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Review

Structural design employing a sequential approximation optimization approach

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ABSTRACT

This paper presents an improved sequential approximation optimization (SAO) algorithm that is suitable for structural design optimization tasks. First, an adaptive sampling strategy is proposed to balance between the competence to locate the global optimum and the computation efficiency in the optimization process. Furthermore, an original estimation of the width of the basis function is proposed based on the local density of sampling points, which enhances the RBF for the SAO. The efficacy of the enhanced SAO algorithm is validated using several benchmark structural design cases and the computing costs are substantially reduced in comparison to other optimization algorithms.

Contents

1. Introduction

Structural design optimization remains an important and challenging topic in the engineering design of lighter, more effective structures [1]. Design optimization aims to determine the optimal shape of a structure by maximizing or minimizing a given criterion, such as stiffness or weight, subject to stress or displacement constraints. Over the past decade, a number of optimization algorithms have been extensively used in structural optimization tasks, such as gradient-based algorithms, evolutionary algorithms (EAs) and approximation-based optimization algorithms [2]. Of course, advantages and disadvantages are associated with any optimization technique.

Several examples of gradient-based optimization applied to structural design problems exist in the literature [3–6]. SQP (Sequential Quadratic Programming) [6], as one of the gradient-based optimization techniques, is integrated in the commercial

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CAE software such as ANSYS [7] and widely used in structural design tasks because of its high computational efficiency. However, gradient-based optimization techniques are extremely sensitive to the initial guess and prone to trapping in local optima. In practical structural design tasks, designers usually have no idea about the global optimum or even the promising areas for global optimum. Therefore, the selection of a proper initial design for SQP is difficult.

In the past few decades, structural design optimization problems have been increasingly solved by EAs such as the genetic algorithm [8], simulated annealing [9], particle swarm optimization [10,11] and the artificial bee colony algorithm [12]. EAs present several advantages over gradient-based methods: (a) the objective function need not be continuous, nor even available in algebraic form, (b) EAs more easily escape from local optima, and (c) no specific domain information is required, although this information can be exploited if available. Drawbacks of these methods are the huge number of function evaluations required. The resulting low computational efficiency precludes their direct application to structural design optimization problems [2,13].

In approximation-based optimization techniques, or meta-modeling techniques, objective functions are expressed as low order polynomial approximations to explicit functions. The accuracy of these techniques is acceptable and the computational cost is much reduced. Commonly applied approximation techniques include the response surface method [14,15], neural network [16,17], polynomial regression models [18], Kriging methods [19] and the radial basis function (RBF) [20] method. In addition to their computational efficiency, approximation techniques are easily connected to simulation programs, enabling a view of the entire design space. On the downside, these techniques introduce error into the meta-model, which reduces their reliability.

In general, structural optimization processes require all of the following attributes: reduced computational cost, generality, robustness, and accuracy [21]. To meet these requirements, researchers are increasingly adopting the sequential approximate optimization (SAO) approach [22,23]. Unlike the classical approximation-based optimization procedure summarized by Kitayama et al. [24], SAO first conducts a small-size design of experiment, using various approximate techniques to construct a surrogate. The global optimum of the surrogate is then found by optimal optimization methods such as EAs. The SAO algorithm terminates when a specified termination criterion is satisfied. Otherwise, the accuracy of the response surface is improved by adding several new sampling points. This iterative process converges to a highly accurate global optimum after far fewer function evaluations than are required by EAs.

The SAO algorithm has been recognized as one of the most attractive approaches for engineering optimization [2,25]. However, because SAO is an emerging concept, a reliable and robust SAO algorithm suitable for mechanical engineering projects remains lacking. The success of an SAO algorithm depends chiefly on the approximation technique and the sampling strategy. Therefore, this paper focuses on improving these two key elements to the extent that SAO becomes applicable to structural design optimization problems. The paper is structured as follows: Section 2 introduces the general formulation of the SAO approach, and proposes an adaptive sampling strategy and a new method for determining the width of the basis function in the RBF network. Finally, the framework of the proposed SAO algorithm is presented and the algorithm is validated by a simple numerical test. Section 3 presents various structural optimization case studies, which are used to demonstrate the efficacy of the approach in obtaining optimal structural optimization solutions. Concluding remarks are presented in Section 4.

2. Sequential approximation optimization

2.1. General framework of the sequential approximation optimization approach

Let us consider a general structural optimization problem with constraints

$$\begin{aligned} &\text{find} \quad \boldsymbol{X}, \\ &\min \quad f(\boldsymbol{X}), \\ &s.t. \quad g_i(\boldsymbol{X}) \leqslant 0 \quad i = 1, 2, \ldots, l, \\ &\qquad h_j(\boldsymbol{X}) = 0 \quad j = 1, 2, \ldots, k, \\ &\qquad \boldsymbol{X}^L \leqslant \boldsymbol{X} \leqslant \boldsymbol{X}^U. \end{aligned} \tag{1}$$

Here $\boldsymbol{X}^L$ and $\boldsymbol{X}^U$ is the upper and lower bound of design variables, respectively. For most structural design problems, the objective function and constraints are implicit functions of design variables, usually obtained by finite element analysis (FEA). Since the computational cost for FEA may be high, the number of analyses carried out during the optimization has the main impact on the efficiency of the algorithm. This has initiated the development of optimization techniques that are suitable for structural design problems [6].

In the classical approximation-based optimization procedure summarized in [24], the accuracy of the surrogate model could be degraded by an ill-chosen initial sample, leading to a deceptively positioned optimum. Here we assume that our optimum design is the best result of the true function, not that of the surrogate. Results from the surrogate are therefore evaluated by comparison with the true function evaluations. Additional calls to the true function are used to both validate the surrogate and enhance its accuracy. Thus, the developed SAO approach selects the new points at which the true function is called. The general framework of the SAO approach is presented in Fig. 1. Applying a series of new infill points based on some infill criteria (also known as a sampling strategy), the objective function is sampled using a constantly changing surrogate model [26]. As mentioned above, appropriate approximation technique and sampling strategy are imperative for successful SAO optimization. The SAO-based structural optimization can be mathematically expressed as

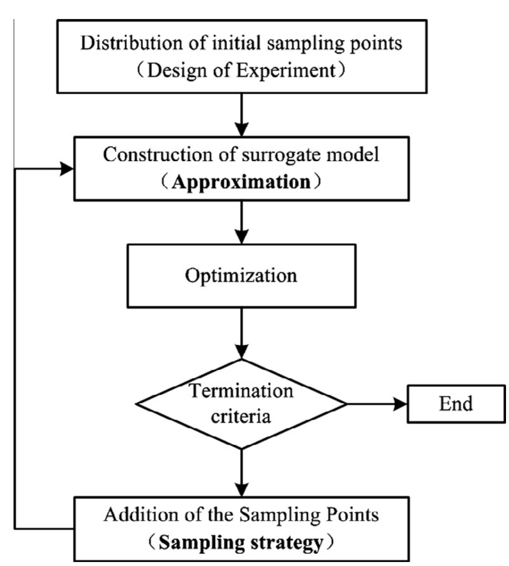

Fig. 1. General framework of the sequential approximation optimization.