Pseudo Dual Energy CT Imaging using Deep Learning Based Framework: Initial Study

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ABSTRACT

Dual energy computed tomography (DECT) has become of particular interest in clinic recent years. The DECT scan comprises two images, corresponding to two photon attenuation coefficients maps of the objects. Meanwhile, the DECT images are less accessible sometimes, compared to the conventional single energy CT (SECT). This motivates us to simulate pseudo DECT (pDECT) images from the SECT images. Inspired by recent advances in deep learning, we present a deep learning based framework to yield pDECT images from SECT images, utilizing the intrinsic characteristics underlying DECT images, i.e., global correlation and high similarity. To demonstrate the performance of the deep learning based framework, a cascade deep ConvNet (CD-ConvNet) approach is specifically presented in the deep learning framework. In the training step, the CD-ConvNet is designed to learn the non-linear mapping from the measured energy-specific (i.e., low-energy) CT images to the desired energy-specific (i.e., high-energy) CT images. In the testing step, the trained CD-ConvNet can be used to yield desired high-energy CT images from the low-energy CT images, and then produce accurate basic material maps. Clinical patient data were employed to validate and evaluate the presented CD-ConvNet approach. Both visual and quantitative results demonstrate the presented CD-ConvNet approach can yield high quality pDECT images and basic material maps.

Keywords: Dual energy CT, single energy CT, convolutional neural network, pseudo DECT images

1. METHODOLOGY

1.1 CD-ConvNet architecture in pDECT imaging

The structure of the ConvNet is shown in Fig. 1. It consisted of sequential convolution modules which are convolution (Conv), batch normalization (BN) and ReLU layers.

From the Fig. 1 it can be seen that the first layer of ConvNet is excluded BN layers and the last module contained only convolution layer. In the training, $3 \times 3 \times 64$ convolution kernels were used in all the convolution layers.

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layers except that the first layer which contains $7 \times 7 \times 64$ convolution kernels in convolution layer, and there are 20 modules in a single ConvNet totally.

Although one ConvNet is intuitionistic for SECT images compound to pseudo DECT images, the image quality might not be satisfactory. A ConvNet with large enough receptive field is needed to fully extract the useful feature information from the low-energy CT images. However, such a ConvNet might need more training samples and longer time to learn excessive number of parameters. Therefore, to address this issue, we presented a cascade deep ConvNet (CD-ConvNet) for the deep learning framework to improve the image quality of pseudo DECT images. The structure of the CD-ConvNet is shown in Fig. 2.

![Figure 2. The structure of our cascade deep convolutional neural network.](image)

In Fig. 2, $X_L$ and $X_{\text{Predict}H}$ denote the low-energy CT images and the pseudo high-energy CT images, respectively. The first ConvNet was trained to map $X_L$ to high-energy CT images, then the $X_L$ was predicted to get the $X_{\text{Predict}H}^{(1)}$. Then a cascaded ConvNet was trained to map $X_{\text{Predict}H}^{(1)}$ to high-energy CT images in the similar way to get the $X_{\text{Predict}H}^{(2)}$. The following cascaded was constructed in the same way with the previous one, as showed in Fig. 2.

### 1.2 Implementation details

The clinical datasets were used for this experiment, and it contains abdominal spectral CT images collected from 8 patients with two energy spectra. In order to increase sample data, we simulated both of the two energy CT images with different rotations of each slice. We choose 7 patients datasets images as the training datasets of each cascade and the remaining one patient data was used as testing dataset. There were 2,121 slices in total in the training datasets and 334 slices in the testing datasets. The presented cascade deep convolution neural network (CD-ConvNet) was implemented using the MatConvNet toolbox in MATLAB (2015b) environment. Less than 10 hours were cost for training one single ConvNet on a workstation equipped with a GPU (Nvidia Quadro M4000) with 4 GB RAM.

The training of the ConvNet in the CD-ConvNet is to determine a set of parameters i.e, $\theta = \{W_d, B_d; d = 1, 2, \cdots, D\}$, via minimizing the loss between the network pseudo high-energy image $X_{\text{Predict}H}$ and the reference high-energy CT image $X_H$. Given a set of pairs{$X_{\text{Predict}H}, X_H$}, a commonly used loss function for regression tasks, is defined as:

$$
(\theta) = \frac{1}{N} \sum_{i=1}^{N} \|X_{\text{Predict}H} - X_H\|^2,
$$

(1)

where $N$ is the number of training samples.

The loss function was minimized via mini-batch stochastic gradient descent (SGD) algorithm. The batch size, momentum, and weight decay for the mini-batch SGD were set to 128, 0.7, and $10^{-4}$, respectively. The learning rate of all the convolution layers set to $10^{-3}$ during the first 5 epochs and $10^{-5}$ in the rest epochs. The filter weights of each layer were initialized with a Gaussian function with a zero mean and standard deviation of $\sqrt{2/M}$, with $M$ indicating the number of incoming nodes of one neuron. The initial biases of each convolution layer were set to 0.
2. RESULTS

Fig. 3 presents the low-energy CT image, high-energy CT image, and pseudo high-energy CT images reconstructed by the CD-ConvNet. It can be observed that the pseudo high-energy CT image from CD-ConvNet is close to the reference high-energy CT image in visual inspection. Moreover, Fig. 4 shows the zoom-in-view of the region of interest (ROI) indicated by red rectangle in Fig. 3. Fig. 5 depicts the line profiles along the red line as indicated in Fig. 4. It can be seen that the profile from the pseudo high-energy CT image from presented CD-ConvNet agrees closely with profile from reference high-energy CT image. The qualitative experiments can demonstrate that the CD-ConvNet can produce accurate pseudo high-energy CT image from low-energy CT image visually.

![Figure 3](image1.png)

Figure 3. Selected single energy image from (a) low-energy CT image (b) pseudo high-energy CT image from CD-ConvNet and (c) reference high-energy CT image. All the images are displayed with the same window: \([0.011 \ 0.024] \ mm^{-1}\).

![Figure 4](image2.png)

Figure 4. Zoomed images indicated by the red rectangle in Fig. 3 (a) low-energy CT image (b) pseudo high-energy CT image from CD-ConvNet (c) reference high-energy CT image. All the images are displayed with the same window: \([0.011 \ 0.024]\)

![Figure 5](image3.png)

Figure 5. Profiles of pseudo high-energy CT image (CD – ConvNet) and reference high-energy CT image.
To further evaluate the performance of the CD-ConvNet, a material decomposition experiment is conducted. The bone equivalent fraction images and the water equivalent fraction images are shown in Fig. 6. From the result, it can be seen that the water equivalent fraction image and bone equivalent fraction image from pDECT images are close to these from DECT images in visual inspection. The mean and SD values of ROI in Fig. 6 are computed and the corresponding results are depicted in Table 1.

![Figure 6. Material decompositions from DECT CT image and pDECT image. The first row is for water equivalent fraction images: (a) DECT (b) pDECT. The second row is for bone equivalent fraction images: (c) DECT (d) pDECT.](image)

|                        | DECT        | pDECT       |
|------------------------|-------------|-------------|
| Water equivalent fraction image | 0.46±6.72e-8 | 0.45±1.02e-8 |
| Bone equivalent fraction image | 0.053±3.86e-8 | 0.061±6.74e-9 |

3. CONCLUSION

In this work, we presented a cascade deep convolution neural network (CD-ConvNet) structure to simulate pseudo high-energy images from the low-energy CT images in deep learning based framework. Clinical patient data were employed to validate and evaluate the presented CD-ConvNet approach performance. Both visual and quantitative results demonstrate the presented CD-ConvNet approach can yield high quality pDECT images. It is also noted that we can obtain various energy-specific pseudo DECT images in the presented network depending on training datasets.

However, the CD-ConvNet can not produce the exact CT value compared with reference images, which is the inherent weakness of convolutional neural networks. In further study, various approaches are can be conducted to improve the performance of the CD-ConvNet. We also investigate other deep learning based network for DECT imaging, i.e., generative adversarial network (GAN)\textsuperscript{2} multi-task learning network\textsuperscript{3}.

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