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Metamodel-based Markov-Chain-Monte-Carlo parameter inversion applied in eddy current flaw characterization

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ABSTRACT

Flaw characterization in eddy current testing usually requires to solve a non-linear inverse problem. Due to high computational cost, Markov Chain Monte Carlo (MCMC) methods are hardly employed since often needing many forward evaluations. However, they have good potential in dealing with complicated forward models and they do not reduce to only providing the parameters sought. Here, we introduce a computationally-cheap surrogate forward model into a MCMC algorithm for eddy current flaw characterization. Due to the use of a database trained off-line, we benefit from the MCMC algorithm for getting more information and we do not suffer from the computational burden. Numerous experiments are carried out to validate the approach. The results include not only the estimated parameters, but also standard deviations, marginal densities and correlation coefficients between two parameters of interest.

1. Introduction

In eddy current flaw characterization, the aim is to extract information about defects possibly found within the inspected part. This information can usually be characterized by several parameters. As an example, a volume crack can be described by length, depth and opening width. Recovering them from observations is an inverse problem with a limited set of unknown parameters, here three. According to the state of art, analytical and statistical solution methods are proposed.

Analytical ones [4,44] address the analytical relation between parameters and measurements and try to inverse it analytically. Yet, they are limited to special cases wherein this relation is simple enough so that analytical inversion is suitable. Furthermore, most are very sensitive to noise, and work only for high (SNR) situations. Statistical ones are popular in parameter inversion because of high inversion accuracy and robustness vs. noise. Yet, what is of the most interest to us here is their ability of managing complicated models. As in the example above, flaw characterization in Eddy Current Testing (ECT) is an inverse problem usually involving a limited number of unknowns [10,16]. However, the problem is still difficult to solve due to the complexity of the forward model which describes the relation between flaw parameters and measurements, nonlinear in most situations.

Statistical methods are usually transformed into an optimization problem solved by a numerical optimization algorithm, as in Refs. [1,14,16,37,47]. Due to the complexity of the problem, statistical methods usually need to overcome two hurdles: high computational cost due to many evaluations of the forward model, non-convex objective function due to nonlinear parameter dependence. Gradient-based algorithms are widely used [1,14,16,37,47]. Yet, to calculate or approximate the gradient subject to the unknown parameters might not always be feasible. Furthermore, they cannot solve the non-convex problem, meaning to be blocked in a local minimum once in it.

Markov Chain Monte Carlo (MCMC) methods [24,31,45] have been used in ECT for Bayesian analysis [19,36]. However, they are not widely used for solving ECT inversion problems because of high computational cost. Though developments have been made in the last two decades to accelerate MCMC algorithms [12,17,23,25], the computational burden remains heavy if willing to apply them directly in ECT.

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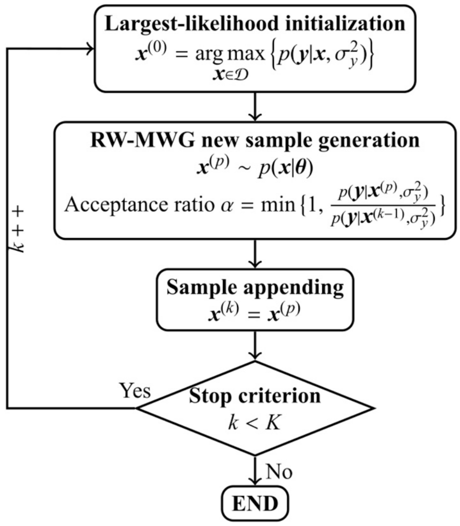

Fig. 1. Implementation of metamodel-based MCMC algorithm for inversion.

We propose a surrogate model based MCMC approach to solve the ECT inverse problem. In this approach, a data-fitting surrogate forward model is introduced into a classical MCMC method where only interpolations are performed to approximate the forward evaluations during a MCMC process, then helping to reduce the computational cost. Since the employed MCMC algorithm is gradient-free and able to leave local minima, this makes it possible to solve non-convex problems. More importantly, by performing Bayesian analysis on MCMC results, it offers more information than the estimated parameters, like variances of estimates, correlation coefficients, and marginal posterior distributions. We describe the forward metamodel in § 2, the MCMC inversion algorithm in § 3, and we provide experimental validations in § 4 and § 5. An Appendix devoted to the forward solever and meatmodel generation follows.

2. Data-fitting metamodel

A general forward model with additive Gaussian noise can be described by

$$\boldsymbol{y} = f(\boldsymbol{x}) + \varepsilon,\ \varepsilon \sim \mathcal{N}\left(0, \sigma_y^2\right), \tag{1}$$

where $\boldsymbol{x} \in \mathbb{R}^N$, $\boldsymbol{y} \in \mathbb{C}^M$ and ε are unknown parameters, observations and noise, resp. N is the number of unknown parameters while M is the total number of measurement points. σ_y^2 is the noise variance of the same size as $\boldsymbol{y}$. $f(\boldsymbol{x})$ is the function that yields the physical relation between $\boldsymbol{x}$ and $\boldsymbol{y}$. Depending upon the configuration of inspection, different methods can be used to get $f(\boldsymbol{x})$. The Method of Moments (MoM) [9,39] is one of the most used.

For statistical parameter inversion, thousands of forward evaluations could be required, hence, in effect overwhelming the algorithm if we employ MoM directly within the inversion. To overcome this problem, data-fitting surrogate models, also called metamodels [7,21,22,30,40], are proposed.

A metamodel includes a database trained off-line, independently from the inversion, and an on-line interpolator, called upon only when a

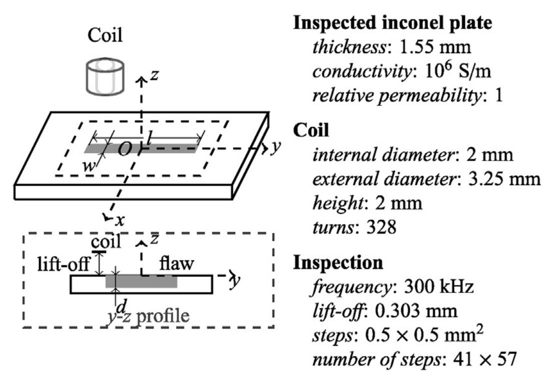

Fig. 3. Sketch of slab flaw inspection problem in 2008 WFNDE eddy current benchmark.

Table 1
WFNDE 2008 eddy current benchmarks.

Flaw	flaw parameters		
	depth d	length l	width w
40I	0.62 (from top)	20	0.11
80I	1.24 (from top)	20	0.14
40E	0.62 (from back)	20	0.11
80E	1.24 (from back)	20	0.14

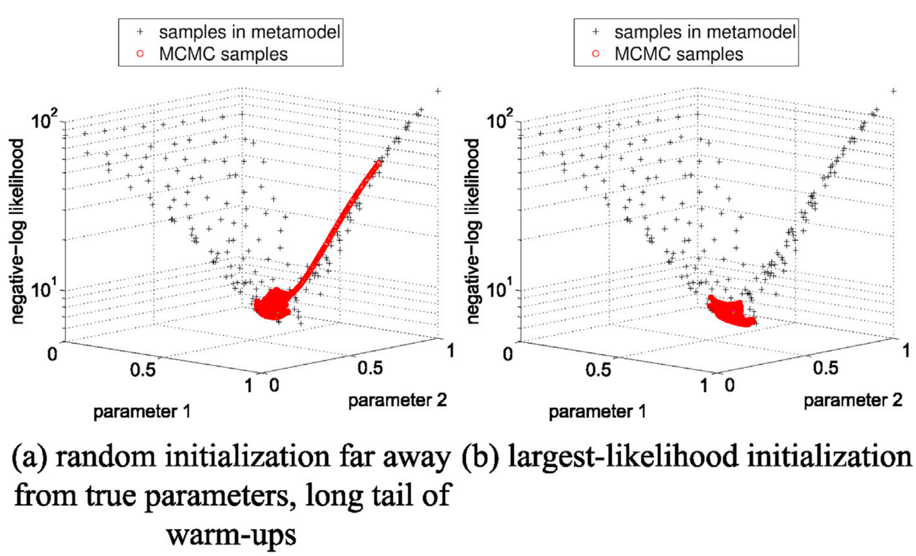

Fig. 2. Comparison between random and largest-likelihood initialization; the true parameters are located within the concave bottom of the negative-log likelihood mesh.