Purpose: We aim to develop tomographic reconstruction methods that utilize prior CT volumes to improve image quality for sparse and undersampled datasets. The ability to handle such data has applications in region-of-interest scanning, tomosynthesis, and intraoperative imaging based on few view angles. While compressed sensing techniques like the PICCS algorithm are attractive, there are potential drawbacks. Such approaches often rely on pre-registered prior images and the forward models for PICCS-type algorithms tend to be simplified and ignore the noise model. We leverage the ability of likelihood-based techniques to incorporate both prior images and sophisticated forward models.

Methods: We have developed a framework for reconstruction of sparse tomographic data based on penalized-likelihood estimation. The objective function for this approach is composed of a likelihood term that incorporates the forward model and noise; and a parameterized penalty term that discourages differences from the prior image. The penalty uses a compressed sensing norm and is parameterized to accommodate registration of the prior scan. An iterative algorithm is used to simultaneously solve for the tomographic volume and the registration parameters. The framework is general and can be used with both rigid and deformable registrations.

Results: Reconstruction of sparse data using the proposed approach is demonstrated in cases where either rigid or deformable registration is employed in the reconstruction objective. We compare reconstruction results with traditional approaches where prior image data is not utilized. We find a substantial improvement in image quality with significant reduction in artifacts that are associated with the sparse data acquisitions.

Conclusions: A new class of penalized-likelihood estimator has been developed that simultaneously refines attenuation and registration estimates. The framework is general and supports both rigid and non-rigid transformations of the prior imagery. Image quality and handling of artifacts using the proposed estimator with sparse data is superior to traditional approaches.