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Abstract. Photon-counting detector CT has a large number of acquisition parameters that require optimization, particularly the energy threshold configurations. Fast and accurate estimation of both signal and noise in photon-counting CT (PCCT) images can facilitate such optimization. Using the detector response function of a research PCCT system, we derived mathematical models for both signal and noise estimation, taking into account beam spectrum and filtration, object attenuation, water beam hardening, detector response, radiation dose, energy thresholds, and the propagation of noise. To determine the absolute noise value, a noise lookup table (LUT) for all available energy thresholds was acquired using a number of calibration scans. The noise estimation algorithm then used the noise LUT to estimate noise for scans with a variety of combination of energy thresholds, dose levels, and object attenuations. Validation of the estimation algorithms was performed on a whole-body research PCCT system using semianthropomorphic water phantoms and solutions of calcium and iodine. Clinical feasibility of noise estimation was assessed with scans of a cadaver head and a living swine. The algorithms achieved accurate estimation of both signal and noise for a variety of scanning parameter combinations. Maximum discrepancies were below 15%, while most errors were below 5%. © 2017 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JMI.4.2.023505]

Keywords: CT; photon-counting detector; multienergy CT; energy threshold configurations; signal and noise estimation.

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1 Introduction

Recent advances in photon-counting detector (PCD) technology may benefit clinical applications of x-ray CT.^{1–6} PCDs can differentiate individual photons and their associated energies, resulting in improved contrast due to better photon weighting.^{7,8} It has better geometric dose efficiency⁹ and improved low-dose performance^{10,11} due to the elimination of electronic readout noise.¹² These synergetic effects result in enhanced image contrast-to-noise ratio (CNR) in photon-counting CT (PCCT), which can be traded for a reduction of radiation dose and contrast agent.^{2,13} In addition, PCCT can perform simultaneous multienergy measurements that may benefit material differentiation and quantification in x-ray CT.^{4,5,14,15} Other reported clinical applications of PCCT include reduction of calcium blooming and beam hardening artifacts^{13,16} as well as high-resolution imaging.¹⁷

PCDs can suffer from nonideal detector responses so that the detected x-ray spectrum (pulse spectrum) can be different from the transmitted spectrum exiting the scanned object.¹ These nonideal responses can be categorized as flux-independent effects (such as charge sharing, Compton scattering, k-escape, and reabsorption) and flux-dependent effects (such as pulse pileup). Pulse pileup is the primary factor that has limited the application of PCDs in clinical CT due to its high x-ray flux. However, this can be overcome by advancements in detector technology, such as the use of small detector pixels, x-ray beam shaping, or compensation by calibration and/or mathematical modeling.^{1,13,18}

Recently published work evaluating the conventional imaging performance of a research whole-body PCCT system demonstrated that the scanner is capable of providing clinical image quality at clinical radiation dose levels.^{16,19} This suggests that the benefits offered by the PCD technology may translate into novel clinical applications in the near future.

PCCT, however, poses a challenge regarding the optimization of acquisition protocols. The signal and noise in PCCT data highly depend on object attenuation and specific scanning parameters, such as tube potential, filtration, and energy thresholds.^{20–24} Hence, PCCT acquisition parameters need to be optimized to maximize the signal-to-noise ratio (SNR) for different patients and imaging tasks. Due to the large number of possible combinations of scanning parameters, especially the threshold values for each energy bin,^{20,22,25} it is impractical to perform conventional phantom experiments that cover the whole parameter space. Although computer simulation of PCCT scans can be performed,^{26,27} the simulation and reconstruction steps can be very time consuming and thus are not suitable for clinical applications where real-time optimization of scanning parameters is required. Hence, a fast and accurate estimation of signal and noise in PCCT is needed to optimize the scan parameters for clinical exams.

Various approaches have been proposed to optimize the choice of energy thresholds to maximize the spectral performance for specific imaging tasks. Tapiovaara and Wagner²⁸ presented an optimization for the differentiation of two objects in x-ray transmission measurements. Alvarez²¹ described a method to achieve optimal detector performance for the detection of

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a feature within a background material. The Cramer–Rao lower bound has been used to evaluate energy thresholds for material decomposition of x-ray transmission measurements.^{20,22} Multivariate statistical analysis has been performed to determine the optimal energy threshold configurations for material separation.²⁵ However, these approaches were generally derived for a specific task in x-ray projection images. In this study, a different approach is proposed to estimate the absolute value of signal and noise in PCCT images. A search of these signal, noise, or SNR data allows the optimal energy threshold configurations to be determined.

In general, CT operators carefully align at the isocenter of the CT system. Hence, it is reasonable to optimize scanning parameters by determining the signal and noise in images acquired with the scanned object located at the isocenter. From the estimated signal and noise data, the scanner parameters, particularly energy thresholds, which yield the highest SNR can be determined.

The purpose of this study, therefore, was to develop and validate models to estimate PCCT signal and noise levels at the scanner isocenter for the purpose of selecting optimal energy thresholds for data acquisition. The proposed methods were validated using physical data acquired with a whole-body research PCCT system and a wide range of combinations of energy thresholds, object shapes and attenuations, beam filters, and radiation dose levels.

2 Materials and Methods

Based on the detector response function and x-ray physics, we derived and validated the mathematical models for both signal and noise in PCCT images.

2.1 Physics of Photon-Counting CT Acquisition

The research PCCT scanner evaluated in this work has been previously shown to have negligible pulse pileup effects.¹⁶ This allows flux-independent effects to be modeled by the detector

response function $D(E', E)$, which represents the probability of a photon of energy E being recorded as a photon of energy E' (Fig. 1).^{27,29} In this study, we obtained the detector response functions from the manufacturer of the research PCCT. Details on how the detector response functions were generated have been discussed in depth in two previous publications.^{26,27}

Knowing the detector response function, the pulse spectrum, which is the number of photons measured at an energy E' , $S_P(E')$ can be expressed as

$$S_P(E') = \int_0^{kVp} S_T(E) \cdot D(E', E) dE, \quad (1)$$

where S_T represents the transmitted spectrum exiting the scanned object and reaching the detector. kVp is the tube potential. With the pulse spectrum, the number of photons detected between a low- and high-energy threshold (Th_L and Th_H) in a PCD can be calculated as

$$N_{Th_L}^{Th_H} = \int_{Th_L}^{Th_H} S_P(E') dE' = \int_{Th_L}^{Th_H} \int_0^{kVp} S_T(E) \cdot D(E', E) dE dE'. \quad (2)$$

By switching the order of integration, this becomes

$$N_{Th_L}^{Th_H} = \int_0^{kVp} S_T(E) \cdot \int_{Th_L}^{Th_H} D(E', E) dE' dE. \quad (3)$$

Therefore, the corresponding portion of the transmitted spectrum detected within $[Th_L, Th_H]$ is

Fig. 1 (a) The two-dimensional detector response function, $D(E', E)$, represents the probability of a photon of energy E being detected at an energy E' . (b) An example of the detector response function [the red 1-D vertical profile in (a)] was plotted for an incident photon of energy 70 keV.

$$S'_T(E) = S_T(E) \cdot \int_{Th_L}^{Th_H} D(E', E) dE'. \quad (4)$$

Equations (3) and (4) can be applied to two types of PCCT data, i.e., energy threshold data and energy bin data. Energy threshold data are those photon counts detected above a given energy threshold, which can be described as a special case in Eqs. (3) and (4), where the higher threshold is set to be the maximum energy (in keV₀ in the input spectrum, which is determined by the peak tube potential setting, kVp). Energy bin data are those photon counts detected between two thresholds, generated from the subtraction of energy threshold data before the logarithm operation. Based on Eqs. (3) and (4), we derived the mathematical models for the estimation of both signal and noise at the isocenter of a PCCT scanner.

2.2 Signal Model

The signal, i.e., the effective linear attenuation coefficient (LAC) for energy bin (Th_L, Th_H), can be derived from Eq. (4)³⁰

$$\mu_{\text{eff}} = \int_0^{kVp} w(E) \cdot \mu(E) \cdot \int_{Th_L}^{Th_H} D(E', E) dE' dE, \quad (5)$$

where, $w(E)$ is a weighting function and can be expressed as

$$w(E) = \frac{S_T(E) \cdot \int_{Th_L}^{Th_H} D(E', E) dE'}{\int_0^{kVp} S_T(E) \cdot \int_{Th_L}^{Th_H} D(E', E) dE' dE}. \quad (6)$$

For a mixture of M materials, LAC can be expressed as

$$\mu_{\text{eff}} = \sum_{i=1}^M \rho_i \int_0^{kVp} w(E) \cdot \left(\frac{\mu}{\rho}\right)_i(E) dE, \quad (7)$$

where $(\mu/\rho)_i$ and ρ_i are the tabulated values of mass attenuation coefficients (MACs) and density of basis material i . When water beam hardening correction (WBHC) is performed, the effective water MAC [the integration for water in Eq. (7)] should be replaced by the corresponding water MAC used for the WBHC.

In Eq. (6), the transmitted spectrum, S_T , can be derived from the spectrum exiting the tube S_0 and material attenuation. For the estimate of signal at the isocenter, the effective attenuation of the object at a given longitudinal position was approximated by a water cylinder with a water equivalent diameter (WED) so that the total attenuation was the same as that of the object. Therefore, Eq. (6) can be expressed as

$$w(E) = \frac{S_0(E) \cdot \exp[-\mu_w(E) \cdot \text{WED}] \cdot \int_{Th_L}^{Th_H} D(E', E) dE'}{\int_0^{kVp} S_0(E) \cdot \exp[-\mu_w(E) \cdot \text{WED}] \cdot \int_{Th_L}^{Th_H} D(E', E) dE' dE}, \quad (8)$$

where $\mu_w(E)$ is water LAC. In this study, the WED (in cm) was directly calculated from CT images that used the full field of view (FOV) for reconstruction, thereby including all attenuating objects, using the following formula:³¹

$$\text{WED} = 2 \sqrt{\sum_{i \in I} (\text{CT}_i + 1000) / 1000 \times A / \pi}, \quad (9)$$

where i represents the index of pixel in image I and A is the pixel area in cm².

Hence, the signal model (illustrated conceptually in Fig. 2) takes the tube spectrum, beam filtration, scanned object, water beam hardening, and detector response into account. With the

Fig. 2 Framework of the signal estimation process. The incident spectrum for the x-ray tube and filtration used on the PCCT is estimated by the DRASIM software tool provided by the system manufacturer. The spectrum information is combined with a virtual model of the scanned object attenuation and the detector response function (also provided by the system manufacturer) to generate the pulse spectrum. With knowledge of the material composition and the system's water MAC, the LAC can be estimated.

knowledge of tube spectrum (through simulation or measurement), detector response function, target material composition, and object attenuation, the PCCT signal at a given energy bin or threshold can be calculated using Eqs. (7)–(9).

2.3 Noise Model

Assuming a Poisson distribution for the number of photons detected at a given threshold, the variance of the measured PCCT energy threshold projection data [i.e., $P = \ln(\frac{N_0}{N})$] can be calculated by

$$(\sigma_{P_{Th_L}})^2 = 1/N_{Th_L} \quad \text{and} \quad (\sigma_{P_{Th_H}})^2 = \frac{1}{N_{Th_H}}. \quad (10)$$

PCCT energy bin projection data are acquired by measuring the attenuation of x-rays between two energy thresholds, Th_L and Th_H

$$P_{Th_L}^{Th_H} = \ln\left(\frac{N_{0_{Th_L}} - N_{0_{Th_H}}}{N_{Th_L} - N_{Th_H}}\right), \quad (11)$$

where $N_{0_{Th_L}}$ and $N_{0_{Th_H}}$ are the mean photon counts detected above the low and high thresholds in an air scan, respectively. N_{Th_L} and N_{Th_H} are the corresponding counts detected after transmission through the scanned object. The number of photons is subtracted between the two energy thresholds before taking the logarithm operation. The noise variance in the energy bin projection can be determined by noise propagation analysis. For subtraction performed between counts measured from the same detector pixel and same exposure, the noise property has been discussed in a previous publication³² and the noise variance is

$$(\sigma_{P_{Th_L}^{Th_H}})^2 = \frac{1}{(N_{Th_L} - N_{Th_H})}. \quad (12)$$

There are scenarios in which energy bin data are created by subtracting photon counts from different detector pixels, e.g., the chess mode of a research whole-body PCCT scanner

(Fig. 3), to create more energy bins than the number of thresholds available on each detector.^{13,16,19,33} For acquisition modes where counts from different detector pixels or different exposures are subtracted, the noise propagation analysis (see Appendix), neglecting the covariance term, yields a noise variance of

$$(\sigma_{P_{Th_L}^{Th_H}})^2 = \frac{(N_{Th_L} + N_{Th_H})}{(N_{Th_L} - N_{Th_H})^2}. \quad (13)$$

The estimation of absolute noise level in CT images requires a calibration because it is affected by a variety of factors, such as acquisition protocol, data preprocessing steps, and reconstruction parameters.¹⁴ That is, absolute noise values cannot be predicted from first principles. For the estimation of local noise variance at the center of an object scanned at the isocenter, a proportional relationship between image noise variance σ_I^2 and the noise variance in the projection σ_P^2 can be approximated by ignoring the variations in the photon counts between neighboring detector channels and different projection views.^{14,34}

$$\sigma_I^2 = k\sigma_P^2. \quad (14)$$

The conversion factor k depends on the detector pitch, pixels size, reconstruction kernel, and interpolation methods. It should be constant for all PCCT images reconstructed using the same reconstruction parameters. Combining Eqs. (10)–(14), the noise in energy bin images for subtractions performed on the same detector and same exposure can be calculated by

$$\sigma_{I_{Th_L}^{Th_H}} = \frac{\sigma_{I_{Th_L}} \sigma_{I_{Th_H}}}{\sqrt{\sigma_{I_{Th_H}}^2 - \sigma_{I_{Th_L}}^2}}. \quad (15)$$

For subtractions performed on different detector pixels or different exposures, the noise in energy bin images can be derived as

Fig. 3 (a) Diagram of a macropixel of the PCD operating in the chess mode and (b) illustration of the notation used in the chess mode.

$$\sigma_{I_{ThL}}^{ThH} = \sqrt{\frac{\sigma_{I_{ThL}}^2 + \sigma_{I_{ThH}}^2}{(\sigma_{I_{ThL}}^2 - \sigma_{I_{ThH}}^2)^2}} \times \sigma_{I_{ThL}} \times \sigma_{I_{ThH}}. \quad (16)$$

Hence, the noise in bin images can be quantitatively derived from the noise in threshold images, which can be directly measured.

These relationships assume a linear system. Thus, in this study, we focused on the estimation of image noise from an analytical reconstruction; use of iterative techniques fundamentally alter the noise properties in a manner not readily predicted without in-depth knowledge of the specific iterative algorithm.

For the noise estimation, a single measurement for each threshold is sufficient. Once the noise measurement is complete for each threshold available on the scanner, the noise in bin images can be predicted for a large number of possible threshold configurations. Consequently, using only a limited number of scans, a noise lookup table (LUT) of image noise levels, $\sigma_{I_{Th}}$, can be acquired for a certain object attenuation (WED) with all available thresholds. The noise LUT can then be fed into the noise estimation algorithm [Eqs. (15) and (16)] for noise estimates.

The noise LUT acquired at a dose level (mAs_0) can also be used for the noise estimation of scans at a different radiation dose (mAs_1).

$$\sigma_{I,mAs1ThL}^{ThH} = \sqrt{\frac{mAs_0}{mAs_1}} \times \sigma_{I,mAs0ThL}^{ThH}. \quad (17)$$

At the same dose level, the noise LUT acquired at certain object attenuation (WED_0) can also be used to derive noise LUT for scans at a different object attenuation (WED_1).

$$\begin{aligned} \frac{(\sigma_{I,WED_1ThL})^2}{(\sigma_{I,WED_0ThL})^2} &= \frac{N_{Th,WED_0}}{N_{Th,WED_1}} \\ &= \frac{\int_0^{kVp} S_0(E) \cdot \exp[-\mu_w(E) \cdot WED_0] \int_{Th}^{\infty} D(E', E) dE' dE}{\int_0^{kVp} S_0(E) \cdot \exp[-\mu_w(E) \cdot WED_1] \int_{Th}^{\infty} D(E', E) dE' dE}. \end{aligned} \quad (18)$$

Correspondingly, the noise estimation for energy bin images can be calculated by

$$\begin{aligned} \sigma_{I,WED_1ThL}^{ThH} &= \sqrt{\frac{\sigma_{I,WED_1ThL}^2 + \sigma_{I,WED_1ThH}^2}{(\sigma_{I,WED_1ThL}^2 - \sigma_{I,WED_1ThH}^2)^2}} \times \sigma_{I,WED_1ThL} \\ &\times \sigma_{I,WED_1ThH}. \end{aligned} \quad (19)$$

Combining Eqs. (17)–(19), the same noise LUT can be used to estimate image noise for scans with different object attenuations and dose levels. Figure 4 shows conceptually how the noise estimation algorithm works.

Fig. 4 Framework of the noise estimation process. First, a noise LUT can be generated by scanning a calibration phantom having a certain water equivalent diameter (WED_0) on the PCCT at a radiation dose level (mAs_0) when other parameters are fixed. The noise LUT contains the image noise (in terms of noise standard deviation) for all available energy thresholds (20 to 90 keV on the PCCT). The noise LUT can be used to estimate the image noise for both thresholds and bin images acquired using a different radiation dose (mAs_1) on a different object attenuation (WED_1). The same process can be applied to generate noise LUT for noise estimation by varying other scan parameters (e.g., tube potential, bowtie, collimation, etc.)

2.4 Validation Experiments

We performed a series of experiments to validate the proposed approaches using data acquired on a research whole-body PCCT system (SOMATOM CounT, Siemens Healthcare, Forchheim, Germany). Both the signal and noise estimation were validated with phantom scans at different beam filtrations, energy thresholds, phantom sizes, and dose levels. In addition, clinical feasibility was evaluated using scans of a cadaver and a living swine.

The estimation errors of both signal and noise were calculated by

$$\begin{aligned} \text{Error} &= (\text{Estimation} - \text{Truth}) \quad \text{and} \quad \% \text{Error} \\ &= \text{Error} / \text{Truth} \times 100\%. \end{aligned} \quad (20)$$

For the phantom experiments, estimations were repeated on 16 adjacent slices, and the mean and standard deviation of error and % error were calculated.

2.4.1 Research photon-counting CT system

The research PCCT was built on the platform of a dual-source CT scanner (SOMATOM Definition FLASH, Siemens Healthcare). It consists of two equivalent x-ray tubes separated by 95 deg, with one coupled to an energy-integrating detector (EID) and the other one to a PCD. The PCD subsystem can simultaneously acquire PCCT data with two or four energy thresholds. At present, the diameters of the scanning field of view (SFOV) at the isocenter are 50.0 and 27.5 cm for the EID and PCD subsystems, respectively. Due to the limited SFOV of the PCD subsystem, truncation artifacts will occur in PCCT images when part of the scanning objects or the patient table is outside of the SFOV. To overcome the truncation artifacts, the manufacturer implemented a method to acquire a data completion scan (DCS) from the EID subsystem to estimate the missing projection data outside the PCD SFOV.³⁵ The DCS can effectively suppress truncation artifacts using minimal radiation dose and has negligible impact on noise magnitude of PCCT images. Detailed information about the PCCT system and DCS can be found elsewhere.^{11,16,33,35}

On this research PCCT scanner, photons were detected in 225 μm detector subpixels, although images were reconstructed using data from 900 μm detector macropixels. Each detector

macropixel is composed of 4×4 detector subpixels. Each detector subpixel is capable of detecting photons above a low-energy threshold and a high-energy threshold. A chess pattern readout mode was used in this work, where four measurements were acquired simultaneously in a single scan (Fig. 3). In the chess mode, two measurements were acquired with eight detector subpixels (e.g., the white squares of a chess board) using one pair of energy thresholds [i.e., threshold low 1 (Th_{L1}) and threshold high 1 (Th_{H1})], whereas the other two measurements used the other eight detector subpixels (e.g., the black squares of a chess board) using a different pair of energy thresholds [i.e., threshold low 2 (Th_{L2}) and threshold high 2 (Th_{H2})]. Energy bin data were derived by subtracting the photon counts detected by two adjacent energy thresholds prior to the logarithm step in the data preprocessing (e.g., Bin1 was derived by subtracting the photon counts between Th_{L1} and Th_{L2}). In this study, we focus on signal and noise estimation for the four energy thresholds of the chess mode. With four energy thresholds, an extremely large number of energy threshold combinations can be used, resulting in large variations of both signal and noise in the resultant images.

All threshold and bin projection data were reconstructed using a commercial weighted filtered back projection algorithm³⁶ to create PCCT images. The reconstructed images from the PCD subsystem were limited to the 27.5-cm SFOV of the PCD detector. For the WED calculations, we used the Th_{L1} PCD images for objects fitting within the 27.5-cm SFOV or the EID DCS images for objects extending beyond the 27.5-cm PCD SFOV.

For the research PCCT scanner, the low-energy threshold can be selected between 20 and 50 keV at every keV, whereas the high-energy threshold can be selected between 50 and 90 keV also at every keV. The smallest interval between two adjacent energy thresholds is 5 keV. The energy threshold configurations (in keV) used in this study are listed in Table 1. Four different energy threshold configurations (A–D) were used for the signal estimation. Configuration A approximates equal image noise level in each energy bin for an air scan and was also used for the noise estimation. In addition, two energy threshold configurations (E and F) were used to assess the impact of nonideal detector responses (charge sharing, k-escape, etc.) on the noise estimation. As these nonideal responses become more severe in the low-energy range, the only difference in the configurations E and F is the lowest threshold.

Table 1 The energy threshold configurations used for the validation experiments.

Configurations	Energy thresholds (keV)						
	Th_{L1}	Th_{L2}	Th_{H1}	Th_{H2}	Bin 1	Bin 2	Bin 3
A	25 to 140	45 to 140	65 to 140	85 to 140	25 to 45	45 to 65	65 to 85
B	20 to 140	25 to 140	57 to 140	77 to 140	20 to 25	25 to 57	57 to 77
C	20 to 140	31 to 140	55 to 140	90 to 140	20 to 31	31 to 55	55 to 90
D	20 to 140	39 to 140	64 to 140	89 to 140	20 to 39	39 to 64	64 to 89
E	20 to 140	50 to 140	64 to 140	79 to 140	20 to 50	50 to 64	64 to 79
F	35 to 140	50 to 140	64 to 140	79 to 140	35 to 50	50 to 64	64 to 79

Table 2 The composition of the solution samples used for the signal estimation validation.

	[CaCl ₂] (mg/ml)	[Iohexol] (mg/ml)	[H ₂ O] (mg/ml)
Sample #1	77.2	0.0	963.3
Sample #2	121.9	0.0	951.4
Sample #3	88.1	19.4	952.6
Sample #4	86.8	11.2	958.7
Sample #5	42.8	17.8	961.8
Sample #6	140.2	7.3	944.8
Sample #7	0.0	15.9	967.8
Sample #8	0.0	11.1	972.2

2.4.2 Validation of signal estimation

Validation of the signal estimation algorithm was performed using scans of calcium chloride (Sigma, CAS #10035-04-8) and iodine [Iohexol, 350 mgI/ml (Omnipaque; GE Healthcare, Shanghai, China)] water solutions. Eight solution samples of different compositions and concentrations (Table 2) were prepared with concentrations relevant to clinical CT angiography scans.

We evaluated a sample of possible combinations of scanning parameters, including those that mimicked a clinical scenario for body imaging as well as lower and higher body CT doses (Table 3). For the head exam mode, a very high dose was used to determine whether potential pulse pileup effects would affect our model. To validate the proposed method for different beam filtrations, both head and body acquisition protocols (different bowtie filters) were tested. Four different threshold configurations (configurations A to D) were evaluated for the head scans of a 20-cm water tank. In the body scans, the accuracy of signal estimation for a larger torso-shaped 30-cm water phantom and multiple radiation dose levels was assessed. The lateral (LAT) dimensions of the two water tanks were 20 and 35 cm, and the anteroposterior (AP) dimensions were 14.9 and 26.1 cm, which yielded WEDs of 18.8 and 32.3 cm, respectively.

Fully preprocessed sinograms were obtained for both threshold and bin data using a raw-data decoding tool supplied by the manufacturer. An in-house Feldkamp–Davis–Kress reconstruction was performed to generate images for the LAC measurements.³⁷ The signal was estimated using Eq. (7), and estimation errors were evaluated using Eq. (20).

2.4.3 Validation of noise estimation

First, we acquired PCCT scans to construct the noise LUTs for both head and body exams. Noise estimation was then validated with phantom scans at different beam filtrations, energy thresholds, phantom sizes, and dose levels. In addition, clinical feasibility was evaluated using scans of a cadaver and a living swine. Noise was estimated using Eqs. (17)–(19), and estimation errors were evaluated using Eq. (20).

Because noise in the reconstructed images strongly depends on the reconstruction method and parameters, all threshold and bin projection data were reconstructed by applying a weighted

Table 3 The combinations of scanning parameters used for the signal estimation validation.

Exam	Head scan	Body scan
kV		140
Collimation (mm)		32 × 0.5
Rotation time (s)		1.0
Threshold configurations (keV)	[25, 45, 65, 85] [20, 25, 57, 77] [20, 31, 55, 90] [20, 39, 64, 89]	[25, 45, 65, 85]
mAs	440	400 200 100
CTDI _{vol} (mGy)	111.03	44.31 22.15 11.08
WED (cm)	18.8	32.3
Test samples	#1 to 8	#2 to 7

filtered back projection algorithm using a quantitative, medium smooth reconstruction kernel (D30).³⁶

Noise lookup table generation. The noise calibration LUT was generated by performing 20 scans of a circular 20-cm water phantom at 440 mAs so that all selectable thresholds (low thresholds: 20 to 50 keV; upper thresholds: 50 to 90 keV) on the research PCCT were sampled at least once. All scans were performed twice to generate difference images to remove potential biases caused by image artifacts resulting from imperfect system calibrations.^{38,39} The noise standard deviation was measured in the difference images using pixels inside a circular region of interest (ROI) of 6-cm radius centered at the isocenter. The data acquisition and reconstruction parameters are listed in Table 4.

Phantom experiments. The noise estimation algorithm was validated using scans of a variety of water phantoms with different shapes and sizes. First, test scans of a circular 20-cm water phantom were acquired separately with three configurations (A, E, and F: none of them used in the noise calibration LUT scans) and three dose levels (mAs: 400, 200, and 100). To evaluate the estimation accuracy for objects with varying shape and size, body scans were performed to measure noise in three semianthropomorphic water tanks (LAT dimensions were 20, 25, and 30 cm, and the AP dimensions were 14.9, 18.6, and 22.4 cm, which yielded WEDs of 18.8, 23.8, and 27.9 cm, respectively) using configuration A at 400 and 200 mAs. Again, image noise standard deviation was measured in the difference images using pixels inside a circular ROI of 6-cm radius centered at the isocenter. The data acquisition and reconstruction parameters are listed in Table 4.

Table 4 The combinations of scanning parameters used for the noise estimation validation.

Exam	Noise LUT		Phantom validation		Clinical feasibility		
	Head	Body	Head	Body	Pig thorax	Pig abdomen	Cadaver head
kV				140			
Collimation (mm)				32 × 0.5			
Rotation time (s)			1.0		0.5		1.0
Pitch			N/A			0.6	
Thresholds (keV)	Randomly selected		[25, 45, 65, 85] [20, 50, 64, 79] [35, 50, 64, 79]		[25, 45, 65, 85]		[20, 50, 63, 83]
mAs	440		400 200 100	400 200	140		220
CTDI _{vol} (mGy)	111.03		101.14 50.70 25.09	44.20 22.15	15.51		55.50
WED (cm)	20.2		20.2	18.8 23.8 27.9	24.8	25.4	19.7
Slice thickness (mm)				2.0/0.8			
Recon kernel				D30			
Recon FOV (mm)				200			

Clinical feasibility tests. Evaluation of clinical feasibility of the proposed noise estimation approach was performed using scans of a cadaver head and a living swine. With approval of our institutional biospecimen committee, the cadaver head was scanned without contrast media. After institutional animal care and use committee approval, scans of the pig were acquired without and with contrast media. The data acquisition and reconstruction parameters are listed in Table 4.

The WEDs for different longitudinal positions were determined from EID images using the full FOV reconstruction. Noise estimation was performed for the test scanning parameters and compared with the noise measurements, which was performed by measuring the standard deviation of CT numbers inside a uniform circular ROI that was manually placed close to isocenter. Measurements of image noise were performed in the same ROI at all energy threshold and bin images.

2.5 Computation Time

We implemented our algorithm in MATLAB (2014b, The Mathworks, Natick, Massachusetts) and performed a speed test on a computer workstation with 128 GB shared memory, 2.5 GHz, two 2.5 GHz 12-core Intel “Haswell” processors

(Intel Xeon E5-2680 v3). The task was to estimate both the signal and noise for scans of an object with 20-cm water attenuation (i.e., WED = 20 cm). The object was composed of calcium, iodine, and water and the LACs of each basis material and their mixtures were calculated. The calculation was repeated for 20 runs, and the computation times were recorded and averaged.

3 Results

3.1 Validation of Signal Estimation

3.1.1 Head protocol with various threshold configurations

For each of the eight solution samples scanned using configuration A with a head protocol and a 20-cm water phantom, the algorithm predicted the LAC value with percent errors $\leq 11\%$ in the low-energy bins, and $< 5\%$ in higher energy bins and in all energy threshold images [Fig. 5(a)]. The signal estimation algorithm performed equally well for head scans with the other three tested threshold configurations (data not shown). The average percent errors of LAC estimation for all samples were below 8% in the lowest energy bins and were generally $< 5\%$ in higher energy bins and in all energy threshold images.

Fig. 5 (a) The percent error for signal estimation for each of the eight solution samples measured using the head protocol and configuration A. (b) The percent error for signal estimation averaged over the six solution samples measured using the body protocol and configuration A at three different dose levels.

3.1.2 Body protocol with different radiation dose levels

Similar performance was achieved for body scans of the solution samples in the 35-cm water tank using configuration A at three dose levels [Fig. 5(b)]. The accuracy of signal (LAC) estimation was typically within a few percent. At lower radiation dose settings and in narrower energy bins with fewer photons, the mean discrepancy was seen to increase to as high as 11%.

3.1.3 Regression analysis of all signal estimation data

Linear regression of all of the signal estimates against the corresponding measurements (Fig. 6) demonstrated good agreement between the measured and estimated values, with R^2 values ranging from 0.910 to 0.999. Although still strongly correlated, the agreement was lower for bins 1 and 2 due to the greater impact of nonideal detector properties in the low-energy bins.

3.2 Validation of Noise Estimation

3.2.1 Noise lookup table generation

The total time needed to construct the noise LUT was about 6.5 h, including three steps: a system calibration for 20 different threshold configurations (about 0.5 h), two sets of 20 PCCT data acquisitions (about 2.5 h), and PCCT image reconstructions (3.5 h).

3.2.2 Phantom experiments

Head protocol with various threshold configurations and dose. For threshold configuration A, the noise estimation

algorithm, in conjunction with the noise LUT, predicted the absolute image noise very accurately (the maximum absolute differences of noise levels were within 2 to 5 HU). For configuration A, average errors were ~ 0.06 HU (1.14%), with errors up to -2.33 HU (-6.45%) at the lowest dose level (Fig. 7).

The performance was the same for configurations E and F, except for the lowest energy bin in configuration E (data not shown), which showed higher percent errors in the estimation, although the error was still below 5 HU (15%). By setting the lowest threshold (Th_{L1}) to 35 keV, the estimation accuracy was improved in configuration F, with errors below 8% in both energy threshold and bin images.

Body protocol with various object attenuations. The noise estimation also worked well for the body scans of the three semi-anthropomorphic water phantoms using configuration A (data not shown). The maximum errors were 3 to 6 HU ($<14\%$) in the lowest energy bin images at the lowest dose level.

Regression analysis of all noise estimation data. Linear regression of all of the noise estimates against the corresponding measurements (Fig. 8) demonstrated good agreement between the measured and estimated values, with R^2 values ranging from 0.983 to 0.991. The y intercept values (bias) were below 1 HU in all cases.

3.2.3 Clinical feasibility tests

The clinical feasibility evaluation of the noise estimation showed good agreement between the estimation and the

Fig. 6 Estimated versus measured signal (LAC, in cm^{-1}). Very good agreement is seen for all threshold images and bin 3 images. For bins 1 and 2, where nonideal detector properties contribute substantially to the signal, the agreement is not as good, although still strongly correlated.

measurement (Fig. 9). The maximum discrepancies were generally below 10% for the cadaver head and pig abdomen scans. Larger percent errors were observed for the noise estimation of the unenhanced pig thorax exam and the contrast-enhanced scan of the pig abdomen, though the maximum errors were still below 15%.

3.3 Computation Time

With all other scanning parameters fixed, the number of available energy threshold configurations is 220,951. The total computation time for the calculation of both signal and noise for all threshold configurations was 8.0 ± 0.6 s.

Fig. 7 (a) The absolute (in HU) and (b) percent error for noise estimation in the head scan of the 20-cm circular water phantom using energy threshold configuration A.

Fig. 8 Estimated versus measured noise (in HU). Very good agreement is seen for both threshold and bin images.

Fig. 9 The percent errors of noise estimation for the clinical feasibility tests. Top: example images from a cadaver head and a living pig scan for the evaluation of noise estimation: (a) unenhanced cadaver head, (b) unenhanced pig chest, (c) unenhanced pig abdomen, (d) enhanced pig abdomen. Bottom: the percent error of noise estimation for the cadaver and *in vivo* pig scans. Filled circles depict the location of isocenter in the image. Open circles represent the ROI for the noise measurements.

4 Discussion

In this study, we derived mathematical models for both signal and noise estimation at the isocenter of PCCT images. We further proposed a noise LUT approach to determine the absolute noise levels based on a limited number of calibration scans. The

accuracy of the estimation methods was demonstrated in a variety of phantom, cadaver, and swine scans performed on a research whole-body PCCT system. The estimation algorithms were based on simple math operations and a predetermined noise LUT and hence can evaluate the complete parameters

space almost in real time. As the scaling factor is a constant that depends on the detector pitch, pixel size, reconstruction kernel, and interpolation method, a few reconstructions of the same projection data are sufficient to determine the conversion factors between different reconstruction parameters. Although noise in the projection data can be derived quantitatively based on the noise model presented in the manuscript, its absolute value requires the actual photon flux rate. Hence, noise calibration LUTs were determined for each tube potential setting and filtration combination (including both flat and bowtie filtration).

The fast and accurate estimation of both signal and absolute noise levels is beneficial for many applications, but especially for optimizing the energy threshold configurations. Previous studies demonstrated that patient attenuation (e.g., WED) can be estimated accurately from the CT localizer radiograph image prior to scanning.^{31,40} Subsequently, the optimal scanning parameters can be determined for the calculated WED prior to the actual scan and for a specific clinical task (e.g., maximum iodine CNR, k-edge imaging). In addition, the proposed method can be used to evaluate the signal-to-noise characteristics of the PCCT system in order to compare against current DECT techniques.

Although the proposed methods were based on several simplified assumptions, the mean percent discrepancy between the estimations and the measurements, evaluated over a range of threshold configurations, doses, object shapes and sizes, and filtrations, were always below 15%, with most of the errors below 5%. Thus, the assumptions and proposed methods appear robust for a variety of CT exams performed with different scan modes, radiation doses, threshold configurations, and scanned objects. The proposed methods may also be applied to other PCCT systems with known detector response information.

In our work on material decomposition,¹⁴ we found that the performance based on energy threshold data outperformed energy bin data results. The ~5% estimation error reported here for threshold data, however, can be magnified by the material decomposition process. The impact of the estimation error can be quantified by performing noise propagation analysis through the material decomposition process. Usually, a nonlinear noise reduction method is needed to suppress the noise in material-specific images and would need to be taken into consideration. We did not take these nonlinear methods into account in our model, as to do so would require proprietary knowledge of the noise reduction algorithms used. Rather, we hypothesize that images acquired with the optimal scanning parameters would provide the best data to work with, regardless of the material decomposition or noise reduction approaches that follow.

Some clinical scenarios may violate the assumptions made in this work and reduce the signal and noise estimation accuracy. First, the WED determined from the CT localizer radiograph (prior to a contrast injection) could differ from that calculated using the contrast-enhanced image. This may lead to errors in estimating the actual patient plus contrast attenuation and subsequent errors in the signal and noise estimation. Second, the Poisson statistics assumption might be violated at the low-energy range due to nonideal physical effects. As demonstrated by phantom experiments, larger errors in noise estimation usually occurred in the lowest energy bins and was likely caused by nonideal physical interactions, such as charge sharing, k-escape

and reabsorption, and Compton scattering, which change the photon statistics and consequently violate the Poisson statistics assumption. By setting the lowest threshold at 35 keV while keeping other parameters unchanged, the estimation error was reduced from 15% (in configuration E) to 8% (in configuration F). Alternatively, previous studies demonstrated that a charge-summing mode could be exploited to mitigate those non-ideal interactions,^{41–43} which might be helpful to reduce the estimation error in the low-energy range. Third, for a very narrow bin width and/or low-radiation dose, photon starvation may occur so that the accuracy of estimation (e.g., signal estimation in 35-cm water tank with lower dose levels) can be degraded. An additional limitation of this study was that the cross-correlated noise between detector subpixels was not included in our mathematical models. Finally, the noise estimation method we proposed was based on an analytical reconstruction method and would not be applicable directly to iterative reconstruction techniques.

5 Conclusions

We have developed an effective framework that is based on simple mathematics (and hence is very fast compared with a full Monte Carlo simulation) to estimate the signal and absolute noise level in PCCT images. The signal model takes into account the tube spectrum, detector response, object attenuation, and WBHC. The noise model was derived based on noise propagation analysis and a noise calibration LUT. We validated the estimation accuracy using data acquired on a research PCCT system. The maximum discrepancies were all below 15%, with most errors below 5%. The estimated signal and noise provide important data for selecting optimal energy thresholds for a variety of clinically relevant tasks.

Appendix

Below is the noise propagation analysis for acquisition modes where counts from different detector pixels or different exposure are subtracted (e.g., chess mode on the research PCCT).

From Eq. (11),

$$P_{Th_L}^{Th_H} = \ln \left(\frac{N_{0_{Th_L}} - N_{0_{Th_H}}}{N_{Th_L} - N_{Th_H}} \right). \quad (21)$$

The noise propagation analysis yields

$$\begin{aligned} (\sigma_{P_{Th_L}^{Th_H}})^2 &= \left[\frac{\partial P_{Th_L}^{Th_H}}{\partial N_{Th_L}} \right]^2 \times (\sigma_{N_{Th_L}})^2 + \left[\frac{\partial P_{Th_L}^{Th_H}}{\partial N_{Th_H}} \right]^2 \times (\sigma_{N_{Th_H}})^2 + \\ &\times \left[\frac{\partial P_{Th_L}^{Th_H}}{\partial N_{Th_L}} \right] \times \left[\frac{\partial P_{Th_L}^{Th_H}}{\partial N_{Th_H}} \right] \times \text{cov}(N_{Th_L}, N_{Th_H}). \quad (22) \end{aligned}$$

In these acquisition modes, if we treat the detected photon counts above the two thresholds, Th_L and Th_H , as statistically independent measurements, the covariance term can be neglected.

$$\begin{aligned}
(\sigma_{P_{ThL}}^{ThH})^2 &= \left[\frac{\partial P_{ThL}^{ThH}}{\partial N_{ThL}} \right]^2 \times (\sigma_{N_{ThL}})^2 + \left[\frac{\partial P_{ThL}^{ThH}}{\partial N_{ThH}} \right]^2 \times (\sigma_{N_{ThH}})^2 \\
&= \left\{ \frac{N_{ThL} - N_{ThH}}{N_{ThL}^0 - N_{ThH}^0} \times \left[-\frac{N_{ThL}^0 - N_{ThH}^0}{(N_{ThL} - N_{ThH})^2} \right] \right\}^2 \times N_{ThL} \\
&\quad + \left\{ \frac{N_{ThL} - N_{ThH}}{N_{ThL}^0 - N_{ThH}^0} \times \left[\frac{N_{ThL}^0 - N_{ThH}^0}{(N_{ThL} - N_{ThH})^2} \right] \right\}^2 \times N_{ThH} \\
&= \frac{(N_{ThL} + N_{ThH})}{(N_{ThL} - N_{ThH})^2}. \tag{23}
\end{aligned}$$

Disclosures

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