Multi-material computed tomography with unsupervised deep learning

Thomas Braure[1], Vincent Brandon[1], Alexandre Friou[1]

[1]Department of Experimental Design, French Atomic Energy Commission (CEA), France

Computed tomography (CT) has revolutionized non-destructive testing by providing detailed cross-sectional images of objects and structures. Industrial and assembled products inspected in this context are often composed of several materials and experimental observations usually consist of sparse projections obtained with a fixed X-ray spectrum source. While providing separate density maps for each material or for parts of the object under inspection might be crucial for some applications, it adds to the underdetermination of the reconstruction inverse problem. Traditionally, discrete tomography made CT with joint material segmentation possible at the expense of assuming materials with discrete constant densities. However, in most use cases, density distribution is a quantity of interest. Other reconstruction workflows sequentially carry out reconstruction, post-processing and segmentation as independent tasks. Nevertheless, each step introduces approximations that are not accounted for by subsequent treatments. More recently, a data-driven 'end-to-end' method for task-adapted reconstruction was developed. This framework integrates the reconstruction procedure with the decision-making associated with the task, in this instance, material segmentation. Although this method is more general and provides unrivalled results for vastly fewer angular projections, it requires supervised datasets which: (i) may not be available and (ii) prevent the method to generalize to unknown inspection setups regarding, for instance, spectrum energy or projection angles. To circumvent these obstacles, we apply the recently proposed unsupervised conditional approach, conditioning Generative Latent Optimization (cGLO), which train a decoder network on an unsupervised dataset of segmented multi-material objects. Reconstructions are then performed on experimental measurements with no necessity for a supplementary and acquisition specific supervised dataset. Material segmentation is the result of the correlation between materials learned during the unsupervised training phase. We present results from both simulated and experimental studies that demonstrate the effectiveness of our approach in differentiating and quantifying various materials in multi-material samples. The experimental study involves a challenging high-energy Bremsstrahlung X-ray source encountered in Linear Induction Accelerators (LIA), with strong scatter noise.