MATERIAL DECOMPOSITION PROBLEM IN SPECTRAL CT USING DEEP LEARNING


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ABSTRACT

Current model-based variational methods used for solving the nonlinear material decomposition problem in spectral computed tomography rely on prior knowledge of the scanner energy response, but this is generally unknown. We propose a deep learning approach to overcome this limitation and perform material decomposition from the projections. Results are compared to a regularized Gauss-Newton method.

Index Terms—Spectral CT, deep learning, transfer learning

1. INTRODUCTION

New generation spectral computed tomography (SCT) scanners include photon-counting detectors, capable of counting single photons and resolve their energy [1]. With this new information, SCT allows for material decomposition, which opens up new diagnosis possibilities. Current model-based variational methods for material decomposition rely on prior knowledge of the detector energy response function [2], but the latter is not perfectly known. In [3], a network was trained to correct the raw data for model deviations. Here, we propose a deep learning approach for material decomposition, which implicitly learns the detector response function.

2. METHODS

We consider a two-step approach where we first decompose the projections before reconstructing the slices from the decomposed projections using some reconstruction algorithm (e.g., filtered back projection). Material decomposition in the projection domain consists in inverting \( s = F(a) \), where \( F \) is the nonlinear forward operator that maps the projected mass densities \( a = [a_1, \ldots, a_M]^T \) for \( M \) different materials onto the SCT data \( s = [s_1, \ldots, s_J]^T \) measured for \( J \) energy bins (in this study \( M = 3 \) and \( J = 4 \)) [2].

We solve the material decomposition problem by learning the inverse mapping \( h_\beta : s \mapsto a \), where \( h_\beta \) is a Unet [4]. For this, we optimise \( \min_\beta \sum_{n=1}^N \| h_\beta(s^n) - a^n \|^2 \), where \( N \) is the number of training projection pairs in the training set \( \{s^n, a^n\} \). Our numerical human thorax phantoms are comprised of soft tissue, bone and gadolinium marking kidneys. They are built from CT volumes obtained from the KiTS19 Challenge [3]. SCT data is simulated using the SPRAY toolbox following [2] and Poisson noise is considered for a total number of \( 10^7 \) photons. Data is normalized for training. We used 40 phantoms for training, 10 for validation, and 10 for test. Each phantom is projected at 360 view angles. Minimization is done with adaptive gradient method under TensorFlow, with a learning rate of \( 10^{-3} \) and a batch size of 45. Early stopping is adopted to avoid overfitting. To assess the effect of model deviations, we randomly shift the detector response function where each detector pixel has an independent shift drawn from a normal distribution \( \mathcal{N}(0, 3^2) \) keV. In this case, we apply transfer learning (Unet+TL) by fine-tuning the network pretrained with an ideal detector function using the perturbed data from one phantom only.

3. RESULTS AND CONCLUSIONS

For an ideal detector response, the Unet shows an improved image quality for soft tissue and bone images compared to a regularized Gauss-Newton (RGN) method [2] (figure 1). For a perturbed response, both methods failed to provide accurate material decomposition (results shown only for Unet). However, transfer learning (Unet+TL), which can account for deviations from the ideal detector assumption, reduces most of the artefacts. In conclusion, deep learning has a great potential for SCT as it allows for material decomposition in the presence of a perturbed detector response function, which provides superior image quality than variational approaches and reduces computation time.

4. REFERENCES


Fig. 1: Phantom and tomographic reconstructions.