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An adaptive global variable fidelity metamodeling strategy using a support vector regression based scaling function

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A B S T R A C T

Computational simulation models with variable fidelity have been widely used in complex systems design. However, running the most accurate simulation models tends to be very time-consuming and can therefore only be used sporadically, while incorporating less accurate, inexpensive models into the design process may result in inaccurate design alternatives. To make a trade-off between high accuracy and low expense, variable fidelity (VF) metamodeling approaches that aim to integrate information from both low-fidelity (LF) and high-fidelity (HF) models have gained increasing popularity. In this paper, an adaptive global VF metamodeling approach named difference adaptive decreasing variable-fidelity metamodeling (DAD-VFM) is proposed, in which the one-shot VF metamodeling process is transformed into an iterative process to utilize the already-acquired information of difference characteristics between the HF and LF models. In DAD-VFM, support vector regression (SVR) is adopted to map the difference between the HF and LF models. Besides, a generalized objective-oriented sampling strategy is introduced to adaptively probe and sample more points in the interesting regions where the differences between the HF and LF models are multi-model, non-smooth and have abrupt changes. Several numerical cases and a long cylinder pressure vessel optimization design problem verify the applicability of the proposed VF metamodeling approach.

1. Introduction

For complex system design, deterministic computer simulations are often used to replace the computation-intensive and controlled real-life experiments. However, running simulations for a complex system with multiple inputs and outputs can become computationally prohibitive as is the case of computational fluid dynamics (CFD) and finite element analysis (FEA). For example, it is reported that it takes Ford Motor Company about 36–160 h to run one crash simulation for a full passenger car [1]. Indeed, it is still impractical to directly use these simulations with an optimizer to evaluate a lot of design alternatives when exploring the design space for an optimum [2]. This limitation can be addressed by adopting global metamodel (or surrogate), which can mimic the original system at a considerably reduced computational cost [3]. There are a lot of

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commonly used metamodels, such as Polynomial Response Surface (PRS) models [4], Kriging [5], Artificial Neural Networks (ANN) [6], Radial Basis Functions (RBF) [7], Moving Least Squares Method (MLSM) [8], and Support Vector Regression (SVR) [9]. A more detailed overview on various metamodeling techniques can refer to Wang and Shan [10]. It is important to point out that the quality of the metamodels has a profound impact on the computational cost and convergence characteristics of the metamodel-based design optimization. The quality of the metamodel directly depends on the sample points at which the computer simulation or physical experiments are conducted. Generally, more sample points offer more information of the system, however, at a higher cost [11]. While less sample points require lower expense, leading to inaccurate metamodels even distorted metamodels. Hence, conflict between high accuracy and low expense seems to be inevitable in building metamodels.

To ease this problem, variable-fidelity (VF) metamodeling approaches based on the interaction of high-fidelity (HF) and low-fidelity (LF) models have been widespread concerned [12]. A HF model is one that is able to accurately describe the physical features of the system but with an unaffordable computational expense, e.g., physical experiment, finite element, computational fluid dynamics, etc. A LF model is one that is able to reflect the most prominent characteristics of the system at a considerably less computationally demanding, e.g., numerical empirical formula. Commonly used VF metamodeling approaches are scaling methods, which calibrate the LF model according to the response values of the HF model. These scaling methods can be divided into two distinct types: local VF modeling approaches and global VF modeling approaches. In local VF modeling approaches, the scaling function is approximated using local metamodels, e.g., linear regression [13], first/second Taylor series [14–16]. The main shortcoming of these approaches is that they are only suitable for local optimization problems [17–19]. While in global VF modeling approaches, the scaling function is approximated using global metamodels, e.g., Kriging scaling methods [20–22], RBF scaling methods [23–25] and Bayesian–Gaussian scaling methods [19,26–28]. Since global VF modeling approaches can mimic the behavior of the system on the entire domain and cope with multiple optimum problems sophisticatedly, there has been widespread concern about these approaches [12,29]. Until now, more researches have been carried out to develop new types of LF model tuning that will further improve the accuracy and reduce the computational effort of VF metamodel modeling, but little attention has been paid to utilize the already-acquired information of difference characteristics between the HF models and LF models during the tuning process. In other words, how to appropriately arrange and make full use of the sample points for HF models to run simulations according to the already-acquired difference information between the HF and LF models during the tuning process should be drawn more attention, especially when the computational cost is limited.

In this paper, an adaptive global variable fidelity metamodeling strategy using a support vector regression (SVR) based scaling function, named difference adaptive decreasing variable-fidelity metamodeling (DAD-VFM), is proposed. In DAD-VFM, SVR with its outstanding generalization performance is adopted to map the difference between the HF and LF models on the entire domain. Besides, a generalized objective-oriented sampling strategy, which can make a trade-off between exploration and exploitation by analyzing data (metamodels and sample points) from previous iterations, is introduced to adaptively select sample points during VF metamodeling process. The approximation performance of DAD-VFM approach is illustrated using some mathematical and engineering cases and a rough comparison of DAD-VFM approach with other metamodeling techniques is made. It is expected that more accurate VF metamodels can be developed with DAD-VFM for the same number of simulation evaluations.

The remainder of this paper is organized as follows. In Section 2, the background and several definitions used in this work are put forward. Details of the proposed approach are presented in Section 3. Several numerical examples and an engineering example are given in Section 4 to demonstrate the applicability of the proposed approach, followed by a conclusion and future work in Section 5.

2. Background and terminology

In this section, we provide the background and related terminology to the proposed approach, including: SVR, VF metamodeling, difference unstable region (DUR).

2.1. Support vector regression

Support Vector Regression (SVR) is derived from the theory of support vector machines (SVM), but it adds the capability to appropriate black box functions. Commonly used SVR is ε-SVR which aims to find a function that has at most ε deviation from the targets of the training inputs [30]. For the linear regression case, ε-SVR can be depicted as:

$$\widehat{f}(\boldsymbol{x}) = \langle \boldsymbol{w} \cdot \boldsymbol{x} \rangle + b \tag{1}$$

where $\langle \boldsymbol{w} \cdot \boldsymbol{x} \rangle$ is the dot product between $\boldsymbol{w}$ and $\boldsymbol{x}$. Another aim of SVR is to make the $\widehat{f}(\boldsymbol{x})$ to be as flat as possible. Flatness in this sense means a small $\boldsymbol{w}$ in Eq. (1). Hence, we solve the optimization problem described in the following equation:

$$\begin{aligned} \min \quad & \tfrac{1}{2}|\boldsymbol{w}|^2 \\ \text{s.t.} \quad & y_i - \langle \boldsymbol{w} \cdot \boldsymbol{x}_i \rangle - b \leqslant \varepsilon \\ & \langle \boldsymbol{w} \cdot \boldsymbol{x}_i \rangle + b - y_i \leqslant \varepsilon \end{aligned} \tag{2}$$