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An efficient adaptive database sampling strategy with applications to eddy current signals

R. Miorelli*, X. Artusi, C. Reboud

Département Imagerie Simulation pour le Contrôle, CEA, LIST, Gif-sur-Yvette 91191, France

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ABSTRACT

Computer simulations are widely used in engineering domains to model complex scenarios and extract meaningful information or improve the understanding of a given problem. Common purposes of simulation studies are inversion, optimization, sensitivity analysis and evaluation of performance. In such contexts, it is often convenient to replace the time consuming forward solver by a metamodel acting as a fast and accurate substitute in a restricted range of input parameters. Focused on applications in the field of Electromagnetic-Non Destructive Testing (E-NDT), this paper proposes an approach to design robust metamodels, based on adaptive databases of simulation results in order to ensure their accuracy. They can then be used as real-time emulators of the physical model and considerably speed up time consuming studies like estimation of probability of detection, defect characterization or sensitivity analysis. The database and metamodel generation problem is first addressed with a meshless approach based on Augmented Radial Basis Function (A-RBF) algorithm. Then, its performance is compared with that of a more standard approach exploiting a n-dimensional Delaunay mesh. Both approaches rely on an adaptive generation technique known in the literature as Output Space Filling (OSF). Performance in terms of computational time and results accuracy of both methods are finally evaluated and compared in the case of a specific application: the simulation of Eddy Current Testing (ECT) inspection problems.

1. Introduction

In the field of Non Destructive Testing & Evaluation (NDT&E), physical models are commonly used by engineers in order to better understand experimental signals, design components, or evaluate the performance of inspection procedures. In the last two decades, numerical simulation tools have widely spread in the community. As a consequence, new kinds of NDT&E studies, which largely employ numerical simulations have been popularized. Among them, one can cite the Model Assisted Probability Of Detection (MAPOD) [1], Sensitivity Analysis (SA) and defect characterization through parametric inversion. A common characteristic of such studies is the necessity of a large amount of information, implying the computation of many simulated signals (up to several tenths of thousands). Such a large number of simulations makes solution of problems too time consuming when using the models directly. In order to overcome this issue, some research has been focused on finding an efficient and general replacement of standard forward solvers [2–5], consisting in a regression over a database of simulation results built in a restricted range of input parameters. In a first step, also known as off-line phase, this database

* Corresponding author.
E-mail address: roberto.miorelli@cea.fr (R. Miorelli).

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is adaptively built in order to maximize the fidelity of its associated interpolator (called metamodel), and used to generate signals in almost real time in the second step (the on-line phase).

1.1. Adaptive database generation using kernel-based methods

Kernel-based database generation has recently been applied with success in the field of NDT. In [6], a Radial Basis Function (RBF) interpolator over an adaptively filled database of simulation results has been proposed. The sampling strategy implemented implicitly relies on a fictitious mesh (even if the RBF interpolator is, in principle, designed to be a meshless approach). To adaptively build the database, both the RBF metamodel and the physical model were evaluated at the center of the edges of the Delaunay mesh connecting the existing points together. Then, new points, for which a significant discrepancy between model and metamodel is observed, are added to the database. In spite of the good performance in terms of robustness and accuracy, the approach badly scaled with respect to the size of the input space. Indeed, the physical solver needed to be called many times all over the mesh to possibly add a small amount of points, thus the database generation could rapidly “explode” in terms of computation time. It is worth mentioning that in [6] an inversion procedure based on particle swarm optimization has been also proposed and tested on a three-dimensional database. An alternative and actually very effective way to tackle the sampling problem was proposed in [7,8]. In these works, a new sampling strategy, called Output Space Filling (OSF), has been associated to a functional Ordinary Kriging (OK) interpolator. The principle of OSF is to regularly distribute signals in the database, with respect to their variations, which is measured with a distance (or dissimilarity) indicator between them. Sampled points locations in the output space thus tend to be evenly spread with respect to this distance, which definition is a key stone of the method and depends on the nature of the signals at hand.

This OSF-Ordinary Kriging (OSF–OK) scheme has achieved a high interpolation accuracy. Furthermore, good parsimony in terms of number of sampling points needed to build the database, has been observed compared to the previous sampling scheme. Moreover, it was shown in [7] that OK can be used to solve inverse problems, too. Unfortunately, due to the mathematical structure of its kernel, which involves the calculation of a covariance matrix based on a Matérn function [7], this interpolator can be costly to setup from a large amount of samples. For Eddy Current Testing (ECT) applications, in the authors’ experience, the generation procedure becomes very difficult when the number of samples exceeds two thousands. In typical ECT problems, limitation makes OK not suitable for generating ECT signal databases when the input space exceeds about six dimensions [9].

1.2. Adaptive database generation using a Delaunay mesh

Beside kernel-based methods, a completely different approach of database generation, using a meshing strategy, has recently been proposed [10,11]. Two kinds of adaptive sampling strategies through mesh refinement and piecewise constant and piecewise linear interpolation have been proposed, respectively. In [12] an OSF-based n-dimensional Delaunay mesh and a linear interpolator have been employed for database generation, the obtained metamodel being dedicated to parametric inversion based on quadratic programming. Generally speaking, the main drawbacks of the mesh-based approach are related to the fact that a refinement of a mesh in a n-dimensional parameter space can be neither trivial nor very fast to perform. Indeed, database refinement in an input space with more than six dimensions, can easily turn into a very cumbersome and time consuming task when the number of samples increases.

1.3. Paper scope and structure

In this paper, the physical model of interest is used to simulate eddy current testing (ECT) signals, consisting of a set of coil impedance variations or voltage with respect to the probe scan over the inspected material. The stored signal is thus a collection of complex values (up to several thousands when considering 2D maps). Due to the vector or matrix nature of the ECT signals, in the following we explicitly intend sampling strategies able to deal with functional outputs (i.e., vector output). The algorithms presented here apply of course to real valued signals and scalar outputs, too.

The paper is organized as follows. In the first part, the OSF sampling paradigm is jointly applied with an Augmented-RBF (A-RBF) interpolation [13,14]. Then, a slightly modified OSF sampling technique, compared to [12], has been developed for the Delaunay mesh-based strategy. The modified approach considerably speeds up the database generation process for large input space dimensions without deteriorating, in an appreciable way, the metamodel accuracy. The two proposed solutions have been applied to database generation on realistic test cases. The first case is associated to the nuclear domain with steam generator tube inspection and the second one to the aeronautic domain with the inspection of planar multilayered structures. In order to show the robustness of the proposed sampling strategy, six- and eight- dimensions databases have been generated for nuclear-related and aeronautic-related test case, respectively. In order to assess the quality of the generated database and thus the associated metamodel results, a Cross Validation (CV) procedure has been carried out. Furthermore, through error analysis of CV results we show how one can employ those data in order to retrieve “for free” meaningful meta-information on the metamodel prediction accuracy. The last part of this paper discusses the obtained results with a highlight on respective advantages and drawbacks of both methods, introducing additional developments that can be envisaged in perspective of this work.