Contents lists available at ScienceDirect

Advanced Engineering Informatics

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

A variable fidelity information fusion method based on radial basis function

Qi Zhou^{a,b}, Ping Jiang^{a,*}, Xinyu Shao^a, Jiexiang Hu^a, Longchao Cao^a, Li Wan^c

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

^b George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA

^c National CAD Supported Software Engineering Centre in Huazhong University of Science and Technology, Wuhan 430074, Hubei, PR China

ARTICLE INFO

Article history: Received 6 September 2016 Received in revised form 21 November 2016 Accepted 16 December 2016

Keywords: Variable fidelity Information fusion Radial basis function Simulation-based design Metamodel

ABSTRACT

Radial basis function (RBF) model has been widely used in complex engineering design process to replace the computational-intensive simulation models. This paper proposes a variable-fidelity metamodeling (VFM) approach based on RBF, in which different levels fidelity information can be integrated and fully exploited. In the proposed VFM approach, a RBF metamodel is constructed for the low-fidelity (LF) model as a start. Then by taking the constructed LF metamodel as a prior-knowledge and mapping the output space of the LF metamodel to that of the studied high-fidelity (HF) model, a variable fidelity (VF) metamodel is created to approximate the relationships between the design variables and corresponding output responses. A numerical illustrative example is adopted to make a detailed comparison between the VFM approach developed in this research and three existing scaling function based VFM approach outperforms the scaling function based VFM approaches both in global and local accuracy. Then the proposed VFM approach is applied to two engineering problems, modeling aerodynamic data for a three-dimensional aircraft and the prediction of weld bead profile in laser welding, to illustrate its ability in support of complex engineering design.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Computational simulation models have been wildly used in engineering design to replace the real-life experiments for the sake of shortening the product developing cycle and cutting down the design cost. However it is still impractical to rely exclusively on high fidelity computational simulations during the product design and optimization process, even though the computer capability and speed have shown sustained growth [1,2]. Just taking Ford Motor Company as an example, it is reported that the simulation cost of one crash for a full passenger car is about 36–160 h [3]. A widely used strategy to address this limitation is to adopt metamodel (or surrogate), which can mimic the original system at a considerably reduced computational cost, replacing the computational-expensive simulation models during the product design process [4]. There are many metamodeling techniques have been reported in support of engineering design, e.g., Kriging [5], Radial basis function (RBF) [6,7], Polynomial response surface

model (PRSM) [8], Multivariate adaptive regression splines (MARS) [9], and Support Vector Regression (SVR) [10]. A more detailed overview on various metamodeling techniques can refer to Ref. [4]. Among these metamodeling techniques, RBF is reported to be one of the most suitable approaches in approximating multidimensional and nonlinear problems [11–14], e.g., [in et al. [11] compared the prediction performance of PRSM, MARS, RBF and Kriging based on multiple evaluation criteria using fourteen test problems representing different classes of problems, concluding that RBF performed best in terms of accuracy and robustness among the four metamodeling techniques both under large-scale and small-scale problems. Elsayed et al. [14] performed a comparison between RBF and Kriging, showing that RBF has a higher prediction ability for multi-dimensional problems and requires less computational time for metamodeling. However, there exists a conflict between high accuracy and low expense in the metamodeling process, i.e., running the high-fidelity (HF) models to obtain the information of metamodeling tends to be very timeconsuming, while only relying on the low fidelity (LF), inexpensive models may result in inaccurate even distorted metamodels.







To ease this problem, variable-fidelity metamodeling (VFM) approaches, which aim to integrate different-levels fidelities information for constructing a variable-fidelity (VF) metamodel, has received widespread attention [15–17]. The core idea of the VFM approaches is that the low-fidelity model is adopted to provide an overall trend of the characteristics of system, while a handful of HF sample information is used to guarantee its prediction [18]. The most popular used VFM approaches are scaling function based approaches which can be divided into three types:

- (1) Multiplicative scaling approach: In multiplicative scaling approach, a scaling function is constructed to depict the ratio between the HF and LF model [19–21], e.g., Chang et al. [19] used a linearly multiplicative scaling factor to correct the response values of LF model to match the HF model. An application of this approach was tested on a wing-box model of a high-speed civil transport; Liu et al. [20] adopted a Gaussian process model as a multiplicative scaling factor to bridge the gaps between the LF and HF models.
- (2) Additive scaling approach: In additive scaling approach, a scaling function is constructed to depict the differences between the HF and LF models [22–25], e.g., Sun et al. [23] integrated the LF solver with a additive scaling function for optimizing sheet metal forming; Tyan et al. [24] adopted RBF metamodel as the scaling function to calibrate the difference between LF and HF models and applied it for the design optimization of transonic and subsonic aerofoils.
- (3) Hybrid scaling approach: In hybrid scaling approach, scaling functions are constructed to make use of the advantages of both multiplicative scaling approach and additive scaling approach [26–28], e.g., Zheng et al. [27] proposed a hybrid VF global metamodeling method, in which a RBF base model and a Gaussian process model correction were combined to make full use of LF and HF information; Gano et al. [26] proposed an adaptive hybrid method that combines the additive and multiplicative approaches so that the designer does not have to determine which is more suitable prior to optimization.

Generally, these three types of scaling function based VFM approaches can be used both in local and global metamodeling scenario, depending on the forms of the selected scaling functions. However, preliminary efforts have demonstrated that due to a multi-dimensional space to one-dimensional space mapping process these scaling function based VFM approaches work, when compared with the single high-fidelity metamodel under a small amount of high-fidelity data [29], they can only be expected to obtain a significant higher accuracy prediction value for problems with a simple relationship between the design variables and the difference response features of HF and LF models.

In this work, a variable-fidelity metamodeling (VFM) approach based on low-fidelity output space mapping (OSM-VFM) through RBF is developed for integrating information from different levels of fidelity models. The goal of the proposed OSM-VFM is to address the limitations of the scaling function based VFM approaches by taking the low-fidelity output values as a prior-knowledge of the studied system and directly mapping it to the high-fidelity model. The approximation performance of OSM-VFM approach is demonstrated using one mathematical and two engineering cases, and a comparison of OSM-VFM approach and other three types of scaling function based VFM approaches for prediction accuracy are made. The main advantages of OSM-VFM approach in support of simulation-based design are analyzed and summarized.

The remainder of this paper is organized as follows. In Section 2, the backgrounds of the scaling function based VFM approaches are provided. Details of the proposed OSM-VFM approach are

presented in Section 3. One numerical and two engineering cases with different degrees of difficulty and comparison results are presented in Section 4, followed by a summary of this research and future work in Section 5.

2. Backgrounds

In this section, some backgrounds of the scaling function based VFM approaches are presented.

2.1. Scaling function based VFM approaches

In the VFM approach, there is an important assumption: apart from a HF model which is sufficiently accurate but requires expensive computational cost, there is another one that is able to reflect the most prominent characteristics of the system at a considerably less computationally demanding [16,30]. Three commonly ways of obtaining a LF models, summarized in our previous work [1], are as follows: (a) simplifying the analysis model (e.g. by using a coarse finite element mesh instead of a refined finite element mesh, etc.), (b) simplifying the modeling concept (e.g. by using a twodimensional (2D) model instead of a three-dimensional (3D) model), (c) simplifying the mathematical or physical description (e.g. by using the Euler non-cohesive equations instead of the Navier-Stokes viscous Newton equations). In the VFM process, a LF model is calibrated using the HF model responses from a suitable size of design experiments. In this way, the VFM can make use of the advantages of both LF and HF models, i.e., LF models are used to reduce the computational cost, while HF models are used to guarantee the accuracy. Three scaling function types are commonly used for the interaction of HF and LF models are depicted below. More details about the process of constructing them can be found in Refs. [28,31,32]

2.1.1. Multiplicative scaling approach

Multiplicative scaling approach was first proposed by Haftka [21]. It adopts the scaling factor to depict the ratio between the HF and LF models at the HF sample points. Then a scaling function is constructed to fit the relationships between the design variables and the corresponding output. The scaling factor $\beta(\mathbf{x})$ can be expressed as:

$$\beta(\mathbf{x}) = \frac{f^n(\mathbf{x}^h)}{\hat{f}^l(\mathbf{x}^h)} \tag{1}$$

The variable fidelity metamodel $\hat{f}_{vf}(\mathbf{x})$ can be obtained by the following equation:

$$f_{vf}(\mathbf{x}) = f^{l}(\mathbf{x})\hat{\boldsymbol{\beta}}(\mathbf{x}) \tag{2}$$

It should be point out that the multiplicative scaling approach may cease to be valid when the values of LF model are equal to zero at some sample points. This property, to some extent, has limited its capability of solving constrained optimization design problems because an optimum generally makes some constraints to be active.

2.1.2. Additive scaling approach

.

Lewis et al. [33] developed the additive scaling approach to address the shortcoming of the multiplicative scaling approach. In additive scaling approach, the scaling factories defined to be the differences between the HF and LF models at HF sample points. Once the scaling factors are obtained, they are fitted using the scaling function to map the difference between the HF and LF models. The scaling factor $\gamma(\mathbf{x})$ can be expressed as:

$$\gamma(\boldsymbol{x}) = f^{h}(\boldsymbol{x}^{h}) - f^{l}(\boldsymbol{x}^{h})$$
(3)

Download English Version:

https://daneshyari.com/en/article/4911032

Download Persian Version:

https://daneshyari.com/article/4911032

Daneshyari.com