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Estimation of X-ray energy spectrum for CT scanner from percentage depth dose measurement

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INTRODUCTION

A computed tomography (CT) imaging has occupied a high position in medicine. Essentially, an x-ray energy spectrum information plays a very important role in a variety of imaging applications[1]. However, the exact energy spectrum used in the CT image reconstruction are unknown and because of the high photon flux in medical CT scanner, it is also difficult to measure the spectra directly. There are several works to estimate the incident x-ray spectrum based on a Monte Carlo (MC) calculation[2] or an indirect transmission or scattering measurement[3]. In MC calculation, the detail of the x-ray system information is required, and the difference among individual CT machines are indistinguishable. Rather, the estimation based on the transmission measurement is preferred. Previously, the energy spectrum estimation from the transmission measurement was performed without considering scattered photons[4]. This situation would be valid in a fan beam CT system with an anti-scatter grid. On the other hand, **there is no studies to a cone-beam CT (CBCT)**, in which the scattered photons are likely to be dominant in the observation.

AIM

In this work, we propose a new method to estimate the CBCT x-ray spectrum by using **percentage depth dose (PDD)** measurement, which is easy to obtain, and is also applicable in the fan beam CT system. We will show that the CBCT x-ray spectrum can be reconstructed from the PDD by using **machine learning (ML) approaches**, which were **the artificial neural network (ANN) models based on SPEKTR3.0[5] and the conventional maximum a posterior (MAP) estimation**.

RESULTS

Figure 2 shows the prediction results to energy spectral curve in 120 kV with 5-keV bin width for practical CBCT scanners, XVI and OBI systems, respectively. The red boxed makers are the reconstructed result by ANN model, while the blue triangle makers are the reconstructed result by MAP model. As seen in the figures, both models can generate similar spectra to those obtained by full MC simulation, indicated by the green circle makers. The lower panels of Fig. 2 display the displacement between the result predicted by the proposed model and the full MC result. Relatively large displacement was observed at high-energy area as well as that including the characteristic x-ray (59.3 keV). The corresponding result of the PDD fittings was also displayed in Figs 2 (a2) and (b2).

Table 1 indicates the RMSE when the MC result is regarded as the ground truth. Except for 100 keV where the hyper parameters were determined in MAP model, all RMES results show that ANN model is slightly superior to MAP model. The corresponding photon-count reproducibility to the MC simulation was approximately 95% in the present estimation with 5-keV bin width.

Because the PDD measurement is routinely performed in the quality control and quality assurance in radiation therapy system, the application of this measurement in the CT scanner is not complicated. Although the present study focused on the CBCT device equipped on the radiation therapy system, details of head structure is not necessary, therefor it would be also easy to design a phantom for the PDD measurement in a general clinical CBCT.

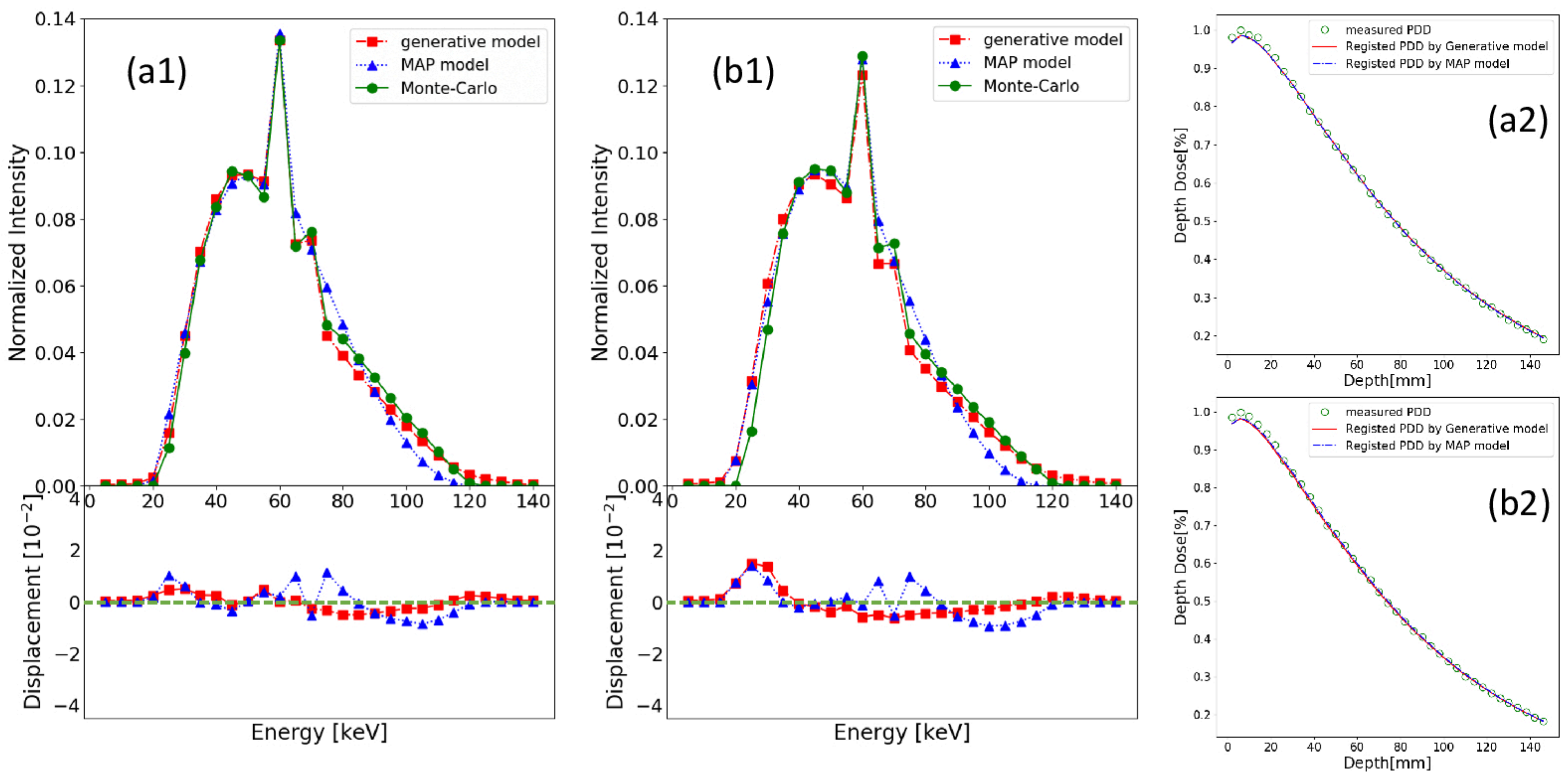

TABLE 1: Root mean square error (RMSE) in spectrum estimation, where, the result in the full Monte Carlo simulation is regarded as the ground truth.

Machine – Tube voltage	RMSE [$\times 10^{-3}$]	
	ANN	MAP
XVI - 100 kV	6.96	6.18
XVI - 120 kV	2.78	5.12
XVI - 130 kV	3.68	6.23
XVI - 140 kV	3.42	5.54
OBI - 100 kV	6.66	6.02
OBI - 120 kV	5.14	5.71
OBI - 130 kV	3.14	5.37
OBI - 140 kV	3.49	5.55

Figure 2 : Spectra curves estimated in 120 kV with 5-keV bin width for (a1) the X-ray Volumetric Imager (XVI) and (b1) On-Board Imager (OBI). The red boxed makers: generative model, the blue triangle makers: MAP model are shown. For comparison, the result of full MC simulation is also indicated by the green circle makers. The lower panels display the displacement between the result predicted by the proposed model and the full MC result.

(a2) and (b2) are PDDs reproduced by generative and MAP models for (a1) the X-ray Volumetric Imager (XVI) and (b1) On-Board Imager (OBI). The predicted energy spectra shown in the manuscript were obtained by the regression of the input PDD (Monte Carlo or measured data). The red solid line: generative model, the blue dashed line: MAP model, the green circle: measured PDD.

METHOD

We assume that the observed PDD is expressed by a weighted mean of ***monochromatic PDDs (mPDDs)*** $\phi_i(d)$ as,

$$PDD(w,d) = \sum_i^M w_i \phi_i(d)\,,(1)$$

where M is the number of samplings in x-ray energies. The w_i is the weight of i's x-ray energy bin, and directly this forms the x-ray spectrum. In this study, the mPDD ϕ_i with the 5-keV interval was prepared by MC simulation using GEANT4 toolkit (version 10.4) , where the x-ray source was located on a virtual plane at 30 cm above from the water surface and the beam direction was set as the virtual point source exists at 100 cm from the water surface.

Using mPDD, we constructed two prediction models with different ML approaches as follows. The mPDDs of monochromatic x-ray energies from 10 keV to 140 keV with a 5-keV interval were prepared by MC simulation **without details of head structure**. With mPDDs, the x-ray spectrum prediction model was constructed with ANN models based on SPEKTR3.0 and MAP model. Figure 1 shows workflow of the proposed spectrum estimation method.

(I) ANN model

Using Eq.(1), various PDDs can be generated by varying the energy spectrum. Various x-ray spectra were generated by sampling a tube voltage, Al-filtration, Cu-filtration, and ripple in SPEKTR3.0. In this study, 10,000 training datasets were generated and used in the ANN modeling.

(II) MAP model

In this model, mPDDs are regarded as the numerical basis set. We assume the observables include the gaussian noise, so that the mean squared error was a part of the loss function as,

$$L(\boldsymbol{w}) = \frac{1}{2}\sum_{n=1}^{N}\{PDD(\boldsymbol{w},d_n) - t(d_n)\}^2 + \frac{1}{2}\left\{\sum_{i\notin 60keV}^{M} \alpha(w_i - w_{i+1})^2 + \alpha(w_{55keV} - w_{65keV})^2 + \sum_{i\in 55keV,60keV} \beta(w_i - w_{i+1})^2\right\} + \lambda\left(\sum_{i=10keV}^{M} w_i - 1\right) - \mu^T \boldsymbol{w}, (2)$$

where we also assumed that the x-ray spectrum is continuous except for the energy of characteristic x-ray from tungsten (2nd-4th terms).

These two models were evaluated by the comparison between the estimated weights and the those calculated by full MC simulations in X-ray Volumetric Imager (XVI) system (ELEKTA) and On-Board Imager (OBI) system (Varian).

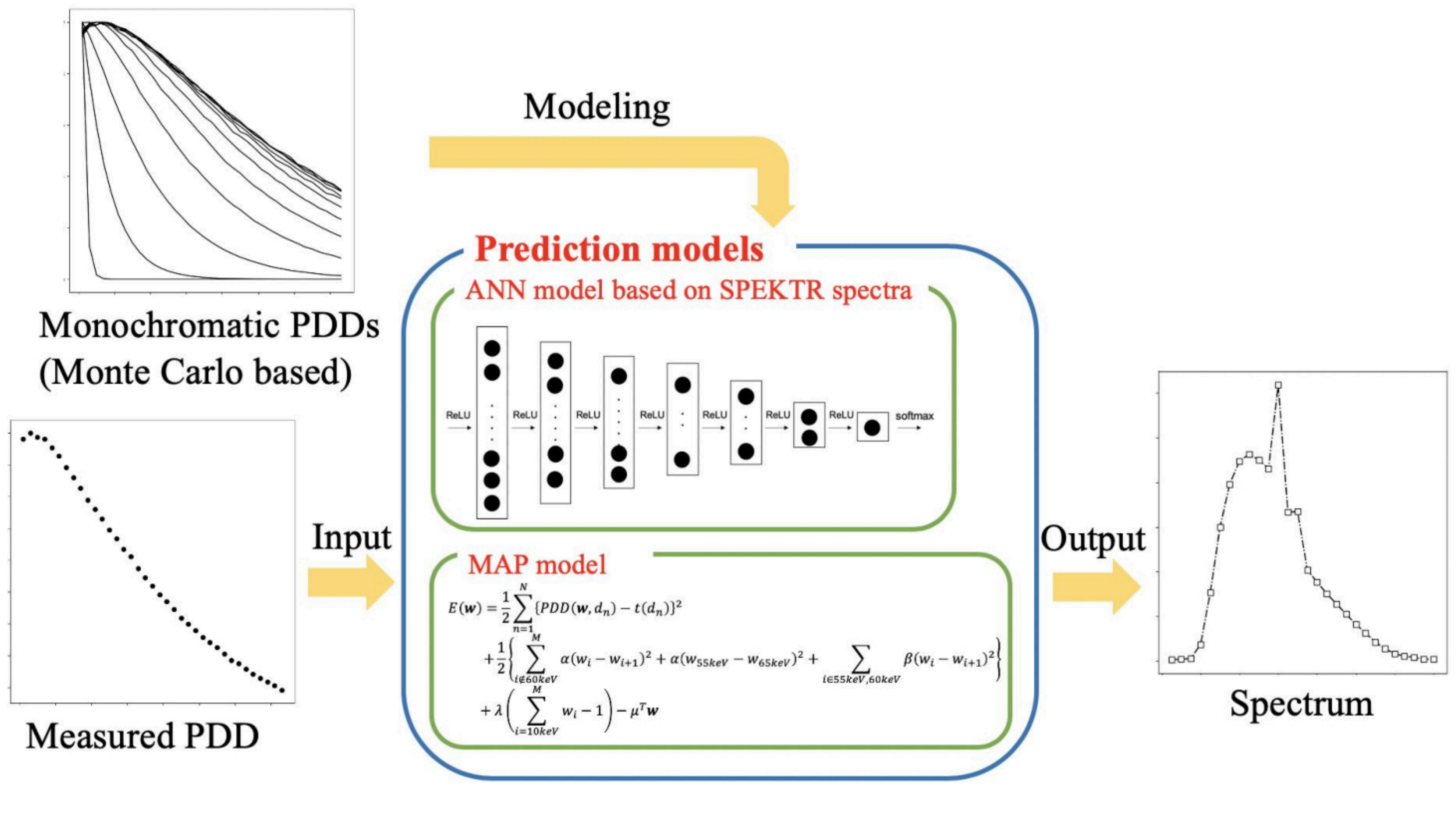

Figure 1: Workflow of the proposed x-ray spectrum estimation method.

CONCLUSIONS

An x-ray spectrum estimation in CBCT system using ML approaches was feasible from a PDD measurement. This research is expected to be applied for the fields such as the beam hardening reduction in CBCT reconstruction and CBCT dose calculation, which require the x-ray spectrum information.

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