Simulation Modelling Practice and Theory 87 (2018) 35–47

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

Introduction of physical knowledge in kriging-based meta-modelling approaches applied to Non-Destructive Testing simulations

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ARTICLE INFO

Keywords:
Ultrasound NDT
Surrogate model
Meta-model
Kriging
Dimension reduction
Space warping
Real-time realistic simulation

ABSTRACT

In this paper, we propose a new way to introduce physical knowledge into the kriging method to improve regression accuracy and obtain real-time realistic simulations. Our technique incorporates a coarse physical model into the correlation function by spatial warping. Tested in the context of the simulation of temporal ultrasonic signals for Non-Destructive Testing (NDT) applications, the obtained results are more accurate than ordinary kriging especially for small datasets. Integrating a physical model also makes the resulting meta-model more generic: using physics, more system use cases are covered without increasing the data requirements. Eventually, applied in the case of noisy experimental data, our enhanced kriging can be tuned to split the deterministic content from the random output fluctuations. As a result, the meta-model can be established directly on real measurements to get a higher degree of realism.

1. Introduction

Numerous physical experiments are expensive to set up and tend to be replaced by computer simulations. Yet, getting an equivalent accuracy requires computationally expensive models. Meta-models bring a solution: from some complex simulation results, a mathematical approximation is estimated and can be used intensively. The regression process is only based on the known system outputs and does not take into account the underlying physics. This paper focuses on kriging — a widespread regression technique — and proposes a method to enhance the regression using physical knowledge.

Different techniques have been developed to take advantage of additional physical information on the system in meta-modelling frameworks. When a closed form of the system behaviour is known, a parametric regression is conducted to determine the unknown parameters. For instance, if a linear dependence among some explanatory variables is advocated, the meta-model will be based on a polynomial regression. When the system behaviour is not explicitly known, such techniques are not suitable due to the lack of accurate a priori knowledge about the output function.

A more flexible regression framework is offered by the non-parametric techniques such as the simple [1] or the ordinary [2] kriging techniques. As is, kriging meta-models give accurate results in numerous cases. However, physical knowledge can enhance the results. A first approach is derived from the parametric regressions: when the system mean can be explained, the universal kriging technique takes into account this knowledge. The idea is to apply a parametric approach on the system mean output and the non-

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https://doi.org/10.1016/j.simpat.2018.05.011
Received 31 December 2017; Received in revised form 30 April 2018; Accepted 22 May 2018
Available online 23 May 2018

parametric approach only on the unexplained residue. In case of unknown system mean output, additional information might still be available. The co-kriging is then a solution.The co-kriging output is a combination of the known system output plus a secondary variable known to be correlated to the primary one. Initially developed to improve geophysical predictions by coupling different ore concentrations [3], this method can be extended to surrogate modelling. For instance, the gradient of the system output is sometimes available and can be used as a secondary variable. By combining several explanatory variables, co-kriging involves large matrices which make computations more cumbersome [4]. Tweaking meta-models to incorporate various additional knowledge is also explored in the community of variable fidelity models. In this research field, the system is simulated by two approaches: a High Fidelity (HF) model, precise but time-consuming, and a Low Fidelity (LF) model, coarse but computationally light. The developed techniques seek to enhance the LF model with the HF model to get accurate and fast computations. Different strategies can be followed to correct the model either internally or externally [5]. The internal correction consists in multiplicative or additive terms which are applied on the LF model inputs to get LF output closer to the HF behaviour. From linear space mapping to neural space mapping, the transformation of the input space can be of various complexity [6]. The external correction consists in multiplicative or additive terms which are applied on the LF model output. External corrections are namely used in the manifold mapping technique [7], an efficient meta-model able to speed up complex design optimisations. As noted and addressed in [5], some physical properties might be destroyed by fitting a correction term on the output, i.e. after the simulation process. The variable fidelity model community also makes use of kriging techniques for instance in the space mapping strategy of [8] or in the co-kriging approach of multi-fidelity gradient enhanced kriging [9].

In this paper, we are investigating a physically enhanced kriging approach able to produce a real-time realistic output. To meet the time constraints, the physical knowledge is injected into the kriging not through an enrichment of the database — which would entail computations on larger matrices — but through a correction of the correlation function. The proposed correction is designed to cope with partial physical models by balancing the use of physical knowledge and ordinary kriging. Even if the model is not able to properly simulate the system output, it can still help the regression process by delivering information on the correlation structure of the underlying physical process. The advantages brought by the introduction of physics make then possible to train the model directly on real data and, thus, to reach a higher degree of realism. This technique is illustrated in the context of the simulation of ultrasonic Non-Destructive Testing (NDT) signals, application which has motivated this work.

NDT techniques aim at assessing the integrity of industrial parts and structures. In this context, simulations are extensively used and, since recently, meta-modeling frameworks are explored namely to reduce computation times of design optimisations or inversion problems [10,11]. Up to now, most efforts have been made on the eddy current testing method. This electromagnetic technique measures the complex impedance of the inspected materials. The output of the resulting meta-model is then a map of scalar quantities. Several groups have tested different approaches: kriging [12], radial basis functions [13], sparse grid surrogate [14], support vector machine [15]. The case of ultrasonic NDT techniques is more difficult since the output of the measurements is a high frequency waveform: electromagnetic NDT essentially works with a scalar output whereas ultrasound NDT deals with vectorial output. In most meta-modelling techniques, vectorial output systems are seen as several independant scalar output systems and the resulting vectorial meta-model is equivalent to several independant scalar meta-models [16]. A waveforms dimension reduction technique is proposed in this work to limit the final number of meta-models and obtain fast computations. Our simulation requirements are driven by the concept of operational NDT simulation [17]: real signals are replaced by simulated ones, namely to train operators without manufacturing expensive real flawed parts. Interested readers may refer to [18] for more details. In this context, the simulation must deliver realistic signals at a high rate, justifying the need for meta-models.

In Section 2, we describe the studied physical system, namely the inspection of a composite structure containing a Flat Bottom Hole (FBH) defect. A very basic physical approximation is proposed and, in Section 3, the method to integrate it into the kriging approach is explained. Section 4 describes the three main advantages of the proposed approach which enable to leverage real data: lighter databases, more generic meta-models, capacity to process noisy data. Eventually, a discussion and conclusion on the physically enhanced kriging method are given.

2. Physics of the studied system

2.1. System description

In order to build a meta-model of the NDT inspection, its inputs and outputs must be identified. An ultrasound NDT inspection is performed with a piezo-electric actuator and sensor: an ultrasound wave is generated, propagates into the material and bounces back if an interface hinders the wave propagation. Like a sonar system, the analysis of the returned energy gives an image of the material internal structure. The fundamental ultrasound signal is therefore the surface displacement evolution over time, i.e. a waveform made of different echoes. The Front Wall Echo (FWE) corresponds to the wave entering the material, the Back-Wall Echo (BWE) is due to the back of the structure. Any echoes in-between the FWE and the BWE may reveal the presence of a flaw. Fig. 1 shows the simplified inspection set-up taken as case-study in this paper: a composite block containing a Flat Bottom Hole (FBH). FBHs are used in the aeronautic industry as calibrated reference defects. So, for this particular case of NDT inspection, the *inputs* of the system are e the part thickness, ϕ the Flat Bottom Hole diameter, d the flaw depth and (p_x, p_y) the probe position. The *output* is the waveform — called an *A-scan* and represented by a vector made of all time samples — measured in these conditions.