
Abstract

Computed tomography (CT) is a widely used non-destructive imaging technique for medical diagnosis, interventional procedures, and treatment planning. CT reconstruction involves accurately recovering linear attenuation coefficients in the form of image pixels from experimentally measured CT data in the form of line integrals. Provided that the acquired data satisfy the data sufficiency condition and other conditions regarding the view angle sampling interval and the severity of transverse data truncation, researchers have devised many solutions, including deterministic and statistical iterative approaches to reconstruct the CT image accurately. However, if these conditions are violated, accurate and robust image reconstruction from ill-posed CT data remains an intellectual challenge. Deep learning methods offer powerful regression capabilities to perform imaging processing tasks such as noise mitigation and artifact reduction. However, these methods face fundamental issues in medical imaging applications, such as accuracy and performance degradation when applied to individual patients or different patient cohorts. When the problem becomes overly ill-posed due to aggressive view angle undersampling and data truncation, the image artifacts in the conventional reconstructed images become so severe that crucial patient information is obscured from the deep neural network. Consequently, the deep learning methods may miss or ‘daydream’ information, potentially leading to disastrous outcomes.

This thesis project proposed several novel CT image reconstruction frameworks that synergistically combine analytical, iterative, and deep learning approaches to tackle three long-standing difficult CT reconstruction problems. The first study proposed a quality-assured deep learning reconstruction framework called “DL-PICCS”, which combined a deep learning strategy with prior image constrained compressed sensing to tackle sparse-view reconstruction problems. The images post-processed by a deep neural network were used as the prior compressed sensing image. In contrast, the measured sinogram data were used to correct falsely reconstructed image details and avoid over-smoothness. The same method was also leveraged to defend against adversarial perturbations intentionally crafted and added to the network input to make the deep neural network unstable. The second study proposed a new reconstruction framework called “Deep-Interior” that leveraged weighted backprojection and a deep neural network to address severe data truncation for both short-scan and super-short-scan data acquisition schemes. The weighted backprojection was derived as a nice feature space, a blurred version of the original CT image with a shift-invariant blurring kernel. The deep learning model learns a generalizable deconvolution scheme that can

be applied to arbitrary regions within the patient's body. The third study leveraged the power of analytical reconstruction and statistical analysis to estimate patient-specific and local noise power spectra from single CT data acquisitions. The statistical properties of the new estimator were rigorously derived to demonstrate its superiority over the conventional method using repeated samples. Completing this thesis project offers promising software advancements that can accelerate the arrival of next-generation novel CT imaging techniques with significantly reduced radiation dose, lower equipment costs, and improved patient care quality.