6-2022

Physics-Informed Machine Learning for Estimating Pulmonary Perfusion From Non-Contract 4DCT

Y Liu

A Nowacki

R Castillo

Y Vinogradskiy

G Nair

See next page for additional authors

Authors
Y Liu, A Nowacki, R Castillo, Y Vinogradskiy, G Nair, C Stevens, and E Castillo

derived and then employed to improve stopping power ratio (SPR) accuracy and reduce range uncertainty. In this work, we propose a one-step iterative estimation method, which employs multi-domain gradient L_0-norm minimization to reconstruct Z and ρ_e maps**. Methods:** The employed gradient L_0-norm is a regularizer that directly and effectively suppresses noise and reduces artifacts in the decomposition domains. In contrast to two-step methods, the investigated optimization model can derive material composition, Z, and ρ_e maps simultaneously. Moreover, we introduce multi-domain regularizers for each search variable. Thus, during the alternative solution process, the noise magnification problem is consistently suppressed. Further, the gradient L_0-norm is superior to traditional Tikhonov and total variation regularizations in sparse representation and edge preservation, which further benefits noise reduction and image fidelity. The algorithm is implemented on a GPU to accelerate the predictive procedure and to support potential real-time adaptive treatment planning**. Results:** Both phantom and patient studies demonstrate the superiority of the proposed method in material-selective reconstruction, noise suppression, artifact reduction, and the accurate estimation of ρ_e and Z maps. Moreover, the proposed method can be accelerated by parallel computing so that all the maps are computed in 2 minutes using a single GPU (NVIDIA GeForce GTX 960M)**. Conclusion:** The proposed one-step iterative estimation method with multi-domain gradient L_0-norm minimization can effectively improve the quality and accuracy of Z and ρ_e maps, which further benefits the SPR calculation for proton therapy and synthesis of monoenergetic images for dose verification or region-of-interest contrast enhancement.

SU-E-201-07, Physics-Informed Machine Learning for Estimating Pulmonary Perfusion From Non-Contract 4DCT: Y Liu[1*], A Nowacki[1], R Castillo[2], Y Vinogradskiy[3], G Nair[4], C Stevens[4], E Castillo[1],(1) University of Texas at Austin, Austin, TX, (2) Emory University, Atlanta, GA, (3) Thomas Jefferson University, Philadelphia, PA, (4) William Beaumont Hospital, Royal Oak, MI

Purpose: Novel methods have been developed for functional avoidance that proposes to use 4DCT to derive lung ventilation and perfusion images. Previous methods for quantifying lung perfusion on non-contrast 4DCT rely either on HU-based physical models or black-box deep learning models. While deep learning typically achieves higher accuracies in image processing tasks, physical models provide a rationale for model predictions. The purpose of this study is to introduce a biophysics-informed machine learning method for estimating pulmonary perfusion from non-contrast 4DCT. Our approach is designed to combine the predictive power of neural networks with the interpretability of physical modeling, with the goal of providing high-fidelity information for radiotherapy functional avoidance planning**. Methods:** Simulation 4DCT scans and SPECT-Perfusion scans for 42 non-small cell lung cancer patients were used to train and validate a 3-layer, fully connected, artificial neural network (ANN). Similar to existing physics-based models for CT-perfusion, the ANN takes as inputs the spatially corresponding inhale/exhale lung densities and Jacobian measured volume changes for the five lung lobes. The output layer predicts the percent of total lung perfusion within each lobe. SPECT-Perfusion images were used for ground truth. The ANN was trained using the stochastic gradient descent optimizer with grid search. Leave-one-out cross-validation was applied to estimate prediction quality**. Results:** The average mean square errors resulting from the leave-one-out process was 5.71±2.77%. The median(interquartile range) of the Spearman correlations between ground truth and predictions was 0.7(0.5)**. Conclusion:** Our proposed physics-informed ANN generates spatial correlations with SPECT-Perfusion that provide improved correlation compared to existing methods. Moreover, the approach is based on lung density and volume change measurements which are well-known physical quantities that have been shown to correlate with disease and functional defects. Therefore, the developed ANN represents a novel and interpretable machine learning methodology for quantifying perfusion from non-contrast CT.

SU-E-201-08, Scatter Correction in Known-Component Model-Based Cone-Beam CT Reconstruction in the Presence of Metal Hardware: A Lopez Montes[1*], W Zbijewski[2], J Siewerdsen[3], J Stayman[4], S Liu[5],(1) Johns Hopkins University, Baltimore, MD, (2) Johns Hopkins University, Baltimore, MD, (3) Johns Hopkins University, Baltimore, MD, (4) Johns Hopkins University, Baltimore, MD, (5) Johns Hopkins University, Baltimore, MD

Purpose: In penalized-likelihood Known Component Reconstruction (KCR), prior models of metal hardware are used to mitigate metal artifacts. We investigate the impact of scatter correction accuracy on the efficacy of KCR in orthopedic Cone-Beam CT (CBCT)**. Methods:** An extremity CBCT system (1.3 magnification, 360 projections) operated at 120 kVp was simulated. The imaging phantom comprised of a water ellipsoid (12 by 10 mm) containing fat and bone inserts and an 4 mm diameter, 50 mm length Titanium screw. Adjacent to the screw, there were two trabecular regions-of-interest (ROIs) with BMD of 175 mg/ml and 100 mg/ml. Polyenergetic primary projections were obtained using ray-tracing, scatter was simulated with an accurate, low-noise Monte Carlo (MC) simulation with 10^{11} photons. Prior to KCR, scatter estimates of varying fidelity were subtracted from the data: (i) projection-wise mean of the original MC simulation (mean correction), and (ii) fast MC-based corrections, involving noisy MC with low number of photons (10^6 – 10^{10}, corresponding to 25s-7h runtime per scan) followed by Gaussian denoising (standard deviation σ=5-40 mm). The KCR forward model incorporated a polyenergetic projection of the Ti screw pre-hardened to account

