Material decomposition in spectral CT using a convolutional neural network: Application to human knee

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Abstract
Spectral computed tomography acquires energy-resolved data, which enables the material components of a sample to be recovered, offering improved contrast compared to conventional computed tomography. Unfortunately, current material decomposition algorithms require knowing the scanner response function and the attenuation of each material. To solve this problem, we propose a deep learning approach that we assess using realistic numerical phantoms of human knee. We train a U-net with augmented data from a control knee data and test it in another osteoarthritic knee phantom. Compared to a state-of-the-art model-based method, our U-net provides comparable results with a significant reduction in computation time.

Keywords: Spectral computed tomography, Convolutional neural network, Material decomposition, Knee phantom.

1. Introduction
Spectral computed tomography exploits energy-resolved data acquired by photon counting detectors to reconstruct material images with higher contrast and resolution than conventional X-ray images (Schlomka et al., 2008; Taguchi and Iwanczyk, 2013). Model-based approaches have been proposed for material decomposition but they require modelling the energy response of the scanner, which is usually unknown or subject to pixel-to-pixel deviations (Schlomka et al., 2008; Ducros et al., 2017). To solve this problem, deep learning has been recently proposed in the image domain (Clark et al., 2018). Here, we propose a U-net convolutional neural network (CNN) for material decomposition in the projection domain, which offers a natural parallelization scheme across viewing angles. Our U-net is evaluated in realistic numerical phantoms of human knees and it is compared to a regularized model-based approach.
2. Methods
2.1. Forward model
X-ray attenuation is energy dependent and can be described by the linear attenuation coefficient \( \mu(E) = \sum_{m=1}^{M} \rho_m \tau_m(E) \), where \( \rho_m \) and \( \tau_m \) are respectively the material mass density and the mass attenuation of the \( m \)-th material. The forward model of spectral computed tomography can be split into two operators: the X-ray transform \( X \) and the spectral mixing operator \( F \). X-ray transformation applies to each material independently, i.e., \( a_{\theta m} = X(\rho_m) \), where \( a_m \) represents the projected material mass density for the \( \theta \)-th projection angle. Spectral mixing applies to each angle view independently, i.e., \( s_{\theta i} = F(a^\theta) \) where \( s^\theta \) is the photon count for the \( \theta \)-th angle view and the \( i \)-th bin of the detector (Schlomka et al., 2008).

2.2. Inverse problem
The inverse problem is divided in two subproblems. First, material decomposition is performed using a U-Net or a model-based approach. Second, tomographic reconstruction is performed using filtered backprojection.

2.2.1. Material decomposition with a model-based method
Material decomposition is a nonlinear inverse problem that can be solved using a regularized Gauss-Newton algorithm (Ducros et al., 2017) that minimizes

\[
C(a^\theta) = \frac{1}{2} ||F(a^\theta) - s^\theta||_W^2 + \alpha \left( ||\Delta a^\theta_{\text{soft}}||_2^2 + ||\nabla a^\theta_{\text{bone}}||_2^2 \right),
\]

where the first term is the data fidelity term with \( W = \text{diag}(1/s^\theta) \) and the second term is the regularization term with \( \alpha \) being the regularization parameter.

2.2.2. Material decomposition with the proposed CNN
Deep learning has been recently proposed for solving inverse problems (Mousavi and Baraniuk, 2017; Jin et al., 2017; Kang et al., 2017). Given \( N \) training input-output pairs \( \{s^n, a^n\}, 1 \leq n \leq N \), we consider the following loss function

\[
L(\beta) = \sum_{n=1}^{N} ||h(s^n; \beta) - a^n||^2,
\]

where \( \beta \) represents the weights of the network \( h \) represented in Figure 1. We minimize (2) using the adaptive gradient method (Duchi and Singer, 2011) under TensorFlow (Abadi et al., 2016) running on a GeForce NVIDIA GTX 2080 Ti graphics card. The learning rate is set to \( 10^{-3} \) and the batch size to 45.

Figure 1: U-net architecture for material decomposition
3. Data

We use two realistic numerical phantoms (control and osteoarthritic knees). Phantoms are composed of soft tissue and bone materials and created from synchrotron CT volumes as described in (Bussod et al., 2019). Photon counting data are simulated using SPRAY tool-box (SPRAY) for 180 projections over 180°, \( I = 4 \) energy bins and assuming Poisson noise distribution with a total number of photons \( N_0 = 10^7 \). Training data are obtained from the control phantom by augmentation using rotation and scaling to obtain 18 different data sets (each set containing \( 180 \times I \) projections). We evaluate the network with the osteoarthritic phantom.

4. Results and Discussion

Figure 2 shows processing steps and errors of each method. We chose \( \alpha = 0.3 \) for RGN as an optimal regularization parameter to decompose soft tissue and bone (Ducros et al., 2017). Cartilage is visible with naked eye on the monoEs but there is cross-talk between soft tissue and bone at the cartilage location because phantoms are simulated using three materials (including cartilage). U-net performs slightly better than RGN as we show in Table 1 and performs all projections in 13 minutes while RGN does it in 2 hours and a half.

<table>
<thead>
<tr>
<th>Projections</th>
<th>Reconstructions</th>
<th>MonoE 70 keV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft Tissue</td>
<td>Bone</td>
<td>Soft Tissue</td>
</tr>
<tr>
<td>Bone</td>
<td></td>
<td>Bone</td>
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Table 1: Quantitative results for the 70 keV monoE

The main contribution is to propose a deep learning-based material decomposition method in the projection domain and validated with knee data sets. Moreover, we compare the deep learning method to the state-of-the-art variational approach. The strength of this network is its ability to perform well in unseen data as the test data set is from totally different knee compared to the training set. Future work will process experimental data and consider three material decomposition considering cartilage. This deep learning method is very promising for the use of spectral CT for the knee osteoarthritis application.
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