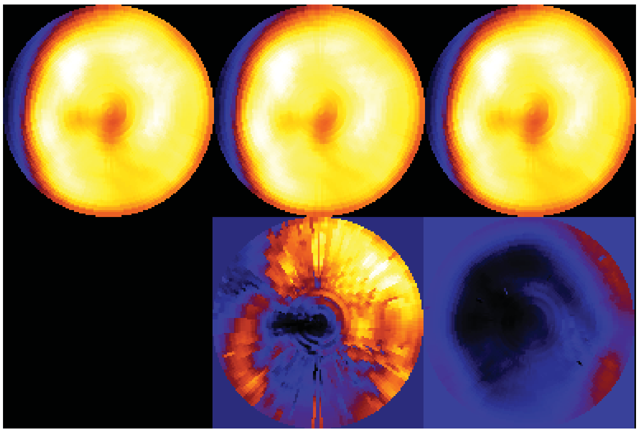

Fig 2. Polar maps quantifying the results of our method. Top left is the polar map from the original cardiac perfusion study using the original CT for attenuation compensation. Top center is the same study with a truncated CT and top right de-truncated CT method. Bottom shows the difference polar maps with respect to the original perfusion study. As you can see, the map from the truncated CT has significantly difference from original compared to our method.