Zig-Zag Sampling for Bayesian Inference of Material Parameter Fields

Leon Riccius[*], Iuri Rocha, Frans van der Meer

Delft University of Technology
Stevinweg 1, Delft, NL
{l.f.riccius,i.rocha,f.p.vanderMeer}@tudelft.nl

ABSTRACT

A key challenge in structural health monitoring is the inference of material properties from measurements. The challenge is particularly acute for cases that involve spatial distributions of uncertain material parameters. These spatially distributed parameters form a random field with high stochastic dimensionality. Bayesian analysis offers a robust method to infer these parameter distributions. However, its dependence on approximations such as Markov chain Monte Carlo (MCMC) sampling, which require many model evaluations, limits the applicability of Bayesian analysis, especially when the model, e.g. a finite element model, is expensive to evaluate. To address this challenge, we investigate the applicability of the Zig-Zag sampling process, a Markov process-based sampler with linear deterministic dynamics, for inferring material parameter fields from displacements measurements.

In theory, the Zig-Zag process offers excellent mixing and low autocorrelation in high-dimensional parameter spaces. However, its application has been limited to simple distributions due to the need for a global upper bound on the gradient of the posterior, a quantity typically unavailable in non-linear Bayesian inverse problems. To address this, we employ a surrogate model to approximate the posterior gradient, allowing us to globally estimate this upper bound and simulate the process efficiently. The bias introduced by the surrogate model is then alleviated with Poisson thinning of the approximate process.

This study marks the first application of a Markov process sampler to Bayesian inference in computational mechanics, yielding promising results. Our methodology demonstrates that the Zig-Zag sampler outperforms traditional MCMC methods, particularly in terms of full model evaluations needed to reach the same accuracy in the posterior moments. Nonetheless, our findings underscore the challenges introduced by the bias of the surrogate model. We present strategies to reduce the impact of correcting for this bias on the efficiency of the sampler.