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VARIATIONAL BAYESIAN FORMULATIONS WITH SPARSITY-ENFORCING PRIORS FOR MODEL CALIBRATION

Isabell Franck[1] **and Phaedon-Stelios Koutsourelakis**[1]

[1] Continuum Mechanics Group, Technical University of Munich, franck@tum.de, p.s.koutsourelakis@tum.de, www.contmech.tum.de

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Bayesian formulations offer one of the prominent approaches for addressing model calibration and validation. They provide a rich probabilistic framework that can incorporate the unavoidable uncertainties in these problems. Their application in large-scale, computationally-intensive models is hampered by the high dimensionality of unknown model parameters and the high computational cost for inference. The former problem relates to the issue of appropriate prior selection which is especially prominent when the unknown model parameters vary spatially/temporally.

The present paper advocates a Variational Bayesian inference engine that retains the probabilistic characteristics of other Bayesian inference schemes but attempts to approximate the posterior through the solution of an optimization problem [1]. We demonstrate how this can be done in order to accelerate inference by exploiting derivative information available from deterministic adjoint formulations [2]. Furthermore we propose sparsity-enforcing priors that provide a natural regularization suited for spatially-varying model parameters and are capable of automatically identifying subspaces of small dimension for the solution of the inference problem [3]. This is coupled with a novel greedy algorithm for learning the associated basis set which exploits second-order derivatives of the associated log-likelihood [4]. Numerical illustrations are drawn from biomechanics where tissue property identification can lead to or improve medical diagnosis.

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