Uncertainty-aware reconstructed image correction for proton computed tomography using Bayesian deep learning

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INTRODUCTION

Integrated-type proton computed tomography[1] (pCT) measures proton stopping power ratio (SPR) images for proton therapy treatment planning, but its image quality is degraded due to noise and scatter. Although several correction methods have been proposed, correction methods that also allow for estimation of uncertainty are limited.

AIM

This study proposes a novel image correction method with uncertainty quantification using a Bayesian convolutional neural network (CNN).

METHOD

432 noisy SPR images of 6 non-anthropomorphic and 3 head phantoms were collected with Monte Carlo simulation[2], while true images were calculated manually using known geometry and chemical components.

Our proposed method calculates both noise-corrected SPR images as well two types of uncertainty images; aleatoric uncertainty mainly caused by noise inherent in input data, and epistemic uncertainty in model parameters or inference[3]. A DenseNet-based CNN was constructed to calculate both the corrected SPR image and aleatoric uncertainty by using a noisy SPR image as input[4] (Figure 1). Epistemic uncertainty was estimated by a Bayesian ensemble approach by independently training 25 CNN models initialized with unique random parameter weights. 200-epoch end-to-end training was implemented for each model including random flips and 90° rotations of inputs as data augmentation.

Finally, accuracy of the CNN correction and impact of the uncertainty images were evaluated by using 48 images of a head phantom as test data.

RESULTS

1. Accuracy of CNN-corrected SPR images

Figure 2 illustrates uncorrected/corrected SPR images in two different slices. The CNN model provides more accurate SPR values than uncorrected images. Mean absolute error in head phantom images was improved from 0.254 to 0.0538. Computation time for calculating one image and its uncertainties with the ensemble of 25 CNN models is 0.7 seconds with a NVIDIA RTX 2080Ti GPU.

2. Correlation between predicted uncertainty and correction error

In addition to corrected SPR images, the CNN model also calculates quantitative aleatoric and epistemic uncertainty images. Figure 3 shows noticeable visual correlations between uncertainty and absolute SPR error in the corrected images. While both uncertainty images have high values at some overlapping regions, several others show only aleatoric uncertainty as high (arrows in Figure 3), indicating that SPR errors at these pixels are mainly input data-dependent. By taking both types of uncertainty images into consideration together, it is possible to identify potential causes of correction errors. To further evaluate relationship between the uncertainty and proton range, water-equivalent thickness (WET) and its total uncertainty from phantom surface to image center were calculated over one rotation in all test data. Absolute WET error as a function of the total uncertainty was plotted in Figure 4. This figure indicates that uncertainty is correlated with absolute WET error. Since this technique estimates proton range uncertainty for each irradiated object and beam path, they have great potential to be used for patient-specific or spot-specific proton range margin determination.

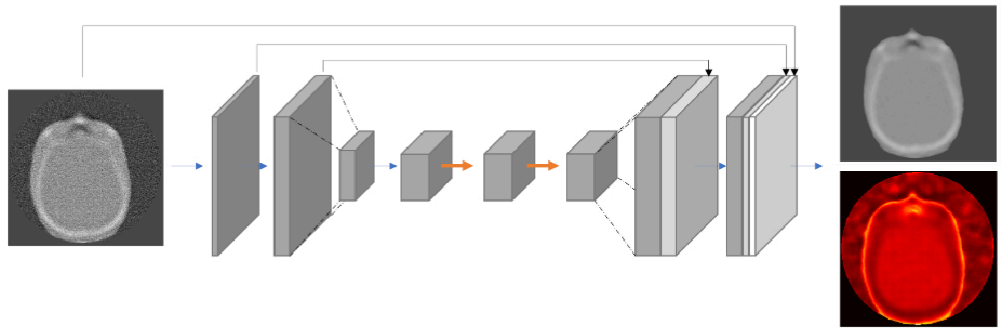

Figure 1. Diagram of Bayesian CNN architecture. Blue and orange arrows represent a single convolutional layer and a DenseNet block with 5 convolutional layers, respectively. Up-sampling and down-sampling were applied with 2D max pooling and 2D unpooling layers, respectively.

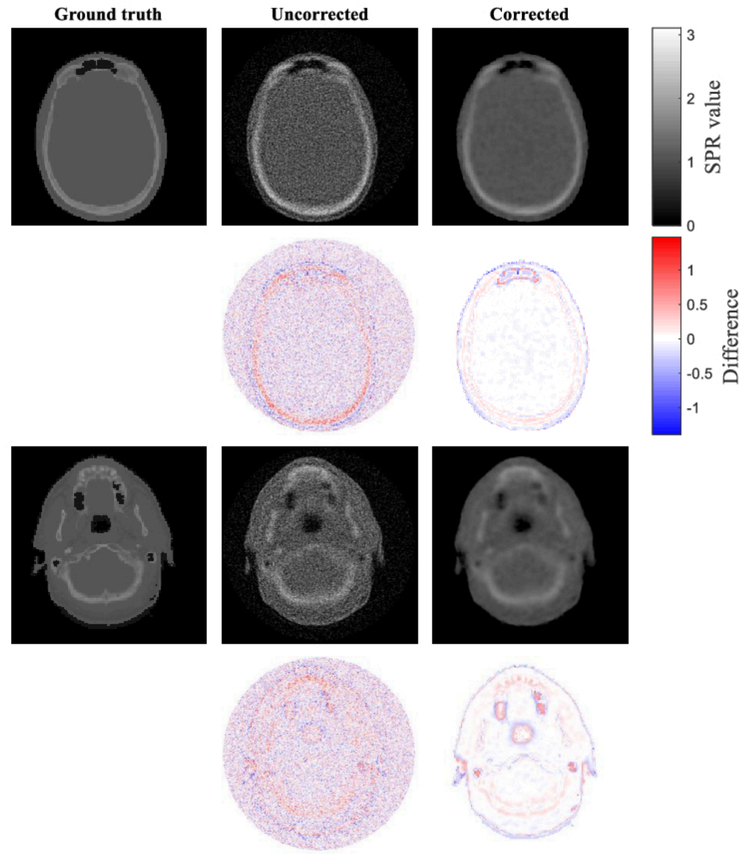

Figure 2. Comparison of uncorrected and corrected SPR image with ground truths in two slices. Subtraction of uncorrected/corrected images from the ground truths are also shown.

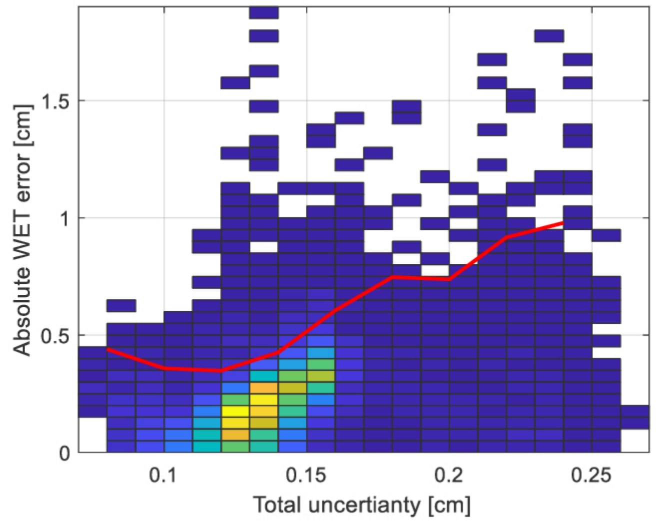

Figure 4. Correlation between total uncertainty and absolute water-equivalent thickness (WET) error. A red line represents a 95th percentile curve.

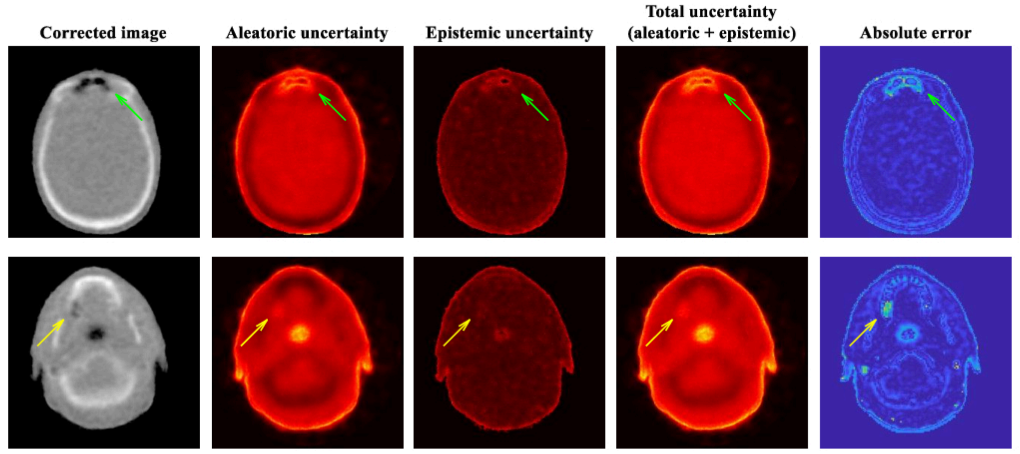

Figure 3. Comparison of corrected SPR images and two uncertainty images with ground truths in two different slices. Arrows indicate regions where only aleatoric uncertainty is high.

CONCLUSIONS

A novel pCT image correction method was established using a Bayesian CNN. Our model is able to predict accurate SPR images as well as two types of uncertainty quickly. These uncertainties will be useful to identify potential cause of range errors and develop a patient-specific or spot-specific range margin criterion. This technique will be tremendously valuable in uncertainty-guided proton therapy treatment planning.

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REFERENCES

1. **Tanaka S et al.** Improved proton CT imaging using a bismuth germanium oxide scintillator. *Phys Med Biol. 2018;63(3).*
2. **Sato T et al.** Features of Particle and Heavy Ion Transport code System (PHITS) version 3.02. *J Nucl Sci Technol [Internet]. 2018 Jun 3;55(6):684–90.*
3. **Kendall A and Gal Y.** What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision? *Advances in Neural Information Processing Systems 30 [Internet]. Curran Associates, Inc.; 2017. p. 5574–84.*
4. **Paszke A et al.** PyTorch: An Imperative Style, High-Performance Deep Learning Library. *Advances in Neural Information Processing Systems 32 [Internet]. Curran Associates, Inc.; 2019. p. 8026–37.*

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