Simulation Modelling Practice and Theory 81 (2018) 64–84

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

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

A space mapping method based on Gaussian process model for variable fidelity metamodeling

Ping Jiang, Tingli Xie, Qi Zhou*, Xinyu Shao, Jiexiang Hu, Longchao Cao

The State Key Laboratory of Digital Manufacturing Equipment and Technology, School of Mechanical Science and Engineering, Huazhong University of Science & Technology, Wuhan, 430074 PR China

ARTICLE INFO

Article history:
Received 22 March 2017
Revised 29 November 2017
Accepted 30 November 2017

Keywords:
Gaussian process model
Simulation-based design
Space mapping
Variable fidelity
Metamodel

ABSTRACT

Computational simulation models with different fidelities are usually available in the design of engineering products for obtaining the quantity of interest (QOI). To integrate and fully exploit variable fidelity information, a space mapping based variable-fidelity metamodeling (VFM) approach is developed in this work. Firstly, a Gaussian process (GP) model is constructed for the low-fidelity (LF) model. Secondly, a variable-fidelity metamodel is constructed by taking the predicted information from this GP model as a prior-knowledge of the QOI and directly mapped into the outputs space of the high-fidelity (HF) model. This space mapping process is performed by constructing another GP model. A mathematic example is first adopted for illustrating how the proposed approach works under different sample sizes and sample noises. Then, the proposed approach is applied to two real-life cases, modeling of the maximum stress for the structure of a Small Waterplane Area Twin Hull (SWATH) catamaran and predicting weld geometry in fiber laser keyhole welding, to illustrate its ability in support of complex engineering design.

1. Introduction

Gaussian process (GP) model has been wildly used to formulate a Bayesian framework for emulating various forms of functions, especially for expensive simulations or physical experiments [1–3]. In the GP modeling process, designers need to choose models with different fidelities to obtain the quantity of interest (QOI). Taking the airfoil design of aerodynamic component as an example, to obtain the aerodynamic coefficients, the available simulation models can differ in terms of the resolutions (e.g. coarse mesh versus refined mesh in finite element models); levels of abstraction (e.g. two-dimensional, (2D), versus three-dimensional, (3D), models) or mathematical descriptions (e.g. the Euler non-cohesive equations versus the Navier–Stokes viscous Newton equations). Generally, high-fidelity (HF) model can provide a more reliable result. However, entirely relying on it to simulate the QOI in building GP metamodel (regression) always tends to be a time-consuming or even computationally prohibitive process. On the other hand, low fidelity (LF) model is considerably less computationally demanding, however, the obtained simulation data may result in inaccurate GP metamodel or even distorted ones.

A promising way to make a trade-off between the prediction accuracy and computational cost is to integrate the information from both HF and LF models by constructing a variable fidelity (VF) metamodel [4–6]. The core idea of the variable fidelity metamodeling (VFM) approaches is that lots of LF simulations are evaluated to provide a general trend of the behavior of HF models, while a small size of HF experiments are used to guarantee the accuracy of the prediction in important

* Corresponding author
E-mail addresses: qizhouhust@gmail.com, qi.zhou@me.gatech.edu (Q. Zhou).

https://doi.org/10.1016/j.simpat.2017.11.010

regions [7,8]. The most widely used VFM approaches are scaling function based approaches. The scaling function based VFM approaches can be divided into three distinct types. First, in the multiplicative scaling approach, a scaling function is constructed to depict the ratio between the HF and LF models. Liu et al. [9] built a VF metamodel by adopting a GP metamodel as a multiplicative scaling function to correct the LF model. An application of this method was tested on a structure optimization of a tee-stiffened panel. Sun et al. [10] adopted a multiplicative scaling function to calibrate the information from LF model according to data from HF model in the design of honeycomb structures. Second, in the additive scaling approach, a scaling function is constructed to capture the differences between the HF and LF models. Gano et al. [11] constructed a GP metamodel to replace the traditional Taylor series response surface models for bridging the difference between the LF and HF models. Zhou et al. [12] put forward an active-learning VFM approach by sequentially reducing the uncertainty of the GP metamodel. This approach was successfully applied in the design of a long cylinder pressure vessel for compressed natural gas. Lastly, in the hybrid scaling approach, scaling functions are constructed to utilize the advantages of both multiplicative and additive scaling approaches. Gano et al. [13] put forward an adaptive hybrid scaling approach that combines the additive and multiplicative functions for VFM and have successfully applied this method in an energy-efficient-transport high-lift airfoil design problem. Xiong et al. [14] proposed a hybrid model fusion approach based on the Bayesian–Gaussian process modeling and combined it with an objective-oriented sequential sampling for assisting engineering design.

Generally, these scaling function based VFM approaches can be applied to both local and global metamodeling to generate an approximation function. However, because the scaling process is a multi-dimensional space to one-dimensional space mapping, preliminary efforts have demonstrated that when compared with the single high-fidelity metamodel under a small amount of high-fidelity data, they can only be expected to obtain a significantly higher accuracy metamodel for problems with a simple relationship between the design variables and the different response features of HF and LF models [15].

To address this issue, a space mapping approach based on Gaussian process model for variable-fidelity metamodeling (SM-VFM) is proposed in this work. In the proposed SM-VFM approach, a GP model is built for the LF model as a start. Then, the output from the constructed GP model is taken as a prior-knowledge and directly mapped into the output space of the studied HF model by constructing another GP model. Therefore, the multiple-to-one dimensional mapping process owned by scaling function based VFM approaches is transformed into a one-to-one dimensional space mapping process. The prediction performance of the proposed SM-VFM approach is compared with other three scaling function based VFM approaches via three numerical examples and two real-life cases. The effectiveness and metrics of SM-VFM approach are analyzed and summarized.

The remainder of this work is organized as follows. Section 2 presents a brief review of scaling function based VFM approaches. Section 3 gives the details of the proposed SM-VFM approach. Section 4 presents five demonstration examples, including three numerical examples with two design parameters, modeling of the maximum stress for the structure of a SWATH catamaran, and predicting weld geometry in fiber laser keyhole welding. Finally, Section 5 gives a summary of this work.

2. Review of scaling function based variable-fidelity metamodeling approaches

The difference between each scaling function based variable-fidelity metamodeling approach is how to calibrate the LF model according to the information of HF model at a suitable size of HF experiments. Suppose the available LF and HF information is

$$\boldsymbol{X}^l = \left\{\boldsymbol{x}_1^l, \boldsymbol{x}_2^l, \ldots, \boldsymbol{x}_N^l\right\}, \quad \boldsymbol{f}^l = \left\{f_1^l, f_2^l, \ldots, f_N^l\right\} \tag{1}$$

$$\boldsymbol{X}^h = \left\{\boldsymbol{x}_1^h, \boldsymbol{x}_2^h, \ldots, \boldsymbol{x}_M^h\right\}, \quad \boldsymbol{f}^h = \left\{f_1^h, f_2^h, \ldots, f_M^h\right\} \tag{2}$$

where $\boldsymbol{X}^l = \{\boldsymbol{x}_1^l, \boldsymbol{x}_2^l, \ldots, \boldsymbol{x}_N^l\}$ is the LF sampling set with N as the numbers of samples, $\boldsymbol{f}^l = \{f_1^l, f_2^l, \ldots, f_N^l\}$ is the corresponding LF response, $\boldsymbol{X}^h = \{\boldsymbol{x}_1^h, \boldsymbol{x}_2^h, \ldots, \boldsymbol{x}_M^h\}$ is the HF sampling set with M as the numbers of samples, $\boldsymbol{f}^h = \{f_1^h, f_2^h, \ldots, f_M^h\}$ is the corresponding HF responses.

Three commonly scaling function based variable-fidelity metamodeling approaches are described as below. More details can be found in Ref. [16,17].

a) Multiplicative scaling function based VFM method

Multiplicative scaling function based VFM method (MS-VFM) was first put forward by Haftka [18]. In MS-VFM, the scaling factor l_i is defined as the ratio between the responses from HF and LF models at HF sample point $\boldsymbol{x}_i^h$

$$l_i(\boldsymbol{x}_i^h) = \frac{f^h(\boldsymbol{x}_i^h)}{\hat{f}^l(\boldsymbol{x}_i^h)} \tag{3}$$

where $l_i(\boldsymbol{x}_i^h)$ is the scaling factor, $f^h(\boldsymbol{x}_i^h)$ is the response value at $\boldsymbol{x}_i^h$ from HF model, $\hat{f}^l(\boldsymbol{x}_i^h)$ is the predicted response value at $\boldsymbol{x}_i^h$ from LF metamodel.