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Tensor decomposition and non-local means based spectral CT image denoising

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Abstract

BACKGROUND: As one type of the state-of-the-art detectors, photon counting detectors are used in spectral computed tomography (CT) to classify the received photons into several energy channels and generate multichannel projections simultaneously. However, FBP reconstructed images contain severe noise due to the low photon counts in each energy channel.

OBJECTIVE: A spectral CT image denoising method based on tensor-decomposition and non-local means (TDNLM) is proposed.

METHODS: In a CT image, it is widely accepted that there exists self-similarity over the spatial domain. In addition, because a multichannel CT image is obtained from the same object at different energies, images among different channels are highly correlated. Motivated by these two characteristics of the spectral CT images, tensor decomposition and non-local means are employed to recover fine structures in spectral CT images. Moreover, images in all energy channels are added together to form a high signal-to-noise ratio image, which is applied to encourage the signal preservation of the TDNLM. The combination of TD, NLM and the guidance of a high-quality image enhances the low-dose spectral CT, and a parameter selection strategy is designed to achieve the optimal image quality.

RESULTS: The effectiveness of the developed algorithm is validated on both numerical simulations and realistic preclinical applications. The root mean square error (RMSE) and the structural similarity (SSIM) are used to quantitatively assess the image quality. The proposed method successfully restored high-quality images (average RMSE=0.0217 cm⁻¹ and SSIM=0.987) from noisy spectral CT images (average RMSE=0.225 cm⁻¹ and SSIM=0.633). In addition, RMSE of each decomposed material component is also remarkably reduced. Compared to the state-of-the-art iterative spectral CT reconstruction algorithms, the proposed method achieves comparable performance with dramatically reduced computational cost, resulting in a speedup of >50.

CONCLUSIONS: The outstanding denoising performance, the high computational efficiency and the adaptive parameter selection strategy make the proposed method practical for spectral CT applications.

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Keywords

Spectral computed tomography; noise estimation; non-local means; tensor decomposition

1. Introduction

With the rapid development of computed tomography (CT) imaging techniques, spectral CT (also known as multi-energy CT) has attracted increasing attention. Compared to the conventional energy integrating CT, spectral CT produces multiple projection data at different energy ranges [1]. The additional information along energy dimension allows the differentiation of multiple materials, producing density distribution maps of specific materials by the material decomposition methods [2-15]. The dual energy CT is a simple and typical spectral CT, which collects projections with two different x-ray spectra. Two scans with high/low voltage [2], the kV-switching technique [6], dual sources [7] and multilayer detectors [8] are common ways to acquire dual energy data [1, 2]. Because most of the dual energy CT scanners use energy-integrating detectors, the high and low energy spectra usually have significant overlap which reduces the energy resolution [9]. The limitation can be overcome by using an energy-resolved photon counting detector (PCD) to discriminate photon energies, and the photon counts are accumulated into specific energy bins/channels [10]. Hence, multichannel projection data are generated simultaneously. The PCD integrated spectral CT usually has two to eight energy bins, providing more spectral information than the conventional dual-energy CT. However, because a specific energy bin only accounts part of the received photons, the generated multichannel projections usually suffer from strong quantum noise, leading to low signal-to-noise ratio (SNR) measurements and less accurate material decomposition results. Currently, how to obtain high-quality images from PCD based spectral CT is a hot topic.

Because of the structural similarity of different energy channel images, they are highly correlated and an image in a specific energy channel can be sparsely represented. Thus, by incorporating this priori knowledge, various spectral CT reconstruction algorithms have been proposed. For example, total variation (TV), dictionary learning, wavelet, low rank and non-local means have been employed to capture sparsity and correlation in different reconstruction approaches [11-20]. In 2012, Xu et al. reconstructed an image in each energy channel independently, and applied the TV as a sparsity regularization [18]. Later, the low rank (LR) was introduced to enhance the correlation among energy channels in spectral CT data [19]. By combining the TV and low rank constraints, the TVLR method demonstrated significant improvements compared to the TV only algorithm [21, 22]. Rigie and La Riviere proposed a joint spectral CT reconstruction algorithm based on a total nuclear variation (TNV) [23], which is an extension of TV and induces a spectral correlation through a pixel-wise penalty on the rank of Jacobian matrix. Fundamentally, the strategy of TNV method is similar to the TVLR. In 2011, Gao et al. developed a spectral CT reconstruction algorithm based on a prior rank, intensity and sparsity model (PRISM) [16], which modeled a multichannel image as the superposition of a low-rank matrix and a sparse matrix. Later, the PRISM was improved by incorporating the higher-dimensional tensor technique [24]. A multi-dimensional array, i.e., a tensor, can be sparsely represented using tensor

decomposition (TD) [25]. In 2014, Semerci et al. developed a tensor-based nuclear norm regularization algorithm [15]. Later, Zhang et al. proposed a tensor-dictionary learning (TDL) based spectral CT reconstruction [26], where the pre-trained tensor-based dictionary was used to sparsely represent image tensor blocks during an iterative reconstruction process. Different from the aforementioned low rank and tensor based methods, others employed a high-quality image as a priori to encourage the correlation among energy channels [9, 17, 27]. In 2016, Wang et al. adopted a reference image to guide the reconstruction [9]. For a given position, the patches extracted from a specific energy bin and the reference image were assumed as two vectors in a high dimensional space, and the space angle between these two vectors was minimized to enhance the correlation. Following the same idea, in the same year, Zhang et al. improved the quality of reconstructed images using the TV and spectral mean (SM) [17] where the SM was motivated by the idea of non-local means (NLM) [28], and they proposed to encourage the similarity patch by patch between each energy-specific image and the mean of multi-channel images. Similarly, Deng et al. proposed an average image-induced non-local means based method (aviNLM) for image restoration in each of energy channels [27]. Different from the aforementioned iterative methods, the aviNLM is an image denoising approach directly performed on the FBP reconstructed images, and the computational cost is highly efficient. However, its effectiveness is compromised in the presence of strong noise. Likewise, the conventional low dose CT (LDCT) image denoising methods can be used to spectral CT as well. Particularly, Chen et al. recently proposed a discriminative feature representation (DFR) algorithm for 3D volumetric LDCT denoising. The algorithm applied two dictionaries trained from full dose images and noise to respectively represent tissue structures and noise [29], and it achieved excellent denoising performance and could be directly applied to spectral CT image processing.

In this study, we restore spectral CT images from the FBP reconstructed noisy images by combining tensor decomposition and non-local means. For a tensor block extracted from a spectral CT image tensor, due to the small size, it usually has simple structures and consists of only one or two materials [19]. These properties respectively lead to sparsity in the spatial domain and correlation in the spectral domain [13]. Hence, on one hand, the tensor decomposition (TD) is used to represent a highly redundant tensor block to encourage the local sparsity and correlation. On the other hand, the non-local means (NLM) explores self-similarity of an image [30-34]. For a specific block, the information of similar blocks collected in a neighboring window can be used for denoising. Because the non-local means and tensor decomposition explore different characteristics of a spectral CT image, they are perfectly complementary. Therefore, we combine them into one algorithm, which is named as TDNLM algorithm. Moreover, the images in all energy channels are added together to form a high SNR image, helping the TDNLM to preserve signal better. This can be viewed as a high-quality image induced strategy [9, 17, 27]. In addition, a noise estimation method is introduced for the parameter selection in NLM. Therefore, our contribution is threefold: First, we combine the merits of TD, NLM and the high-quality image induced methods, allowing comparable image quality and material decomposition results with respect to the state-of-the-art methods. Second, a parameter selection strategy is applied to adaptively determine proper parameters for different imaging cases. Third, the proposed method is

directly performed on the FBP reconstructed images, allowing high computational efficiency.

The rest of this paper is organized as follows. In Section 2, the TDNLM method is presented, and a parameter selection strategy is described. In Section 3, numerical simulations are performed and real preclinical application data sets are employed to evaluate the proposed TDNLM method. In Section 4, we discuss the computational cost issue and the denoising performance of two derivative versions of TDNLM. Finally, conclusion is made in Section 5.

2. Method

In this work, the TD and NLM are carried out in sequence on small tensor blocks extracted from a multichannel CT image. Specifically, each extracted small tensor block is approximated by a low-rank tensor using TD. Hence, the noise in a tensor block is significantly reduced. Then, the generated low-rank tensors are added back into their original positions to form a higher SNR image tensor. Based on this image tensor, the NLM is performed to further suppress noise. To adaptively determine the strength of NLM filtering, a method is applied to estimate the noise level. The detail methodology and implementation are as follows.

2.1. Tensor decomposition

A tensor is a multidimensional data array. A tensor of order n is denoted as $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_k \times \cdots \times I_n}$, where I_k is length of the k^{th} dimension and $k = 1, 2, \cdots, n$. Entries of $\mathcal{X}$ are denoted as $x_{i_1 i_2 \cdots i_n}$, $1 \leq i_k \leq I_k$, $k = 1, 2, \cdots, n$. Specifically, tensors are vectors and matrices respectively for $n = 1$ and $n = 2$. A tensor can multiply with a matrix or a vector. The mode- k product ($k = 1, 2, \dots, n$) of a tensor $\mathcal{X}$ by a matrix $\mathbf{U} \in \mathbb{R}^{J \times I_k}$ is denoted by $\mathcal{X} \times_k \mathbf{U} \in \mathbb{R}^{I_1 \times \cdots \times I_{k-1} \times J \times I_{k+1} \times \cdots \times I_n}$, whose entry in $(i_1, \cdots, i_{k-1}, j, i_{k+1}, \cdots, i_n)$ is computed by $\sum_{i_k=1}^{I_k} x_{i_1 i_2 \cdots i_n} u_{ji_k}$. Without loss of generality, we consider a 3rd-order tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$ in the rest of this paper.

A tensor can be approximated by a low-rank tensor by the tensor decomposition methods. As one of the widely used tensor decomposition methods, higher-order singular value decomposition (HOSVD), also referred to as multilinear SVD or Tucker decomposition, can decompose a tensor into a core tensor multiplied by a matrix along each mode (dimension) [25]. Thus, for a 3rd-order tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$, we have

$$\mathcal{X} \approx \mathcal{Y} = \mathcal{G} \times_1 \mathbf{A} \times_2 \mathbf{B} \times_3 \mathbf{C}, \quad (1)$$

where $\mathcal{Y} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$ is a low-rank tensor and $\mathcal{G} \in \mathbb{R}^{J_1 \times J_2 \times J_3}$ is the core tensor ($J_k \leq I_k$); $\mathbf{A} \in \mathbb{R}^{I_1 \times J_1}$, $\mathbf{B} \in \mathbb{R}^{I_2 \times J_2}$ and $\mathbf{C} \in \mathbb{R}^{I_3 \times J_3}$ are decomposed matrices along each mode. The HOSVD can be viewed as an extension of the conventional matrix based SVD, and the core tensor is a high-dimensional form of singular values, which represent the variability of both signal and noise contributions at each component. The principal

components mainly consist of signal while the rest components are mainly related to noise. By selecting a proper J_k ($1 \leq J_k \leq I_k$), the principal components in the tensor are preserved, and noise can be reduced.

A spectral CT image with two spatial dimensions and one spectral dimension is a third order tensor, denoted as $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times S}$, where I_1 and I_2 are image height and width, and S is the number of energy bins. In the TD step, we aim at reducing noise and preserving correlated signals. As demonstrated in Refs. [9, 27], the average/summation of all the energy channels has a higher SNR, which is helpful to preserve the signals during the TD processing. Hence, in this proposed method, a sum-channel image is embedded into the multichannel image as the $(S+1)^{\text{th}}$ channel to form a $\mathbb{R}^{I_1 \times I_2 \times (S+1)}$ tensor. A window with the size of $(2M+1) \times (2M+1)$ moves pixel by pixel in the image tensor, and tensor blocks with the size of $(2M+1) \times (2M+1) \times (S+1)$ are extracted, where M is half size of a tensor block along a spatial dimension. Similar to Refs. [17, 26], the mean value (also known as direct current) in each channel of a tensor block is removed. In this way, the rank along spectral dimension is smaller and structures can be represented more sparsely. For the k^{th} tensor block $\mathcal{X}_k \in \mathbb{R}^{(2M+1) \times (2M+1) \times (S+1)}$, it is decomposed as

$$\mathcal{X}_k \approx \mathcal{Y}_k = \mathcal{G}_k \times_1 \mathbf{A}_k \times_2 \mathbf{B}_k \times_3 \mathbf{C}_k, \quad (2)$$

where the size of core tensor controls the representation sparsity. For a special case when the core tensor size is $(2M+1) \times (2M+1) \times 1$, the matrix $\mathbf{C}_k$ turns into a vector. Hence, the matrix in each channel of the block is forced to be proportional to one another, and the high-quality sum-channel image can be viewed as a guidance for the denoising process. From this point of perspective, the TD performed on a sum-channel embedded image tensor can be viewed as a generalized high-quality image induced method [9, 17, 27]. After the TD processing, the removed mean values are added back to the tensor block $\mathcal{Y}_k$, and then it is returned to their original positions. Because the blocks are overlapped, the overlapped pixels are averaged to serve as the TD processed pixel value. Thus, a tensor $\mathcal{X}_{TD} \in \mathbb{R}^{I_1 \times I_2 \times (S+1)}$ with less noise is obtained.

2.2. Non-local means

In 2005, Buades et al. proposed a non-local means strategy for 2D image denoising [28]. The NLM estimates a pixel value by a weighted average of the pixel values in a neighboring window. Given a 2D noisy image $\mathbf{x} = \{x(i) \mid i \in I\}$, where i is the pixel index and I is the number of pixels, then the NLM denoising process can be summarized as follows:

$$x^{NLM}(i) = \sum_{j \in \mathcal{V}_i} w(i, j) x(j), \quad (3)$$

where $\mathcal{V}_i$ is a square neighborhood of the pixel i referred to as the “search window”, and $w(i, j)$ is the weight depending on the similarity between the pixels i and j and satisfying the conditions $0 \leq w(i, j) \leq 1$ and $\sum_j w(i, j) = 1$. The weight is constructed as follows

$$w(i, j) = \frac{1}{Z(i)} \exp\left(-\frac{\|\mathbf{x}(\mathcal{N}_i) - \mathbf{x}(\mathcal{N}_j)\|_2^2}{h^2}\right), \quad (4)$$

where $\mathcal{N}_i$ is a square neighborhood of fixed size and centered at a pixel i , referred to as the “similarity window”, $\mathbf{x}(\mathcal{N}_i)$ denotes the vector of pixel values within the similarity window, and $Z(i)$ is the normalizing factor,

$$Z(i) = \sum_j \exp\left(-\frac{\|\mathbf{x}(\mathcal{N}_i) - \mathbf{x}(\mathcal{N}_j)\|_2^2}{h^2}\right), \quad (5)$$

where the parameter h controls the degree of filtering. A larger h results in a smoother image.

Later, the original NLM was extended for 3D and multispectral image denoising problems [35, 36]. Inspired by these works, we apply a modified 3D NLM filter to the TD processed image tensor $\mathcal{X}_{TD}$. To explore the non-local spatial-spectral correlation of a spectral CT image, instead of updating an image pixel by pixel, the improved 3D NLM is performed on the spectral vector for a given spatial position simultaneously. Hence, we have

$$\mathbf{x}_i^{NLM} = \sum_{j \in \mathcal{V}_i} w(i, j) \mathbf{x}_j, \quad (6)$$

where $\mathbf{x}_i^{NLM}$ is the filtered vector with the spatial position index i , and $\mathbf{x}_j \in \mathbb{R}^{S+1}$ is the vector with the spatial position index j in $\mathcal{X}_{TD}$. The search window is with the size of $(2W+1) \times (2W+1)$, where the half window size W is an adjustable parameter. In 2D case, the weight is computed via the similarity of two patches. However, its accuracy decreases dramatically in the presence of strong noise. For spectral CT, it is more accurate to calculate the weight via the similarity of two 3D tensor blocks centered at positions of spatial indices i and j . Hence, the weight $w(i, j)$ is rewritten as,

$$w(i, j) = \frac{1}{Z(i)} \exp\left(-\frac{\|\mathcal{X}(\mathcal{O}_i) - \mathcal{X}(\mathcal{O}_j)\|_F^2}{h^2}\right), \quad (7)$$

where $\mathcal{X}(\mathcal{O}_i)$ denotes the tensor block of pixel values within the similarity window $\mathcal{O}_i \in \mathbb{R}^{(2M+1) \times (2M+1) \times (S+1)}$ which has the same size to that in the TD procedure, and $\|\cdot\|_F$ is the Frobenius norm. Accordingly, the normalization factor $Z(i)$ in Eq. (5) is computed by replacing two image patches with image blocks.

2.3. Noise estimation

In the NLM step, the filter strength h is a crucial parameter which depends on the standard deviation of noise in an image tensor. To adaptively select h , it is necessary to estimate the noise level. Filter-based noise estimation is a class of fast methods [35, 37], which apply a filter on an image to obtain the high-frequency component. This high-frequency component

is assumed as noise, and the noise variance is computed. In this work, we employ the Sobel operator to estimate the noise level. The Sobel operator consists of two 3×3 high-pass filters, defined as $\frac{\sqrt{6}}{12}[-1 \ -2 \ -1; 0 \ 0 \ 0; 1 \ 2 \ 1]$ and $\frac{\sqrt{6}}{12}[-1 \ 0 \ 1; -2 \ 0 \ 2; -1 \ 0 \ 1]$, respectively. These two filters are convolved with each channel image separately to measure the pixel variations along horizontal and vertical directions. The obtained image tensors are denoted as $\mathcal{D}_x$ and $\mathcal{D}_y$. Hence, the variance at pixel (i, j) in the s^{th} channel is approximated by $\mathcal{D}_x(i, j, s)^2 + \mathcal{D}_y(i, j, s)^2$, and then the average noise level of the image tensor can be computed. However, $\mathcal{D}_x$ and $\mathcal{D}_y$ contain not only noise but also image edges, which results in a greater noise level estimation than the expectation, especially for weak noise cases. To avoid this bias, it is necessary to exclude the edge pixels in noise estimation [37]. Because the sum-channel image has the highest SNR, it is easier to distinguish edges from noise in the sum-channel image than other energy channels. Therefore, we introduce a 2D binary mask image $\mathbf{B}$ based on the variance image $\mathcal{D}_x(\cdot, \cdot, S+1)^2 + \mathcal{D}_y(\cdot, \cdot, S+1)^2$, where the pixels with the top 10% largest values are assumed as strong edge pixels and are set to be zero, and the rest pixels are set to be one. Thus, the average standard derivation of noise in the image tensor $\mathcal{X}_{TD}$ is calculated as

$$\hat{\sigma} = \sqrt{\frac{\sum_{i,j,s} \mathbf{B}(i,j) (\mathcal{D}_x(i,j,s)^2 + \mathcal{D}_y(i,j,s)^2)}{(S+1) \sum_{i,j} \mathbf{B}(i,j)}}. \quad (8)$$

Similar to other filter-based noise estimation methods [35, 37], the real standard derivation of the noise is approximated by the obtained $\hat{\sigma}$ multiplied a constant coefficient. In this work, because the NLM filtering strength h is set to be the standard derivation of the noise multiplied by a scaling factor λ , the constant coefficient can be absorbed by λ . The detail parameter selection strategy is presented as follows.

2.4. Parameter selection and implementation details

In 2008, Coupé et al. applied a blockwise NLM denoising filter for 3D MRI, and the parameters were optimized [35]. The smoothing parameter h was automatically tuned depending on the estimated noise level and the block size. Inspired by their work, we compute the filter strength h as

$$h = \lambda (2M + 1) \sqrt{S + 1} \hat{\sigma}, \quad (9)$$

where λ is a smoothing parameter to adjust the filtering strength. Because we take into account the noise level, patch size and spectral channels, h is automatically tuned for various spectral CT configurations.

In the TD step, the noise reduction performance is mainly determined by the core tensor size. A smaller size reduces noise remarkably, while part of the signal might be lost. On the contrary, a greater size preserves signal well, and meanwhile it keeps most of noise. We need to make a trade-off between the signal and noise. Along the spectral dimension, because a tensor block usually contains only one or two materials and the mean in each channel is

removed, the signal in each channel is proportional to one another. Therefore, the core tensor size along the spectral dimension is set to be one. Along two spatial dimensions, we find that a half spatial size can preserve signals well. Thus, the size of a core tensor is selected as $(M + 1) \times (M + 1) \times 1$.

There are three major parameters in our method: half size of the search window W , half size of the block M and the smoothing factor λ . The parameters were empirically selected by testing various possible settings. The search-window parameter W was set to 5, i.e., we applied a 11×11 search-window for the NLM. The block parameter M was set to 3. Thus, a size of $7 \times 7 \times (S + 1)$ was used for the similarity window in NLM and for tensor blocks in TD, and core tensor size was $4 \times 4 \times 1$. The smoothing parameter λ was set to 0.2. In our experiments, parameters were fixed for both numerical simulations and realistic preclinical experiments.

In summary, our method includes four basic steps, and they are implemented in MATLAB environment. First, for a FBP reconstructed image tensor, all channel images are added to form a sum-channel image, which is embedded into the image tensor as a new channel. Second, the image tensor is blockwise sparsely represented using tensor decomposition, which is carried out using the Tensorlab Toolbox [38]. Third, noise estimation step is performed on the TD processed image tensor. Fourth, with the automatic tuning parameters, non-local means method is employed for image denoising. For strong noise cases, the obtained images after TD and one NLM still contain obvious noise. Hence, we apply the noise estimation and the NLM steps once again to further suppress noise. The core codes of the NLM filtering were written in C and called by the main function in MATLAB via the mechanism of dynamic link library. Overall, the proposed TDNLM method is summarized in Fig. 1.

3. Experiments and results

In this work, several state-of-the-art iterative spectral CT reconstruction methods, including TV [18], TVLR [21, 22] and TDL [26], were implemented as the competing approaches. We also implemented a state-of-the-art 3D LDCT method DFR [29] and applied it to the spectral CT for comparison, where the parameters were set as the same values in [29]. We compared the proposed and competing methods on both simulated and real preclinical datasets. First, a numerical digital phantom was used to comprehensively evaluate the performance of the proposed and the competing algorithms. This includes image quality improvements and material decomposition capability. Then, the proposed method was validated on realistic preclinical datasets of two mice with injected contrast agents.

3.1. Numerical simulation

In the numerical simulation, a realistic mouse thorax phantom, generated from the MOBY software at an arbitrary specific energy, was applied to produce spectral CT projections [39]. Iodine contrast agent was superimposed into the blood circulation, and the concentration distribution of iodine is shown in Fig. 2. The iodine concentration was 1.2% (by weight) in regions A, B and C, and 0.6% in region E. The concentration in region D varied from 0.32% to 1.2%. It was modeled by a 2D Gaussian distribution centered at the pixel (265, 165) with

a standard derivation of 20 pixels. An equi-distant fan-beam geometry was assumed. There were 512 detector bins, each of which was 0.1 mm, and 640 projection views were uniformly sampled over a full scan range. The distance from the x-ray source to the detector was 180 mm, and the distance from the x-ray to the rotation center was 132 mm. Fig. 3 shows a 50 kVp polychromatic spectrum generated from a free software [40]. The spectrum was divided into eight energy channels: [16, 22), [22, 25), [25, 28), [28, 31), [31, 34), [34, 37), [37, 41) and [41, 50) keV. The spectrum resolution was 1 keV. An ideal PCD detector was assumed and the projection data at each energy channel was generated based on the spectral weights in Fig. 3. Meanwhile, Poisson noise was superimposed into the measurements, and 5000 photons were assumed along each x-ray path for blank scan.

To test the accuracy of noise estimation, we reconstructed several groups of mouse phantom images which were contaminated by different noise levels, and then performed the TD and noise estimation steps. Fig. 4 plots the estimated noise standard deviation versus the true noise standard deviation, and a line is given by data fitting. The data corresponding to 5×10^3 incident photons is indicated in the figure, and noise standard deviations of the rest test data are 0.1 - 3 times of this data. The fitted linear function is $y = 0.8623x + 0.01334$, and the RMSE of data fitting is 0.001342. It is obvious that the noise estimation works very well over a large range of noise level.

Fig. 5 presents the intermediate results of the proposed TDNLM and a single NLM filtering, and an ROI of iodine is magnified. The images in Fig. 5(a) correspond to three representative channels 1, 6 and 8. After the TD procedure, the noise is reduced, and some finer details are discriminated from the noise. However, images still contain obvious noise. By comparison, the FBP images filtered by the NLM have blurry edges. Based on TD's results, the NLM filtering is conducted. It is clear that the visual quality of images using one NLM filtering is improved dramatically, and it was further improved by using an extra NLM filtering step. Particularly, the image quality of ROI is improved constantly after each step, and finally the iodine can be observed clearly. Fig. 5(b) shows the difference images with respect to the noise-free images. It can be seen that the remaining noise is reduced constantly after each step of the TDNLM method. By comparison, for this strong noise case, the reference image guidance based methods can hardly obtain a good reference by averaging images along the spectral dimension, which results in a suboptimal performance [9, 27]. To quantitatively evaluate the performance, the values of the contrast-to-noise ratio (CNR) [41] of the iodine with respect to soft tissue in the ROI are listed in Table 1. It is clear that the CNRs are improved significantly after each step of the proposed method.

Fig. 6 presents the reconstructed results of three representative channels of the mouse phantom. These images were obtained by using the FBP, TV, TVLR, TDL, DFR and the proposed TDNLM, where the images reconstructed from noise-free measurements are assumed as references. A square in the first column is highlighted as a region-of-interest (ROI) which has abundant fine structures. The ROI is zoomed-in, where thoracic vertebra bones are separated by low density tissues. It can be observed that the last channel has the worst SNR and most bony structures are lost in the FBP and TV reconstructed results. The TVLR results are slightly better. Although the DFR preserved structures well, a considerable noise is kept. By comparison, the TDL and TDNLM obtain the closest ones to the noise-free

images. Fig. 7 plots the representative profiles indicated by the two lines at iodine regions in the top-left image in Fig. 6. Three plots are obtained from the energy channels 1, 6 and 8, respectively. In energy channel 1, the TDL and TDNLM have the closest plots with respect to the noise-free one, and the TV is the worst one. In the energy channel 6, the TVLR shows obvious poor fidelity for the iodine contrast agent, which attributes to the low rank regularization performed in the whole image domain. In the energy channel 8, all the plots of TVLR, TDL and TDNLM are close to the ground truth.

To quantitatively evaluate the performance of the proposed algorithm with respect to other competing methods, the root mean squared error (RMSE) [26] and structural similarity (SSIM) [42] were used to assess the reconstructed images in each energy channel. Images reconstructed from noise-free projections using the FBP were used as references. Tables 2 and 3 list the RMSE and SSIM indices of each energy channel and their mean values for each method. It is clear that FBP has the worst image quality indices, followed by the TV and DFR. Both the TDL and TDNLM have the smallest mean RMSE, while the TDL, TDNLM and TVLR have very close SSIM indices. By comparison, the proposed TDNLM reaches comparable image quality to the best one among the iterative reconstruction methods. However, the TDNLM is ultra fast because it is non-iterative.

The full width at half maximum (FWHM) was computed to evaluate the resolution of reconstructed images [43]. Table 4 lists the measured FWHM of each method along the vertical line in the zoomin bony ROI in Fig. 6(a). To minimize the impact of noise on FWHM, we averaged the FWHM of neighboring pixels and all energy channels. Reference image was reconstructed by FBP with the Shepp-Logan filter from noise-free projections, and its FWHM is 2.06. TV and TVLR have remarkably larger FWHMs because of their blurry structures. By comparison, the TDL has the smallest FWHM, followed by the DFR and TDNLM. Because the DFR and TDNLM were post-processing methods based on FBP images, their FWHMs can be further reduced if a sharper filter kernel is applied in the FBP reconstruction.

To study the influence of the parameters in TDNLM, we quantitatively compared the results of TDNLM with different parameter settings. Fig. 8 plots the RMSE, SSIM and FWHM of TDNLM with respect to different smoothing parameters λ , half block sizes M and half search window sizes W , respectively. The default parameters were $\lambda=0.2$, $M=3$ and $W=5$, and only one parameter varied in each plot and keeping others unchanged. λ is a key parameter. The smallest RMSE is obtained at $\lambda = 0.25$, and the largest SSIM is reached at $\lambda = 0.15$. The FWHM increases rapidly with the increase of λ . Regarding the half block size, both RMSE and SSIM reach the best results at $M=3$. The FWHM rises constantly with the increase of M . By comparison, the half search window size has very limited influence on the image quality and resolution. The TDNLM obtained similar results with a search window size varying from 5 to 10, and 5 was selected in our implementation for computational cost efficiency. In summary, the smoothing parameter λ and the half block size M are key parameters to the proposed method.

To validate the proposed TDNLM for material decomposition capability, the multichannel images obtained with various methods were decomposed into three basis materials (bone,

soft tissue and iodine contrast agent) using a post-reconstruction material decomposition approach [44]. Fig. 9 presents the material decomposition results from the phantom study. From the third row, it is observed that many pixels from the competing methods are wrongly classified as containing iodine, and the TDL and TDNLM provide the most accurate iodine components. To quantitatively evaluate the decomposition results, the RMSE values of each decomposed basis material are summarized in Table 5. The FBP has the greatest RMSE for all materials, and the error decreases for TV, TVLR and DFR. By comparison, the TDL has the most accurate decomposition with RMSEs of 0.0086, 0.0274 and 0.0131 for bone, soft tissue and iodine components, respectively. The TDNLM has very close indices to the TDL, and reducing the RMSEs to 26.5%, 16.2% and 22.4% of that for the FBP, respectively.

3.2. Preclinical mouse study

The developed algorithm was also evaluated using preclinical measurements from two mice with injected contrast agents. The mice were scanned on MARS micro-CT systems [45]. The first mouse was injected with 0.2 ml of 15 nm Aurovist II gold nanoparticles (GNP) (Nanoparticles; Yaphank, NY) followed by an euthanasia procedure. The distances from the source to the system origin and the source to the detector were 158 and 255 mm, respectively. 371 projections were uniformly collected over a full scan range. The x-ray source was Source-Ray SB-120-400 (Source-Ray Inc., New York), whose minimum focal spot is 75 μm . Thirteen energy channel projections were collected by multiple scans with the source tube operated at 120 kVp and 175 mA. The detector chip was moved horizontally with overlapped pixels to cover a wider FOV of 34.89 mm in diameter and to correct production defects in the detector sensor layer. A wavelet-Fourier filtering method [46] was applied on the collected projections to reduce ring artifact. For the second mouse, three contrast agents were injected. 10 mg of Fenestra (iodine) in 200 μL was injected via the tail vein. After 15 minutes, 4 mg of Aurovist (gold) in 100 μL was injected via the tail vein. Euthanasia was carried out 17-20 minutes after the first injection. Post-mortem 15.7 mg/mL of MultiHance (gadolinium) in 1000 μL were placed in the bowel through both rectal and gastric gavage. The distances from the source to the system origin and the source to the detector were 118 and 200 mm, respectively. The x-ray sources worked under 118 kVp and the tube current was 24 mA. Projections were collected with four energy channels: 33.0–48.9, 48.9–65.0, 65.0–77.8 and >77.8 keV. The slice thickness of the reconstructed volumetric image was 0.9 mm, and the pixel size was $0.09 \times 0.09 \text{ mm}^2$.

Fig. 10 shows the first mouse's images in the first and last energy channels. Images reconstructed using FBP contain strong noise, particularly, some tissue structures cannot be distinguished from noise in the last channel. The DFR and TV alleviate the noise to some extent. However, considerable blocky artifacts are introduced. By comparison, the TVLR, TDL and TDNLM faithfully preserve the tissue features. The difference image of TVLR in the first channel presents obvious rib structures, which is caused by the low rank processing performed in the whole image domain. The other difference images have no obvious tissue structures, demonstrating excellent signal preservation.

Fig. 11 presents the material decomposition results from the first preclinical mouse study. They correspond to an ROI indicated by the squared in Fig. 10. From top to bottom rows,

images are the decomposed bone, soft tissue and GNP components, respectively. In the top row, the FBP result suffers from high noise, followed by the DFR and TV. As indicated by the arrows, several GNP pixels are wrongly classified as bone in the TV result, and the ribs have lower brightness in the TVLR result. By comparison, the TDL and TDNLM have more accurate bony components. For the soft tissue component, the TV, TVLR, TDL, DFR and TDNLM can get satisfactory results. In the bottom row, from the structures indicated by arrows, it can be clear seen that some bony pixels are mistakenly assumed as containing GNP, especially for the FBP, TV and TVLR results. Overall, the TDL and TDNLM provide the most accurate decomposition results.

Fig. 12 shows two reconstructed image slices and material decomposition results of the second mouse, located at abdomen and chest, respectively. Concise with the previous experiments, the TDNLM suppresses noise remarkably. As a consequence, more accurate material components are obtained, especially for the contrast agent components indicated by arrows.

4. Discussion

The proposed TDNLM is highly computational cost efficient compared to other iterative algorithms. All the methods were implemented in MATLAB R2014a programming environment on an Intel(R) Core(TM) i7-4790 CPU, 3.60 GHz and 16 GB RAM PC platform. For all the iterative reconstruction methods, the forward and backward projections totally cost about 5 minutes in each iteration for the eight-energy-channel data in our simulation, which were the most time consuming procedures. There was 50 iterations for each iterative reconstruction method. The total computational times were 364, 366 and 263 minutes for TV, TVLR and TDL, respectively. By comparison, the image processing based methods have significant less computational cost. For the DFR method, it took 8.8 minutes to train dictionaries and then the image processing cost 2.4 minutes. For the proposed TDNLM, the computational cost was 4.5 minutes. Although the TDNLM and TDL can obtain comparable image quality, the TDNLM has remarkably higher computational efficiency than the TDL. That is, the TDNLM is ~58 times faster than the TDL. Additionally, the TDNLM directly works on the reconstructed images without the raw projections. These advantages make the proposed method a great potential for practical applications.

In the proposed method, the TD and NLM steps were carried out in sequence. This is due to the fact that strong noise has significant influence on the NLM step. Hence, TD was implemented in advance to alleviate noise to some extent, which benefits the NLM. To analyze this difference, we first conducted the NLM twice followed by the TD step, and this strategy is named as the NLMTD algorithm. Fig. 13 presents the representative channel of the images restored using NLMTD. It can be observed that the image quality was reduced slightly. Quantitatively, the mean RMSE and SSIM indices among channels are respectively 0.0225 cm^{-1} and 0.982, which are worse than the indices of TDNLM listed in Tables 2 and 3.

In our implementation, a sum-channel image was embedded into the multichannel image before using the TDNLM. Otherwise, the image quality is compromised to some extent. Representative results of TDNLM without the sum-channel are shown in Fig. 14. It can be observed that the image quality declines slightly. Particularly, the edges of iodine contrast agent regions with low concentration are remarkably blurred as indicated by the arrow. Quantitatively, the mean RMSE and SSIM indices among channels are respectively 0.0252 cm^{-1} and 0.978, which are worse than the indices of TDNLM listed in Tables 2 and 3.

5. Conclusion

In this paper, the inherent non-local self-similarity, the local spatial sparsity and spectral correlation of spectral CT images are fully explored. Tensor decomposition, non-local means and the guidance of a high-quality image are naturally fused together in the TDNLM, making it powerful to directly restore signal from intensely noisy spectral CT images. Results of qualitative and quantitative evaluations on both numerical simulations and real preclinical mouse studies demonstrated that the developed approach is comparable to the state-of-the-art methods in terms of image quality and material decomposition with a speedup of >50 times. Moreover, the high computational efficiency and adaptive parameter determination strategy make it practical for applications of spectral CT.

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Fig. 1.
Flowchart of the proposed TDNLM algorithm.

Fig. 2. The mouse thorax phantom (left) and the iodine contrast agent distribution (right) for numerical simulations. The brightness in the five regions A-E indicates the concentration of iodine.

Fig. 3.
Spectrum and the eight energy channels used in the numerical simulations.

Fig. 4. Data fitting of the estimated noise standard deviation versus the true noise standard deviation.

Fig. 5. Intermediate results of the TDNLM. (a) From top to bottom rows, the images correspond to three representative energy channels 1, 6 and 8. The left two column images were reconstructed from the noise-free and noisy data using FBP, respectively. From the third to sixth columns, the images were obtained after the processing of TD, NLM, TD and one-NLM, TD and two-NLM, respectively. The square ROI of iodine in each image is magnified. From top to bottom rows, the display windows are $[0 \ 2.5]$, $[0 \ 1.2]$ and $[0 \ 1] \text{ cm}^{-1}$, respectively. (b) Difference images of (a) with respect to the noise-free FBP images in the first column in (a), and the display window is $[-0.5 \ 0.5] \text{ cm}^{-1}$.

Fig. 6. Images reconstructed from different methods in numerical simulations. (a) From top to bottom rows, images correspond to three representative channels 1, 6 and 8. The first column images were reconstructed from noise-free projections using the FBP. From the second to seventh columns, the images were obtained from noisy data using FBP, TV, TVLR, TDL, DFR and TDNLM, respectively. The square ROI of each image is magnified. From top to bottom rows, the display windows are $[0, 2.5]$, $[0, 1.2]$ and $[0, 1] \text{ cm}^{-1}$, respectively. (b) Difference images of the results in (a) with respect to noise-free FBP images in the first column of (a), and the display window is $[-0.5, 0.5] \text{ cm}^{-1}$.

Fig. 7.

Representative profiles indicated by the line in the top-left image in Fig. 6(a). From the left to right, plots are obtained from energy channels 1, 6 and 8, respectively.

Fig. 8.

Plots of the image quality and resolution with respect to different parameters. From the top to bottom rows, the plots are the mean RMSE, mean SSIM and the mean FWHM. From left to right columns, the plots are indices with respect to different smoothing factors λ , half block sizes M and half search window sizes W , respectively.

Fig. 9.

Material decomposition results of the phantom study in numerical simulations. From top to bottom rows, images are the decomposed bone, soft tissue and iodine contrast agent components, respectively. From left to right columns, images correspond to material decomposition results of noise-free FBP, FBP, TV, TVLR, TDL, DFR and TDNLM, respectively. The display windows for bone, soft tissue and iodine are $[0 \ 1]$, $[0 \ 1]$ and $[0 \ 0.8]$, respectively.

Fig. 10.

Reconstructed results of the first preclinical mouse study. (a) The images in top and bottom rows correspond to the first and the last channels, respectively. From left to right columns, images were obtained using FBP, TV, TVLR, TDL, DFR and TDNLM, respectively. The display window is $[0.2 \ 0.8] \text{ cm}^{-1}$. (b) Difference images of the results in (a) with respect to the FBP images in the first column of (a), and the display window is $[-0.15 \ 0.15] \text{ cm}^{-1}$.

Fig. 11.

Magnified material decomposition results of the first preclinical mouse study in the rectangle in the top left image in Fig. 10(a). From top to bottom rows, images are the decomposed bone, soft tissue and GNP, respectively. From left to right columns, images correspond to material decomposition results of FBP, TV, TVLR, TDL, DFR and TDNLM images, respectively. The display windows for bone, soft tissue and iodine are [0 0.8], [0.4 1] and [0.1 0.5], respectively.

Fig. 12.

Reconstructed images and material decomposition results of the second preclinical mouse study. (a) The image slice of the mouse abdomen. The first to fourth columns correspond the first to fourth energy channels, and the fifth to seventh columns are the decomposed bone, soft tissue and gadolinium, respectively. The two rows correspond to the FBP and TDNLM, respectively. (b) The image slice of the mouse chest. The first to sixth columns have the same meaning as those in (a) and the seventh column is the gold component. The display windows are $[0 \ 0.35] \text{ cm}^{-1}$ for the first four columns, $[0 \ 1]$ for the fifth and sixth columns and $[0.1 \ 0.6]$ for the last column, respectively.

Fig. 13.

Images reconstructed by the NLMTD method. The left image is a representative result in channel 8 in a display window $[0 \ 1] \text{ cm}^{-1}$. The middle and right images are differences of the left image with respect to TDNLM result and the noise-free image in display windows $[-0.2 \ 0.2] \text{ cm}^{-1}$ and $[-0.2 \ 0.2] \text{ cm}^{-1}$.

Fig. 14.

Results restored by the TDNLM method without introducing the sum-channel image. The left image is a representative result in channel 8 in a display window $[0 \ 1] \text{ cm}^{-1}$. The middle and right images are differences of the left image with respect to standard TDNLM result and the noise-free image in display windows $[-0.2 \ 0.2] \text{ cm}^{-1}$ and $[-0.2 \ 0.2] \text{ cm}^{-1}$.

Table 1

Values of CNR in the ROI in Fig. 5

Channel Number	Method				
	FBP	TD	NLM	TD+1NLM	TD+2NLM
#1	0.170	0.294	0.638	3.54	13.1
#2	0.146	0.405	0.646	4.53	13.1
#3	0.171	0.718	0.655	6.49	21.6
#4	0.152	0.717	0.647	5.22	13.6
#5	0.0778	0.405	0.631	3.89	10.5
#6	0.417	2.10	0.607	11.4	27.7
#7	0.415	2.06	0.513	8.70	15.3
#8	0.288	0.953	0.621	7.68	26.0

Table 2

RMSEs of the reconstructed images in Fig. 6 (cm^{-1}).

Channel Number	Method					
	FBP	TV	TVLR	TDL	DFR	TDNLM
#1	0.350	0.0658	0.0513	0.0430	0.0799	0.0423
#2	0.253	0.0433	0.0312	0.0270	0.0420	0.0270
#3	0.207	0.0328	0.0225	0.0196	0.0269	0.0201
#4	0.190	0.0270	0.0183	0.0155	0.0204	0.0159
#5	0.187	0.0246	0.0167	0.0129	0.0166	0.0135
#6	0.196	0.0228	0.0176	0.0127	0.0171	0.0132
#7	0.187	0.0203	0.0150	0.0111	0.0147	0.0116
#8	0.180	0.0180	0.0142	0.0098	0.0163	0.0098
Mean	0.225	0.0318	0.0261	0.0217	0.0359	0.0217

Table 3

SSIMs of the reconstructed images in Fig. 6

Channel Number	Method					
	FBP	TV	TVLR	TDL	DFR	TDNLM
#1	0.737	0.987	0.990	0.994	0.967	0.993
#2	0.709	0.985	0.992	0.994	0.974	0.992
#3	0.670	0.984	0.992	0.993	0.977	0.991
#4	0.654	0.984	0.991	0.992	0.975	0.989
#5	0.611	0.974	0.988	0.990	0.976	0.987
#6	0.581	0.966	0.981	0.986	0.968	0.984
#7	0.557	0.959	0.979	0.982	0.960	0.982
#8	0.525	0.947	0.975	0.976	0.940	0.980
Mean	0.633	0.973	0.986	0.988	0.967	0.987

Table 4

The average FWHM at selected location in the ROI of Fig. 6(a)

FBP (noise-free)	FBP	TV	TVLR	TDL	DFR	TDNLM
2.06	2.92	4.59	3.63	1.95	2.27	2.28

Table 5RMSEs of each decomposed material component in the numerical simulation study (cm^{-1})

Tissues	FBP	TV	TVLR	TDL	DFR	TDNLM
Bone	0.0328	0.0139	0.0117	0.0086	0.0100	0.0087
Soft tissue	0.179	0.0400	0.0412	0.0274	0.0438	0.0293
Iodine	0.119	0.0304	0.0335	0.0131	0.0267	0.0157