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Lump-loaded antenna optimization by manifold mapping algorithm with method of moments

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ABSTRACT

We propose a new method of manifold mapping optimization method for the lump-loaded antennas to obtain a miniaturization. The surrogate model can be constructed using explicit formulas during optimization iterations. The coarse and fine models of manifold mapping method are evaluated with an adaptive precision method of moments (MoM) simulator. The computation precision is determined by compression thresholds in the adaptive cross approximation (ACA) for the MoM far coupling evaluations. Numerical optimization of the lump-loaded log-periodic dipole antenna is tested to validate the efficiency of the proposed method.

1. Introduction

For shortwave communication antenna, the size is about half wavelength of the corresponding operated frequency, thus large size antenna is required. Lump loading is an effective way to obtain a miniaturization. As a result, design and optimization of the lump-loaded antennas becomes a promising and challenging research topic [1]. In [2], the lump loaded folded monopole with 2–40 MHz bandwidth is optimized using genetic algorithm (GA). In [3], the GA optimization tool for the design of broadband and multi-band loaded antennas is proposed. A modified particle swarm optimization (PSO) algorithm with the commercial method of moments (MoM) solver is proposed to optimize lump-loaded wire antennas with a wide frequency in [4]. In these optimization processes, the full-wave electromagnetic simulations repeatedly are required for each optimization parameter, which leads to large computation time and memory cost.

The space mapping optimization method was introduced by Bandler et al. as a surrogate-based optimization technique in [5]. It introduces a reasonable trade-off between optimization precision and time consumption, where the process can be implemented with coarse model optimization and fine model validation. The space mapping has been extended to optimize the antenna and substrate integrated waveguide (SIW) filter problems successfully [6–10]. However, the coarse model optimizations are required during fine model iterations [11] in the standard space mapping. As a result, the manifold mapping (MM) is proposed in [12,13], where the surrogate model is constructed using available fine and coarse model data. The response of surrogate model is a sufficiently good approximation of the fine model response. As a result, a better convergence can be obtained than standard space mapping method [14].

For general simple antenna structure, the analytical formula or equivalent circuit model can be used as coarse model. But for antennas with complex structure, the coarse model cannot be obtained easily. As a result, the electromagnetic simulation methods are explored as coarse model. In [6], a coarse-mesh electromagnetic model with Kriging interpolation is employed to construct the coarse model for the antenna optimization. However, a lot of repeatedly electromagnetic simulations should be implemented to obtain an interpolation basis for Kriging interpolation. In [7], the thin-wire model has been proposed as coarse model for optimization of handset antennas. However, the thin-wire models are only used for a small number of handset antennas and are not universal. In [15], we propose a space mapping optimization for the 2D antenna array elements arrangements, the analytic formulations are employed for each antenna element radiation field expression [15], while it is not suitable for the lump-loaded log-periodic dipole antenna proposed in this work.

In this work, a robust coarse model simulated with low precision MoM is proposed in the manifold mapping method, the near field couplings are evaluated with full MoM directly, while the far couplings are evaluated with adaptive cross approximation (ACA) [18]. The full wave simulation precision can be determined by the threshold of the ACA, as a result, the low and high precisions are chosen automatically in the optimization framework for coarse and fine model simulations, respectively. Numerical optimization for a reduced size lump-loaded log-periodic dipole antenna is proposed to validate the proposed method.

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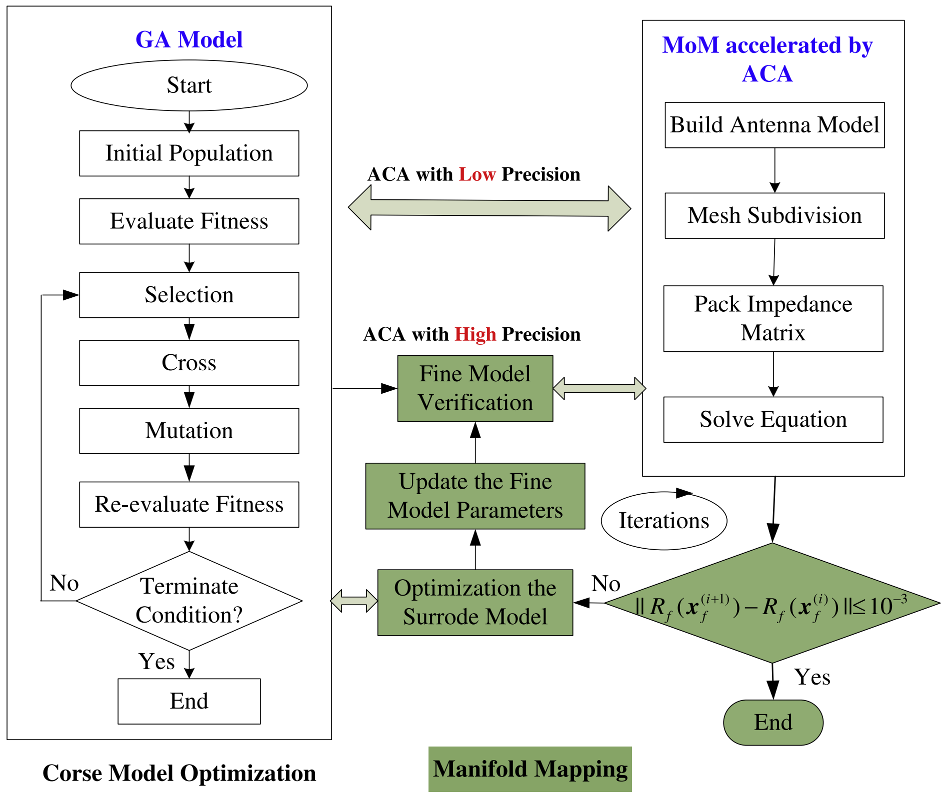

Fig. 1. The flowchart of manifold mapping.

2. Manifold mapping optimization framework

In this paper, the manifold method is employed as the main optimization tool, and the procedure of it is shown in Fig. 1. In the flowchart, there are mainly three parts: GA coarse model optimization, ACA-MoM coarse/fine model evaluation, and manifold method optimization.

2.1. Manifold mapping

The design specification is denoted by $y \in \mathbb{R}^m$, the fine model response $R_f(x)$ is defined over the set $X \in \mathbb{R}^n$ (e.g. voltage standing wave ratio (VSWR) or gain evaluated for the antenna), and $x \in X$ is the design variable (e.g. the size of the antenna). In this work, we want to solve the following optimization problem

$$x_f^* = \arg\min_{x \in X} \left\| R_f(x) - y \right\| \tag{1}$$

x_f^* is the optimal solution of the fine model.

The coarse model response $R_c(x)$ is also defined over the set X. The coarse model optimum is defined as:

$$x_c^* = \arg\min_{x \in X} \left\| R_c(x) - y \right\| \tag{2}$$

x_c^* is the optimal solution of coarse model.

In order to accelerate the optimization process, it is to find the corresponding surrogate model R_s [12,13] instead of solving the fine model in formula (1) directly. The fine model evaluation is assumed to be computationally expensive, typically obtained by a time-consuming electromagnetic simulation. The proposed surrogate model is more efficient than the fine model, and also with a reasonable accuracy [13]. At this time, the solution of surrogate model $x^{(i)}$ is as

$$x^{(i+1)} = \arg\min_{x \in X} \left\| R_s^{(i)}(x) - y \right\| \tag{3}$$

where $x^{(i)}$ means a series of approximate solution of formula (1), $R_s^{(i)}(x) \in \mathbb{R}^m$ is a surrogate model response at iteration i. A surrogate model is defined in the manifold mapping as

$$R_s^{(i)}(x) = R_f\left(x^{(i)}\right) + S^{(i)}\left(R_c(x) - R_c\left(x^{(i)}\right)\right) \tag{4}$$

$S^{(i)}$ is a linear correction matrix, which would be defined in (5). Following are the main processes of the manifold mapping algorithm.

Initialization:

(1) Initialize the parameter of GA: crossover probability of 0.8, mutation probability of 0.05, population size of 50, and the maximum iteration number of 200.
(2) Initialize the first iteration step $i = 1$ and let $S^{(i)} = I^{m \times m}$. Obtain the coarse model x_c^* with a low precision adaptive MoM together with GA, and let $x_f^{(1)} = x_c^*$.

ith iteration:

(1) Set $x_f^{(i)}$ for fine model simulation using MoM solver with high precision MoM, if the fine model response can achieve the design goal, the optimization is end; if not, go on;
(2) Construction of the surrogate model $R_s^{(i)}(x)$ shown as formula (4); $S^{(i)}$ is the $m \times m$ correction matrix as following:

$$S^{(i)} = \Delta F \cdot \Delta C^{\dagger} \tag{5}$$

where,

$$\Delta F = \left[R_f\left(x^{(i)}\right) - R_f\left(x^{(i-1)}\right), \cdots, R_f\left(x^{(i)}\right) - R_f\left(x^{\max(i-n,0)}\right)\right]$$

$$\Delta C = \left[R_c\left(x^{(i)}\right) - R_c\left(x^{(i-1)}\right), \cdots, R_c\left(x^{(i)}\right) - R_c\left(x^{\max(i-n,0)}\right)\right]$$

ΔF and ΔC is constructed using the previous results of R_f and R_c accumulated during the previous optimization, $(\bullet)^{\dagger}$ denotes the pseudo-inverse operator, n is the number of step for iteration, m is the number of optimized frequencies.

(3) Optimization of the surrogate model $R_s^{(i)}(\boldsymbol{x})$, get the $(i+1)$ iteration fine model parameter values $\mathbf{x}_f^{(i+1)}$, checking whether a termination condition is satisfied $\| R_f(\boldsymbol{x}_f^{(i+1)}) - R_f(\boldsymbol{x}_f^{(i)}) \| \le \eta$. If satisfied, the optimization will be end; if not, set $i = i + 1$. We choose $\eta = 10^{-3}$ in this work.