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A multi-fidelity shape optimization via surrogate modeling for civil structures

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A B S T R A C T

Shape optimization serves as a powerful tool to reduce wind effects on buildings. Past studies have demonstrated the superiority of the shape tailoring technique in aerodynamic mitigation through recessing or chamfering building corners, etc. Nonetheless, conventional approaches highly rely on wind tunnel experiments for which only a limited number of candidate geometries are tested to identify the best-performing one. In an attempt to globally and automatically explore the optimal geometry, the shape optimization via surrogate modeling is introduced in this study. Particularly, CFD is employed for calibration of the surrogate model. The CFD analyses can be conducted either through low-fidelity simulations such as RANS model, or through high-fidelity ones including LES. The low-fidelity model can provide a large ensemble for surrogate calibration, yet it suffers from the lack of accuracy. On the other hand, the high-fidelity model exhibits satisfactory accuracy, while it can only accommodate a small ensemble which may result in a large sampling error in the surrogate calibration. In order to take advantages of the merits of two types of CFD models, a multi-fidelity surrogate modeling is investigated in this research to guarantee the model accuracy as well as to maintain the computational efficiency.

1. Introduction

Shape optimization plays a crucial role in the design of tall buildings from the aerodynamic mitigation standpoint. A creative tailoring of the external geometry can benefit in the reduction of dynamic wind loads on the building, leading to many economic advantages (Kareem et al., 2013; Bernardini et al., 2015). To this end, an automatic search for identifying the optimal external geometry of the building through advanced computing would represent an effective approach for replacing the methods based on time-consuming and costly wind tunnel tests. Furthermore, an approach of this type would enable a far more comprehensive exploration of the design space that is rigorously guided by the optimization algorithms, potentially resulting in more innovative and efficient solutions as compared to conventional ones (Bernardini et al., 2015).

In an attempt to develop an automated strategy for shape optimization as mentioned above, flow simulation is carried out through computational fluid dynamics (CFD) to assess the aerodynamic response of the system, which is then coupled with optimization algorithms in order to enable the search for the optimal geometry of the building. Despite the promise of the proposed methodology, a significant number of computational resources are necessary due to the computationally intensive CFD simulations required at each iteration of the optimization process. In order to overcome this significant computational hurdle, a surrogate-based modeling approach is introduced, providing a computationally inexpensive approximation of the original problem built from a limited set of runs of the original model, referred to as the design of experiments (Forrester and Keane, 2008). Therefore, the accuracy of aerodynamic measures obtained from CFD analyses in each run is directly associated with the fidelity of the surrogate model, as is the subsequent optimal solution.

Observations from limited runs of the original model may involve data sources of multiple fidelities with different computational costs (Zaytsev and Burnaev, 2017). With regard to the numerical simulation of the wind flow around bluff bodies, e.g., civil structures, at high Reynolds numbers, the CFD analyses can be either carried out through low-fidelity simulations, such as Reynolds-averaged Navier-Stokes (RANS), or high-fidelity simulations such as Large Eddy Simulation (LES). With the low-fidelity model it is necessary to generate large numbers of samples for calibration. However, these simulations can result in noticeable modeling errors because the unsteadiness of the turbulence is averaged out in Reynolds-averaged approaches (Ferziger and Peric, 2012), which

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causes difficulties in modeling complex phenomena such as the vortex shedding. In this respect, the high-fidelity model helps refine the accuracy of the low-fidelity model as it only requires the modeling of small-scale turbulence. Because of the huge computational effort associated with the high-fidelity model, only a small ensemble can be generated, leading to large sampling errors. Therefore, it's necessary to blend the information sources from multiple fidelities of CFD analyses for calibrating surrogate models.

In an effort to construct sophisticated surrogates based on regression against multiple sets of data, modern statistical learning techniques such as Gaussian process regression provide reliable tools in capturing intrinsic features of the output of complex engineering systems (Perdikaris et al., 2015). Multi-fidelity surrogate modeling has been successfully applied to a host of engineering problems including the beam design using finite element analyses with variable mesh sizes (Leary et al., 2003), optimization of a transonic aircraft wing with two levels of CFD fidelity (Forrester et al., 2007), rotor bade design based on the code with simplified aerodynamics as well as high-fidelity numerical simulations (Collins, 2008), etc. Yet it hasn't been explored in the computational design optimization of building forms under winds using CFD. In this paper, a member of Gaussian process regression called co-kriging (Forrester et al., 2007) is built using correlated CFD inputs with two model fidelities as mentioned above. The co-kriging model serves as a high-fidelity predictor of the aerodynamic quantities of buildings with different cross-sectional forms. We further apply this approach to a shape optimization problem with multi-fidelity inputs.

2. The shape optimization problem formulation

The shape optimization problem can be expressed as follows (Bernardini et al., 2015):

$$\begin{aligned} \min_{\mathbf{q}} \quad & \mathbf{G}(\mathbf{q}) \\ \text{s.t.} \quad & C_r(\mathbf{q}) = 0 \quad r = 1,2,\ldots,R \\ & D_s(\mathbf{q}) \le 0 \quad s = 1,2,\ldots,S \end{aligned} \tag{1}$$

where $\mathbf{q}$ is the design variable vector that is used to define the external geometry of the bluff body, $\mathbf{G}(\mathbf{q})$ is a vector of objective functions. The constraint functions represent R equality constraints and S inequality constraints imposed on the design variables. The goal is to minimize the competing aerodynamic objectives represented by the mean drag force coefficient μ_{Cd} and the standard deviation of the lift force coefficient σ_{Cl}. The objective function vector is therefore defined as:

$$\mathbf{G}(\mathbf{q}) = [\mu_{Cd}, \sigma_{Cl}] \tag{2}$$

where μ_{Cd} and σ_{Cl} are determined through CFD simulations. The constraints are used for geometric requirements on the shape, such as symmetry properties, maximum absolute displacements, etc.

Since multiple objectives are involved in the optimization, the optimization problem will yield a set of optimal solutions called Pareto-optimal set or Pareto front (Deb, 2001).

3. Solution strategy

3.1. Design of experiments (DoEs)

The purpose of conducting design of experiments is to generate sampling points for the calibration of the surrogate model. At each sampling point, the aerodynamic objective functions are evaluated through CFD analyses, which serve as the training set for surrogate modeling. Since we have no prior knowledge about how the objective output functions vary over the input space, the principle of a sampling plan is to fill the design space with sampling points as uniformly as possible. For this purpose, we employ a space filling strategy named Latin Hypercube sampling (LHS) (Forrester and Keane, 2008) for uniform random sampling.

In the context of multi-fidelity sampling data, the subset design strategy can be used, in which samples for a high-fidelity model are taken as a subset of low-fidelity samples. If multiple subsets of the high-fidelity points can be found to satisfy the Latin Hypercube design requirements, we choose the one with maximal minimum distance between sampling points. If no subset can satisfy the Latin Hypercube design requirements, we choose one with maximal minimum distance between the points in the subset (Huang et al., 2006). It should be noted that high-fidelity sampling points are not necessarily constrained to be a subset of low-fidelity points. Here we employ the subset design strategy due to its numerical convenience for the case study.

3.2. Surrogate modeling

Once the sampling points for multiple fidelity models have been generated in DoEs, CFD simulations are ready to be run at each sampling point to obtain the observations of aerodynamic quantities of interest. These are used to build surrogate models based on Gaussian process regression.

3.2.1. Basic kriging modeling

The Gaussian process regression for a single-fidelity surrogate model was initially introduced in geostatistics as kriging (Matheron, 1963). First an overview of the kriging scheme for the function prediction is presented. The fundamental hypothesis is that the true underlying function $Y(\mathbf{x})$ can be modeled as a realization of a Gaussian stochastic process of the form

$$Y(\mathbf{x}) = \mu + Z(\mathbf{x}) \tag{3}$$

where μ is an unknown constant trend function and Z is a Gaussian process with zero mean and stationary covariance

$$\Sigma(\mathbf{Y},\mathbf{Y}) = \sigma^2 K = \sigma^2 \begin{pmatrix} corr\left[Y(\mathbf{x}^{(1)}), Y(\mathbf{x}^{(1)})\right] & \cdots & corr\left[Y(\mathbf{x}^{(1)}), Y(\mathbf{x}^{(n)})\right] \\ \vdots & \ddots & \vdots \\ corr\left[Y(\mathbf{x}^{(n)}), Y(\mathbf{x}^{(1)})\right] & \cdots & corr\left[Y(\mathbf{x}^{(n)}), Y(\mathbf{x}^{(n)})\right] \end{pmatrix} \tag{4}$$

The generalized exponential kernel function can be used to construct the covariance function, which has the correlation form as (Forrester and Keane, 2008)

$$K(\mathbf{x},\mathbf{x}') = \exp\left(-\sum_{j=1}^{d} \frac{\|x_j - x'_j\|^{p_j}}{\theta_j} \right) \tag{5}$$

The hyper-parameter p_j determines the smoothness of the approximated function, and θ_j indicates whether the function is active or not along dimension j. The values of hyper-parameters can be obtained through the maximum likelihood estimates principle (MLE), in which the log-likelihood function of the observations $\mathbf{y} = [y_1, \ldots, y_n]^T$ can be expressed as

$$\ln\left(L(\mathbf{y})|\mu,\sigma^2,\mathbf{p},\boldsymbol{\theta}\right) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2}\ln|K| - \frac{(\mathbf{y}-1\mu)^T K^{-1}(\mathbf{y}-1\mu)}{2\sigma^2} \tag{6}$$

Given a set of the observations $\mathbf{y} = [y_1, \ldots, y_n]^T$, the function value is predicted at an arbitrary location $\mathbf{x}^{(p)}$ based on its kriging correlations with observations, which can be analytically derived as the conditional Gaussian process. The joint distribution over $\mathbf{y} = [y_1, \ldots, y_n]^T$ and $y^{(p)}$ can be written as

$$P\left(\mathbf{y}, y^{(p)}\right) = N\left(\mathbf{y}, y^{(p)} \middle| 1\mu, \Sigma\left(\mathbf{y}^{(1:n,p)}, \mathbf{y}^{(1:n,p)}\right)\right) \tag{7}$$

Then the mean and variance for the conditional Gaussian process $P(y^{(p)}|\mathbf{y})$ can be computed as