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A metamodel optimization methodology based on multi-level fuzzy clustering space reduction strategy and its applications

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Abstract

This paper proposes metamodel optimization methodology based on multi-level fuzzy-clustering space reduction strategy with Kriging interpolation. The proposed methodology is composed of three levels. In the 1st level, the initial samples need partitioning into several clusters due to design variables by fuzzy-clustering method. Sequentially, only some of the clusters are involved in building metamodels locally in the 2nd level. Finally, the best optimized result is collected from all metamodels in the 3rd level. The nonlinear problems with multi-humps as test functions are implemented for proving accuracy and efficiency of proposed method. The practical nonlinear engineering problems are optimized by suggested methodology and satisfied results are also obtained.

Keywords: Multi-level; Metamodel; Fuzzy clustering; Nonlinear; Kriging interpolation

1. Introduction

When simulations become computationally expensive, the number of simulation-based function evaluations required for optimization must be carefully controlled. Due to the development of complexity and scale of optimizations in industries, much of today's design involves the use of highly computation-intensive analyses and simulations. To incorporate such simulations in design optimization imposes daunting computational challenges, since at least one function – the objective function or a constraint function – requires a computation-intensive process for function evaluation, such as metal forming and crashworthiness optimization problems. To that end, researchers have explored the use of metamodels, namely, simpler approximate models calibrated to sample runs of the original simulation. The approximate or metamodel can replace the original one, thus reducing the computational burden of evaluating numerous designs. Metamodels can be used to aid in improving the efficiency of computationally expensive optimization algorithms in a variety of applications.

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These techniques are currently being employed to develop inexpensive surrogates of these analyses and simulations. Many of metamodeling techniques in engineering design and other disciplines have been well developed, and recent reviews can be found in Simpson, Peplinski, Koch, and Allen (2001), Haftka, Scott, and Cruz (1998), and Sobieszczanski-Sobieski and Haftka (1997).

Among the various metamodeling techniques for optimization, response surface methodology (RSM) and Kriging attract the most attention. RSM explores the relationships between several explanatory variables and one or more response variables. The method was introduced by Box and Wilson (1951). The main idea of RSM is to use a sequential experimental procedure to obtain an optimal response. Box and Wilson suggested using a first-degree polynomial model to do this. They acknowledged that this model was only an approximation, but used it because such a model was easy to estimate and apply, even when little was known about the process. RSM originated from the formal design of experiments theory (Box, Hunter, & Hunter, 1978; Myers & Montgomery, 1995). Kriging is a regression technique used in geostatistics to approximate or interpolate data. The theory of Kriging was developed from the seminal work of its inventor, Danie G. Krige and further developed by Matheron (1963). In the statistical community, it is also known as Gaussian process regression. Kriging is also a reproducing kernel method (like splines and support vector machines). Comparisons on the performance of these two types of methods and other metamodeling methods have been archived in Simpson, Mauery, Korte, and Mistree (1998).

Generally, RSM that employs low-order polynomial functions (two-order is implemented often) can efficiently model low-order problems, and the computation of a RS model is fast and cheap. In addition, RSM facilitates the understanding of engineering problems by comparing parameter coefficients and also in the elimination of unimportant design variables. Low-order polynomial response surfaces, however, are not good for highly nonlinear problems, especially those with wavy (multi-hump) behaviors. On the contrary, Kriging models can accurately approximate an unknown system even with high nonlinearity, and the number of samples needed to construct a Kriging model, theoretically, is lower than that for RS (Koch, Simpson, Allen, & Mistree, 1999). However, the computational effort required to fit a Kriging model is much greater, and the interpretation of Kriging model parameters is not intuitive. Kriging models can be used for screening, but the procedure is not as straightforward as it is with RS (Welch et al., 1992).

According to Kriging models, it is observed that the modeling efficiency and accuracy are directly related to the design space. An active branch of research in metamodeling is in designing methods that can gradually reduce the design space to improve modeling accuracy as shown in Fig. 1.

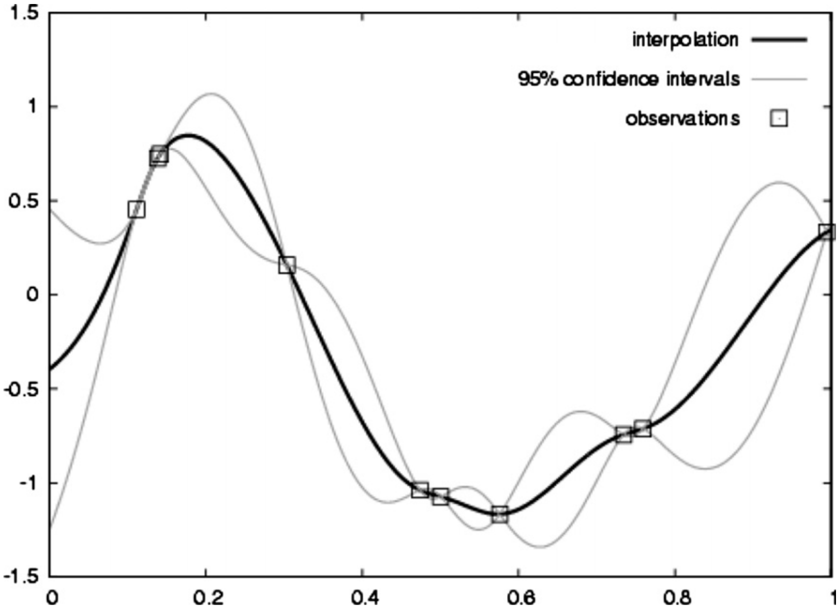

Fig. 1. Example of one-dimensional data interpolation by Kriging, with confidence intervals. Squares indicate the location of the data. The Kriging interpolation is in red. The confidence intervals are in green (http://en.wikipedia.org/wiki/Kriging).