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Adaptive Non-Local Means Method for Denoising Basis Material Images from Dual-energy CT

Yuan Yuan, PhD¹, Yanbo Zhang, PhD², and Hengyong Yu, PhD^{2,*}

¹Department of Physics and Applied Physics, University of Massachusetts Lowell, Lowell, MA, 01854 USA

²Department of Electrical and Computer Engineering, University of Massachusetts Lowell, Lowell, MA, 01854, USA

Abstract

We propose an adaptive non-local means (ANLM) approach for image-domain material decomposition in low-dose dual-energy micro-CT. The key idea is to create a distribution map for decomposition error and assign a smooth weight for a given pixel. This method is applied to the decomposed images of three basis materials: bone, soft tissue and gold in our applications. We assume that bone and gold cannot co-exist in the same pixel and regroup these basis materials into two categories. For soft tissue, the proposed algorithm is implemented in a non-iterative mode. For bone and gold, an iterative mode is used and followed by a post-iteration process. Both our numerical simulation and *in vivo* preclinical experiment results show that the proposed ANLM outperforms other state-of-the-art denoising algorithms, such as the original non-local means and total variation minimization methods.

Keywords

Image-domain material decomposition; Adaptive non-local mean; Edge detection; Dual-energy CT

1. Introduction

Compared with standard single-energy CT, the dual-energy CT employs two x-ray spectra. It can be used to determine the fractions of constituent materials in a mixture, named as material decomposition [1]. Taking the advantages of material decomposition, the dual-energy CT has been widely used in various clinical applications, such as automated bone removal in CT angiography, identification of iodine voxels, discrimination between uric acid and non-uric acid stones, and detection of silicone from breast implant leak [2]. Material decomposition can be implemented in either projection domain [3] or image domain. The projection-domain material decomposition converts the measured projections into line integrals of basis materials using a nonlinear model [4] and then the decomposed CT images

*Corresponding author: Hengyong Yu, hengyong-yu@ieee.org.

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are reconstructed using the conventional CT reconstruction algorithms. The image-domain decomposition is directly operated on the reconstructed CT images using a linear model. The basic idea of image-domain material decomposition is that the linear attenuation coefficients at the same position derived from the reconstructed images at low- and high-energy scans can be expressed as a linear combination of two basis material pixel values. Although the projection-domain decomposition offers more accurate decomposed images in dual-energy CT, the image-domain decomposition is convenient and timesaving since it could be applied directly on the reconstructed CT images in the DICOM format.

This study will focus on the decomposed basis materials in image-domain from a direct matrix inversion method. Although the direct matrix inversion method is easy to implement, it comes with amplified noise and reduces signal-to-noise ratio, and there are several methods available to improve image quality. Clark *et al.* [5] applied a joint bilateral filtration to the reconstructed CT images before decomposition. In the joint bilateral filtration, the range weights were jointly computed by using both the low- and high-energy images, and each image was filtered independently. Niu *et al.* [4] designed an iterative noise suppression algorithm in the decomposition process to optimize the decomposed images. In this method, the noise suppression and the material decomposition are performed alternatively in an iterative fashion. Zhao *et al.* [6] established a new framework that can be directly applied to the decomposed material-specific images. The algorithm was based on the HYPR-LR (local Highly constrained back-Projection Reconstruction) framework, a reconstruction method of time-resolved magnetic resonance imaging (MRI). For the dual-energy CT, this method treated the energy dimension as the time dimension in MRI. However, for the low dose dual-energy material decomposition images, the aforementioned denoising methods still cannot obtain satisfied results. To address this issue, we will develop a new adaptive non-local means (ANLM) method that can preserve details in material specific images and meanwhile suppress severe noises. The main idea comes from a fact that the decomposed material images have additional edges compared to the reconstructed images. We demonstrate the advantages of the proposed approach in numerical simulations and *in vivo* experiments.

In this study, we will implement the proposed method on three-material decomposition: bone, soft tissue and contrast agents. Here, we select gold-base contrast agents instead of iodine-base contrast agents because the iodine-base contrast agents are usually associated with renal toxicity and have a short circulation time. Meanwhile, the gold-based contrast agents have higher x-ray absorption coefficients, lower toxicity and a longer circulation time [7]. We also evaluate the proposed method at different noise levels and compare it with other denoising methods. The rest of this paper is organized as follows. The next section describes our methods. The third section presents the results. The last section discusses some related issues and concludes the paper.

2. Methods

2.1. Material Decomposition

A conventional direct matrix inversion method [8] is applied to obtain material specific images from dual energy micro-CT images. The material specific images are quantitative

maps representing the fractions of each material. In each material specific image, each voxel value is one of the solutions to a equation set with three unknowns:

$$\begin{bmatrix} \mu_{1,H} & \mu_{2,H} & \mu_{3,H} \\ \mu_{1,L} & \mu_{2,L} & \mu_{3,L} \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} \mu_H \\ \mu_L \\ 1 \end{bmatrix}, \quad 1$$

where μ is the effective linear attenuation coefficient value and the unit is cm^{-1} , the subscripts 1–3 represent the sequence number of three basis materials and f_1, f_2 and f_3 represent the corresponding volume fractions, and the subscripts H and L represent the high scanning energy and the low scanning energy, respectively. We assume that each voxel contains only basis materials and the sum of volume fraction is equal to 1.

Let the total number of voxels of one CT image be N. Eq. (1) can be rewritten as

$$\vec{\mu} = \mathbf{A} \vec{x},$$

$$\vec{\mu} = \begin{bmatrix} \vec{\mu}_H \\ \vec{\mu}_L \\ \vec{\mu}_0 \end{bmatrix},$$

and $\vec{x}$ is formed from the decomposed material specific images:

$$\vec{x} = \begin{bmatrix} \vec{x}_1 \\ \vec{x}_2 \\ \vec{x}_3 \end{bmatrix}, \quad 4$$

where $\vec{x}_1, \vec{x}_2$ and $\vec{x}_3$ represent three material specific images, respectively. $\mathbf{A}$ is a $3N \times 3N$ matrix which could be treated as a $2N \times 3N$ material decomposition matrix and an $N \times 3N$ all-ones constraint matrix:

$$\mathbf{A} = \begin{bmatrix} \mu_{1,H}^I & \mu_{2,H}^I & \mu_{3,H}^I \\ \mu_{1,L}^I & \mu_{2,L}^I & \mu_{3,L}^I \\ I & I & I \end{bmatrix}, \quad 5$$

where I is an $N \times N$ identity matrix.

Then, the material specific images could be easily obtained from the high- and low-energy CT images by solving Eq. (2)

$$\vec{X} = \mathbf{A}^{-1}\vec{u}, \quad 6$$

where

$$\mathbf{A}^{-1} = \mathbf{M} \begin{bmatrix} (\mu_{2,L} - \mu_{3,L})I & (\mu_{3,H} - \mu_{2,H})I & (\mu_{1,H}\mu_{2,L} - \mu_{1,L}\mu_{2,H})I \\ (\mu_{3,L} - \mu_{3,H})I & (\mu_{1,H} - \mu_{3,H})I & (\mu_{1,L}\mu_{3,H} - \mu_{1,H}\mu_{3,L})I \\ (\mu_{1,L} - \mu_{2,L})I & (\mu_{2,H} - \mu_{1,H})I & (\mu_{2,H}\mu_{3,L} - \mu_{3,H}\mu_{2,L})I \end{bmatrix}, \quad 7$$

and

$$\mathbf{M} = \left((\mu_{1,H}\mu_{2,L} - \mu_{1,L}\mu_{2,H}) + (\mu_{1,L}\mu_{3,H} - \mu_{1,H}\mu_{3,L}) + (\mu_{2,H}\mu_{3,L} - \mu_{3,H}\mu_{2,L}) \right)^{-1}.$$

In fact, material decomposition in direct matrix inversion method can magnify noise and decrease the decomposition accuracy. Here, we will introduce a new method to reduce the noise caused by the decomposition error and preserve the basis material features.

2.2. Numerical Simulation Configuration

A realistic mouse thorax phantom (Fig.1 (a)) generated by the Moby software is used for numerical simulations. The diameter of this phantom is 30.0mm, and 16mg/ml gold contrast agent is superimposed to the blood circulation system. The concentration of gold is constant in this study. Fig.1 (b), Fig.1 (c) and Fig.1 (d) are the corresponding bone, soft tissue and gold images, respectively. These reference images are decomposed from noise-free micro CT images scanned with the optimal energy combination, and they will serve as references to evaluate the denoised image quality in the rest of this paper. The qualities of decomposed images are significantly affected by the scanning energies. In our previous study, the optimal decomposition results are obtained when the scanning energies are 45 kVp and 65 kVp in dual-energy micro CT [9]. The linear attenuation coefficient of the gold contrast is calculated using the mixture rule. The corresponding values of linear attenuation coefficients are obtained from the National Institute of Standards and Technology (NIST) database. In this study, the x-ray spectra are obtained from an online software provided by Siemens [10] and an extrinsic 1mm Aluminum (Al) filtration is adopted. A 2D fan-beam CT geometry is assumed with circular scan. The distance from source to rotation center is 351.0mm, the distance from source to detector is 541.0mm, and 720 projections are uniformly acquired over a full scan range. The detector includes 1024 elements and each element is 0.078 mm. Poisson noise is superimposed into the projections. The total number of photons is 5×10^4 for each detector element and the ratio of the number of photons with high- and low- energy spectrum is 1.8. A conventional filtered back-projection algorithm is employed for image reconstruction.

2.3. Adaptive Non-Local Means Filtering

In the conventional non-local means (NLM) filter [11], the filtered value at a pixel i is calculated as a weighted average of all the pixels across the whole image. Given a 2D noisy image $x = \{x(i) | i \in I_{pos}\}$ with I_{pos} being all the pixel positions, the NLM can be written as:

$$X_{NLM}(i) = \sum_{j \in \Omega_i} \omega(i, j) * x(j), \quad 8$$

where Ω_i is referred to as a search window centered at the pixel i and it usually is a square neighborhood with a fixed size. The weight $\omega(i, j)$ represents the similarity between the pixels i and j , and it satisfies the constraint conditions $0 \leq \omega(i, j) \leq 1$ and $\sum_j \omega(i, j) = 1$. The weight is constructed as follows:

$$\omega(i, j) = \frac{1}{Z(i)} \exp\left(-\frac{\|x(N_i) - x(N_j)\|_2^2}{h^2}\right), \quad 9$$

where N_i is a square neighborhood of fixed size and centered at a pixel i . It is usually referred to as the similarity window. The similarity of two pixels i and j measured by Gaussian weighted Euclidean distance of pixel gray values $x(N_i)$ and $x(N_j)$ between the two neighborhoods N_i and N_j within the searching window Ω_i . $Z(i)$ is the normalizing factor to make sure $\sum_j \omega(i, j) = 1$. The parameter h controls the degree of filtering by adjusting the weight decay of the exponential function. In general, h directly affects the image quality in the non-local mean denoising. In our proposed adaptive NLM (ANLM) filter, h is calculated as

$$h = h_{whole} * (1 + w * M_{error}), \quad 10$$

where h_{whole} is a smoothing parameter across the whole image to preserve as many detail basis materials features as possible, M_{error} represents a decomposition error distribution map to indicate the error region where the filtering strength is enhanced, and w is the weight of M_{error} and an appropriate selection of w can balance the whole image smoothing and basis material feature enhancement. The method to construct decomposition error distribution map M_{error} will be separately discussed in next section. The ANLM filter can be reduced to the conventional NLM filter when w is equal to zero. The new adaptive non-local means filter designed in this paper takes advantages of the decomposition error distribution map. The smooth parameter h includes two parts: the first one is a constant for the whole image and the second one is used to tune the weight of decomposition error distribution map. Thus, the proposed adaptive non-local means filter is able to preserve material-like features and remove artifact-like features simultaneously when it is used to denoise material specific

images. In this study, we will apply the new ANLM filter directly to the original decomposed images. Based on the basis material structures, we label them as bone-like, soft-tissue-like and gold-like images. We assume that the most non-zero pixels in bone-like image have a high likelihood to belong to bone. It is the same for soft-tissue-like and gold-like images.

2.4. Decomposition Error Distribution Map

As the aforementioned, a decomposition error distribution map is employed to adjust the smooth parameter for each pixel. In the rest of this paper, we call it error map for simplicity. We create the error map from an original basis material image. Each pixel in the error map represents the probability of decomposition error of the corresponding pixel in the material images. A quantitative pharmacokinetics study result [12] showed that after gold nanoparticle injection, the highest gold concentration was in the kidney followed by tumor, liver and muscle. Here, we reasonably assume that there is no gold nanoparticle diffusion in bone. In other words, there is no pixel in the material specific images belonging to the mixture of bone and gold.

2.4.1. Bone and Gold—To construct error maps for bone-like (Fig.2 (a)) and gold-like images (Fig.2 (d)) , we calculate binarized images (Fig.2 (b) and Fig.2 (e)) using Eq.(11)

$$x_{BW}(i) = \begin{cases} 0, & x(i) < \lambda \\ 1, & x(i) \geq \lambda \end{cases} \quad 11$$

Here, $x(i)$ represents the pixel value of bone-like or gold-like image, and $x_{BW}(i)$ is the corresponding binarized pixel value. We choose a threshold value $\lambda = 0.1$ to select the pixels whose values in the decomposed images are above 0.1 and ignore the pixels whose values are below 0.1.

In a binarized image, the distribution of ‘bright’ pixel is visually nonuniform. We assume that the regions with high concentrated level of ‘bright’ pixels have high likelihood to belong to the basis material and the regions with low concentrated level have high likelihood to be errors. The concentrated level is defined as pixel density, and pixel density maps of bone image and gold image are shown in Fig.2 (c) and Fig.2 (f). The pixel density $P(i)$ at a given pixel i is computed as the ratio between the pixel number in a certain category to the total number in a small neighborhood window centered at the pixel :

$$P(i) = \left(\frac{\Delta N_w}{N_w} \right)_{A_i}, \quad 12$$

where N_w is the total number of pixels in a given small neighborhood window A_i centered at i and N_w is the number of pixels in A_i that the value of the pixel is one. The radius of A_i is 2 in our study.

However, it is difficult to set a threshold to distinguish the basis material features and the decomposed noises based on the pixel density. Here, we incorporate the Canny edge detection to construct the error map. The Canny edge detection is one of the most strictly defined methods by searching for a local maximum in its neighborhood in the direction of gradient at each pixel in a Gaussian filter smoothed image. As demonstrated in Fig. 3, the edge of Moby phantom CT image (Fig.3 (d)) is obtained by detecting the edges of a composite image (Fig.3 (c)) which are generated by averaging the high- (Fig.3 (b)) and low-energy images (Fig.3 (a)) with equal weighting.

Since all the edge detection results are easily affected by image noise, the non-preprocessed decomposition images, such as bone-like image (Fig.4(a)) and gold-like image (Fig.4(d)) have additional edges compared to the composite image. We assume that these additional edges are caused by noise. Although noise is randomly distributed, the region of additional edges could be identified. The additional edges of bone in Fig.4 (c) are obtained by subtracting the edges of the composite image Fig.3 (d) from the edge of non-preprocessed decomposed images Fig. 4 (b). The additional edges of gold Fig. 4 (f) is obtained using a similar method.

The additional edge probabilities (Fig. 5 (a) and Fig. 5 (d)) are derived from the additional edges (Fig. 4 (c) and Fig. 4 (f)) by applying Eq. (12). The noise contaminated probability (Fig.5 (b) and Fig.5(e)) are calculated by $X_{nc} = X_a(1 - X_d)$, where X_{nc} represents the noise contaminated probability, X_a represents the additional edges probability and X_d represents pixel density.

To preserve fine details in the post-processed images, in Fig. 5 (b) and (e), some regions with low pixels density (indicated by red arrows) are not treated as noise contaminated ones. Fig. 5 (c) and (f) show the error maps that will be used in our ANLM filtration.

In this subsection, the parameters used for ANLM filtration are listed as follows: 1) the radius of search window is 5; 2) the radius of similarity window is 2; 3) $h_{whole} = 0.01$; 4) $r=200$. As to the post-iteration images, the isolated bright pixels are removed because pixels belong to the same basis material are spatially connected. A quantitative pharmacokinetics study [5] showed that after gold nanoparticle injection, the highest tissue gold concentration was in the kidney followed by tumor, liver and muscle. This indicates that gold cannot propagate to bone. Therefore, we assume that bone and gold cannot co-exist in the same pixel. Here, we add an additional constraint:

$$P_i = \begin{cases} \text{belongstobone} & \text{if } L_B > L_G \\ \text{belongsto gold} & \text{if } L_G > L_B \end{cases}, \quad 13$$

where P_i is the pixel i , $L_{B(G)}$ is the number of pixels in M_i which is greater than a certain threshold T_h , the subscript B (G) represent bone or gold, M_i is a square neighborhood of fixed size and centered at a pixel i . Here, the threshold $T_h = 0.25$ and the radius of M_i is 11.

2.4.2. Soft Tissue—The pixel density map for soft tissue-like image (Fig.6 (c)) is obtained using the same method as above. To obtain a qualified classification result, a proper threshold is needed to identify pixels likely belong to the decomposition error. Namely, a pixel likely belongs to the decomposition error when its corresponding pixel density value is below the threshold. Here, the threshold is empirically set as 0.7. The distribution of non-zero pixels in the error map (Fig.6 (d)) represents the region where decomposition error located. The value of each pixel shows the error strength.

In this subsection, we assure that there is no mixture of bone and soft tissue in the original phantom (Fig.1 (a)). That is, one pixel inside the phantom belongs to either the bone or the soft tissue regions. Therefore, the soft tissue and bone should have similar error maps, and we can take advantages of the bone error map to modify the error map of soft tissue. The modified error map of soft tissue is obtained by combining the error map of bone and the error map of soft tissue (Fig. 7):

$$X_{STm} = X_{ST} * W_{ST} + X_B * W_B, \quad 14$$

where X_{STm} represents the modified error map of soft tissue, X_{ST} represents the error map of soft tissue, W_{ST} represents the weight of the error map of soft tissue, X_B represents the error map of bone, and W_B presents the weight of the error map of bone. Here, $W_{ST}=0.1$ and $W_B=1$. From Fig. 7, one can see that the main function of the soft tissue error map is to eliminate gold component.

Furthermore, a small mean filter window is used to smooth the background without reducing the spatial resolution. The parameters used in the ANLM are listed as follows: 1) the radius of search window is 5; 2) the radius of similarity window is 2; 3) $h_{whole} = 0.02$; 4) $t=50$. For the soft tissue images, the proposed method was implemented in a non-iterative mode. The processing procedure of bone and gold images is more complicated, and we used an iterative mode, i.e. the ANLM processed material images were set as the input images of the next iteration and the iteration number is 3.

In summary, the proposed algorithm for Adaptive NLM filter works in three steps. **Step 1:** Calculation of binarization according to the threshold condition Eq. (11); **Step 2:** Construction of the pixel density image by using Eq. (12), which is the ratio of the number of pixels that satisfy Eq. (11) to the total number of pixels in a selected small neighborhood; **Step 3:** Generation of a denoised image in the form of the Gaussian weighted average Eq. (9) in which the coefficient is given by Eq. (10), which is based on Euclidean distance measurements and the decomposition error distribution map-guided smooth parameters.

2.5. Comparison

To verify the advantages of the proposed ANLM method, the same decomposed images are processed by using the conventional NLM and TV methods for comparison. In the conventional NLM, the same parameters are used as those in the ANLM. In the TV method,

the parameters are optimized for selection. Further, PSNR (Peak Signal-to-Noise Ratio) is used to quantitatively evaluate the quality of post-processed images.

To investigate the effect of the proposed ANLM method across different noise levels, we also evaluate it using various numbers of photons (dose levels). Beside the numbers of photons selected above (5×10^4 per detector element at low energy), there are three more additional dose levels at low energy used for noise evaluation: 1×10^5 , 2×10^5 , and 4×10^5 . The ratio of the number of photons with high- and low- energy spectrum is 1.8. For all the simulations, the parameters of the ANLM are the same.

The parameters in the NLM filter would directly affect the quality of denoised image, and the proposed ANLM method has an additional parameter: the weight of decomposition error distribution map (w). To investigate the effects of the parameter selection on the denoised material-specific images, the radius of search window is set to four different values: 5, 6, 7 and 8; the radius of similarity window is 2, 3, 4 and 5; the smoothing parameter across the whole image (h_{whole}) is **0.01, 0.02, 0.03 and 0.04**; **the weight of decomposition error distribution map (w) is 50, 100, 200 and 250.**

2.6. *In vivo* Experiment

To verify the merits of the proposed method for preclinical applications, an *in vivo* study was performed on a small animal radiation research platform (SARRP, Xstrahl Ltd. United Kingdom). Dual-energy raw data sets were acquired with the same x-ray tube successively using the following parameters: high-energy, 65kVp, 0.5mA; low-energy, 45kVp, 3.5mA. Both spectra were filtered with 1.0 mm Aluminum filtration. Projections were uniformly collected over a full scan range. All images were reconstructed using a conventional filtered back-projection algorithm. The matrix size was 512×512 , and the pixel size was $0.078 \times 0.078 \text{ mm}^2$. The subcutaneous xenograft model of human lung cancer mentioned in [13] was used in this study. Fig. 8 shows micro-CT images of the left flank of the mouse at 45kVp and 65kVp. The high- and low-energy images are first decomposed by using the direct matrix inversion, and then the decomposed images are denoised by the TV, NLM and the proposed ANLM methods.

3. Results

Fig.9 shows the effect of post-iteration process. The two rows represent the bone and gold images before and after the process, respectively. The last two columns are the magnified details in the red square. For each basis material, the display windows are the same. Fig.10 shows the post-processed bone and gold images by different methods. For each image, the magnified square region is shown at the top right corner. The reference images in Fig.10 are the copies of Fig.1 (b) and Fig.1 (d). Fig.11 shows the denoised soft tissue images by different methods. The first image is the reference image copied from Fig.1 (c). The next three images are the denoised images processed by the NLM, TV and ANLM. Similarly, the magnified regions highlighted in red squares are shown at the top right corner of the corresponding denoised images. The results show that the ANLM outperforms the NLM and TV methods.

The accuracy of the proposed ANLM method with different noise levels are evaluated by calculating the PSNR values. Table 1 shows that PSNR values of the denoised bone, soft tissue and gold images processed by different methods at four dose levels, respectively. For all the denoised basis materials images, the PSNR values (marked as 'TV', 'NLM' and 'ANLM') are higher than those of the original material specific images (marked as 'No filtration'), and the PSNR values of the proposed ANLM are higher than those of the NLM and TV at the selected dose level: 5×10^4 , 1×10^5 , 2×10^5 and 4×10^5 (unit: photons per detector). Particularly, the advantages of ANLM are more distinct for the bone and gold images when the dose level is higher. For the soft tissue image, the ANLM has slight advantages comparing with the NLM and TV.

To simplify the process of parameter evaluation, four parameters are divided into two categories (I and II). Category I consists of the radius of search window (t) and the radius of similarity window (f), and Category II consists of the smoothing parameter of the whole image (h) and the weight of decomposition error distribution map (w). For parameters evaluation in Category I, the smoothing parameter of the whole image (h) and the weight of decomposition error distribution map (w) are fixed. In the bone and gold images, $h=0.01$ and $w=200$; in the soft tissue image, $h=0.02$ and $w=100$. The selected radii of search window (t) are $t=5$, $t=6$, $t=7$ and $t=8$ and the radii of similarity window (f) are $f=2$, $f=3$, $f=4$ and $f=5$. Similarly, for parameters evaluation in Category II, the radius of search window (t) and the radius of similarity window (f) are fixed. $t=5$ and $f=2$ are used for all the images. The selected weights of decomposition error distribution map (w) are $w=50$, $w=100$, $w=200$ and $w=250$ and the selected smoothing parameters of the whole image (h) are $h=0.01$, $h=0.02$, $h=0.03$ and $h=0.04$. Since in the NLM method, the radius of search window (t) is always greater than the radius of similarity window (f), when $t=5$, we only select three values for the radius of similarity window (f): $f=2$, $f=3$ and $f=4$. Fig.12 shows the parameter evaluation results. Each plot represents the average PSNR values of the corresponding parameter. For each parameter, the average PSNR values of various parameter values are very close. Among these four parameters, the smoothing parameter of the whole image (h) has the greatest impact on the PSNR. Among these three material specific images, the optimal parameter combinations are slightly different. For the bone image, the optimal parameter combination is that $t=5$, $f=2$, $h=0.04$ and $w=100$. For the soft tissue image, the optimal parameter combination is that $t=5$, $f=4$, $h=0.01$ and $w=50$. For the gold image, the optimal parameter combination is that $t=5$, $f=2$, $h=0.02$ and $w=50$.

The proposed method is also applied to decomposed images from the *in vivo* experiment, and the results are shown in Fig.13. It further confirms that the proposed ANLM algorithm outperforms other competing algorithms in preclinical applications.

4. Discussion

This study introduces an ANLM algorithm for noise reduction of image-domain dual-energy material decomposition. It can be directly applied to the original decomposed images. In order to satisfy the established ALARA (As Low As Reasonably Achievable) principle, the proposed method is intended to denoise low SNR images while preserving basis material-like features. In this filter, the smooth factors include two parts: the first one is a constant for

the whole image and the second one is a decomposition error distribution map that allows us to greatly denoise the selected regions. The decomposition error distribution map is especially created for enhancing weak material-like pixels and greatly suppressing noise-like pixels at the same time. In addition, we divide three decomposed images into two categories: 1) bone and gold; 2) soft tissue. For soft tissue-like image, a non-iterative mode is used and for the other two decomposed images, an iterative mode is applied to further denoise since the noise levels of these two basis material images are higher and the decomposition error distribution maps are more complicated. The quantitative PSNR values confirm that the proposed ANLM outperforms other competing algorithms, and it can significantly improve the decomposition accuracies for bone, soft tissue and gold.

We evaluate the proposed ANLM at different noise levels. At these four selected noise levels, both the denoised images and quantitative PSNR values show that the proposed ANLM outperforms the NLM and TV algorithms. In this study, the values of four parameters are empirically selected for evaluation: the radius of search window, the radius of similarity window, the smoothing parameter of the whole image and the weight of decomposition error distribution map. The PSNR values slightly change with respect to these parameters. This implies that the proposed ANLM algorithm is reliable and not sensitive to the parameter choice. The advantages of our method are also demonstrated in *in vivo* experiment.

In the proposed method, the crucial part is the construction of decomposition error distribution map. It is obtained by detecting edge of the decomposed images. While it is easy to implement, the obtained edges may be not accurate enough in case of high noise level which might compromise the performance of the proposed method. In the near future, we will develop advanced algorithms to estimate edges more precisely or explore alternative methods to construct decomposition error distribution map.

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Figure 1.
Moby mouse phantom for study. (a) is the 2D mouse thorax phantom. (b), (c) and (d) are the reference images of bone, soft tissue and gold, respectively.

Figure 2.
Demonstration of pixel density map construction: Bone-like (a) and gold-like images (d);
bone-like binarized image (b) and gold-like binarized image (e); the corresponding pixel
density maps (c and f) of Moby phantom.

Figure 3.
Simulated Moby mouse phantom images at 45kVp (a) and 65kVp (b), the composite image (c) and its edge (d).

Figure 4.
Illustration of additional edges. (a) and (d) are bone-like and gold-like images, respectively;
(b) and (e) are their edge images; and (c) and (f) are additional edge maps.

Figure 5. Illustration of additional edge probability. (a) and (d) are the additional edge probability maps for bone and gold. (b) and (e) are noise maps; and (c) and (f) are error maps.

Figure 6. Example of error map for soft-tissue. (a) is soft-tissue-like image; (b) is binarized image; (c) is pixel density map; and (d) is error distribution map.

Figure 7.
Illustration of a) error map of soft tissue; b) error map of bone; c) the modified error map of soft tissue.

Figure 8.
Micro-CT images of the left flank of an immune-compromised athymic nude mouse (supine position). Tumors are indicated with red squares.

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Figure 10.

The post-processed bone and gold images by different algorithms and the corresponding magnified regions in the red squares.

Figure 11.
The denoised soft tissue images by different algorithms and the corresponding magnified regions in the red squares.

Figure 12.

The average PSNR values of each parameter. From top to bottom rows, the plots are for bone, soft tissue and gold images. From left to right columns, the plots are for varying t, f, w and h, respectively.

Figure 13.
The basis materials images decomposed from in vivo experiments with different denoising algorithms. The first column consists of the decomposed image without filtration.

Table 1.

The PSNR results of basis materials images at four dose levels: 5×10^4 , 1×10^5 , 2×10^5 and 4×10^5 .

Dose Level	Basis materials	No Filtration	NLM	TV	ANLM
5×10^4	Bone	23.71	24.14	24.96	25.68
	Soft Tissue	19.96	20.41	20.92	21.15
	Gold	16.42	16.69	18.52	20.35
1×10^5	Bone	24.38	24.86	25.68	27.42
	Soft Tissue	20.89	21.40	22.04	22.27
	Gold	16.99	17.30	19.19	20.65
2×10^5	Bone	25.38	26.06	26.77	28.29
	Soft Tissue	22.18	22.85	23.49	23.74
	Gold	17.94	18.37	21.12	23.27
4×10^5	Bone	26.83	27.60	28.20	31.61
	Soft Tissue	23.31	24.01	24.08	24.45
	Gold	19.17	19.61	22.26	23.14