Bayesian separation of small and large features for defect detection in CT of subsea pipes.

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Abstract

A non-destructive testing (NDT) application of X-ray computed tomography (CT) is defect detection in multi-layered subsea pipes in operation via 2D cross sectional scans. Detection of a defect and its location and size has associated uncertainties that are sought quantified to support decisions of whether or not to replace the pipe. To allow uncertainty quantification (UQ), we take a Bayesian approach to CT reconstruction and seek to determine the most informative prior. A pipe contains both large-scale structures (the pipe layers) and small-scale structures (defects). We have extensive knowledge of the pipe's internal layer structure and materials, which can be utilized to formulate a very informative prior. On the other hand, the prior must also allow deviations from the expected structure in order for the posterior to represent defects. This makes it challenging to formulate a single prior for the reconstruction.
In this work we propose to separate the reconstruction into a sum of two images; one representing expected, large features and one representing small, unknown features. Doing this allows us to impose a prior representing the well known pipe structure in one image and letting the other image contain any deviations from this. To express that only few and small defects are expected we employ a sparsity prior for the second image. A posterior is formulated w.r.t. both the large- and small-feature images and a Gibbs sampling approach is devised for exploring the posterior. An advantage of the proposed method is that defect detection is embedded in the reconstruction rather than being a post-processing step, which also simplifies UQ related to the defects. We demonstrate the method in numerical experiments and give an example of how to analyze the posterior samples to perform defect detection with UQ.