Noise reduction of the material-decomposed projection images in dual-energy imaging

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Introduction

- Dual-energy imaging is useful for providing material-specific images.
- Material-decomposed images in general have higher noise than the original projection images.
- We implemented a penalized weighted least-squares (PWLS) method using iterative Gauss-Seidel updating strategy to reduce the noise.
- We tested the implemented PWLS method using a micro-CT data.

Methods

Micro-CT system and phantom

- The come beam CT imaging system used in this project is the Polaris-G90 system(NanoFocusRay. Co. Ltd) and acryl-aluminum mixed cylinder phantom.
- We scanned the phantoms at the tube voltages of 40kV and 90kV sequentially for dual energy imaging.

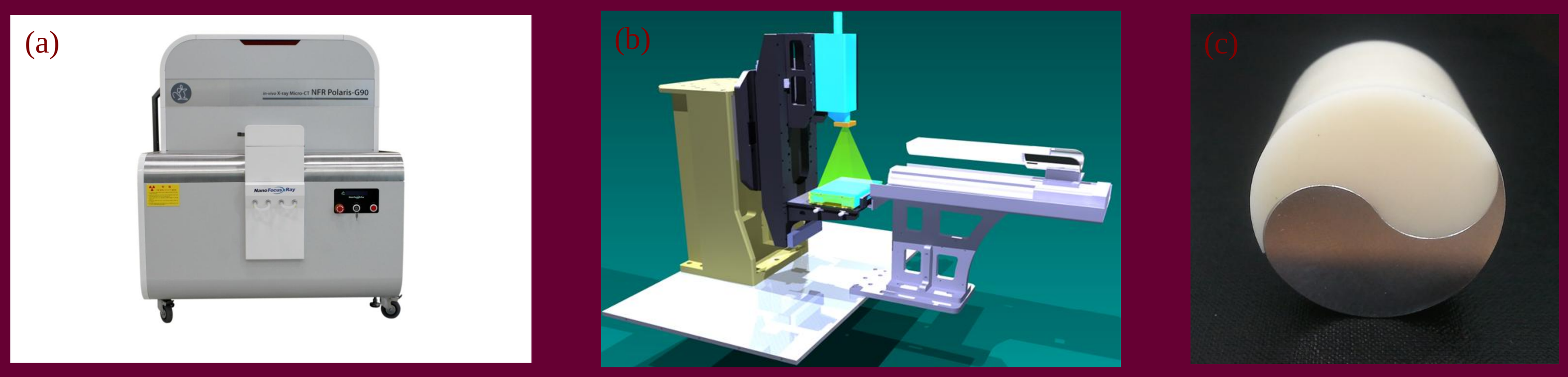

Fig. 1 (a) Micro-CT system. (b) schematic of system design (c) calibration phantom

Empirical dual energy decomposition

- We used a pre-reconstruction type of decomposition, the projection data (q_1,q_2) acquired at low- and high-voltages are converted into the material-specific projection data (p_1,p_2).

Simple polynomial decomposition formula

$$p_i = \sum_{k=0}^{K} \sum_{l=0}^{L} c_{in} q_1^k q_2^l$$

Linear system

$$a = B \cdot c$$

Coefficients $\boldsymbol{c}$ can be find that minimizes the least square deviation

$$a_n = \int d^2 r \, w(\mathbf{r}) f_n(\mathbf{r}) t(\mathbf{r})$$

$$B_{nm} = \int d^2 r \, w(\mathbf{r}) f_n(\mathbf{r}) f_m(\mathbf{r})$$

$$c = B^{-1} \cdot a$$

Noise reduction using PWLS algorithm

- For reducing noise, we applied a penalized-weighted least squares (PWLS) algorithm.
- A reduction of noise can be achieved by minimizing the PWLS objective function. In our approach, an iterative Gauss-Seidel updating strategy was used to implement PWLS algorithm.

The PWLS objective function is

$$\Phi(p) = (\hat{y} - \hat{p})^T \sum^{-1} (\hat{y} - \hat{p}) + \beta R(p)$$

$\hat{y}$: measured data

$\hat{p}$: ideal data to be estimated

β : smoothing parameter

Gauss-Seidal update strategy to minimize PWLS function

$$p_i^{n+1} = \frac{y_i + \beta\sigma_i^2 \left(\sum_{m \in N_i^1} \omega_{im} p_m^{i+1} + \sum_{m \in N_i^2} \omega_{im} p_m^i \right)}{1 + \beta\sigma_i^2 \sum_{m \in N_i} \omega_{im}}$$

The variance of the material specific projection is given as

$$Var(p) = (\partial_1 p(q_1, q_2))^2 Var(q_1) + (\partial_2 p(q_1, q_2))^2 Var(q_2)$$

$$\partial_i p = \partial p / \partial q \qquad Var(q_i) = \gamma_i e^{q_i} / I_i$$

Results

- We obrained the aluminum material-specific data using empirical dual-energy decomposition(Fig. 2 (a)). The results of implementing PWLS method to the phantom is also shown(Fig. 2 (b), (c)).

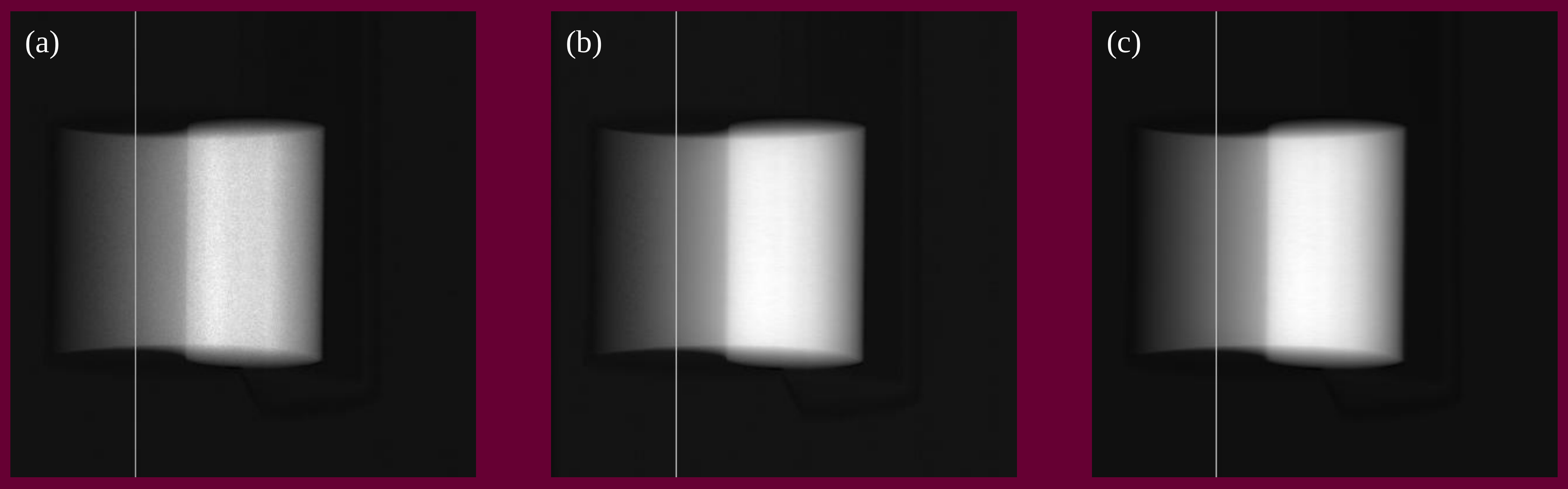

Fig. 2 (a) Converted aluminum-specific projection data. (b) Noise reduced data of (a) using PWLS algorithm. (β =0.0001) (c) Noise reduced data of (a) using PWLS algorithm. (β =10000)

- It can be compared that the line-profiles of vertical lines on Fig. 2. By applying PWLS algorithm, the noise of original material-specific projection data is sufficiently smoothen.

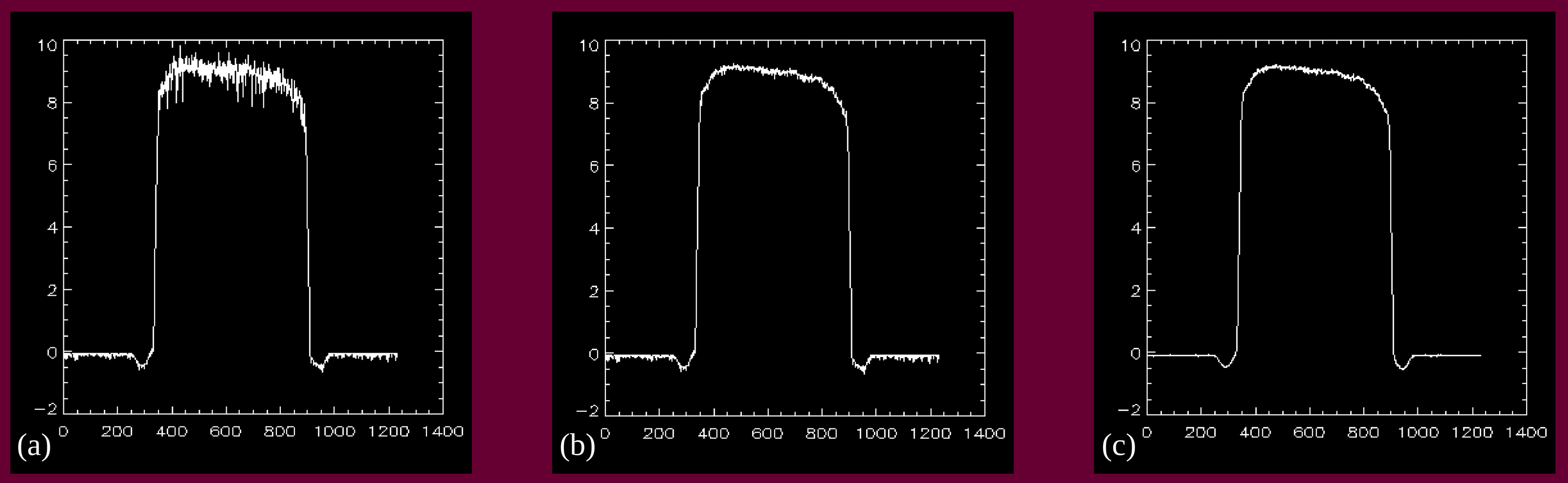

Fig. 3 (a) Line profile of converted aluminum-specific projection data on the white vertical line in Fig. 1. (a). (b) Line profile of noise reduced using PWLS algorithm. (β =0.0001) (c) Line profile of noise reduced using PWLS algorithm. (β =10000)

- The contrast-to-noise ratio (CNR) was used for evaluation of image quality within a selective ROI relative to background ROI

CNR	
PWLS not applied	66.15
PWLS applied(β=0.0001)	94.80
PWLS applied (β=10000)	106.4

Table. 1 CNR of aluminum-specific projection data and noise reduced data using PWLS algorithm. Selective ROI is pixel number (401-410,601-610) and background ROI is pixel number (1-10,1-10).

Conclusions

- The noise of material-specific images converted from dual-energy projection data was effectively suppressed by applying the PWLS algorithm to the images.
- We envision that image quality of the dual-energy CT can accordingly be improved via denoised material-specific data.

References

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