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Fast multi-objective optimization of multi-parameter antenna structures based on improved MOEA/D with surrogate-assisted model

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For multi-objective design of multi-parameter antenna structures, optimization efficiency and computational cost are two major concerns. In this paper, an improved multi-objective evolutionary algorithm based on decomposition (MOEA/D) is proposed to improve global optimization capability by diversity detection operation and mixed population update operation. Further, in order to reduce the computational cost, a hybrid optimization strategy integrating a dynamically updatable surrogate-assisted model into the improved MOEA/D is proposed. The numerical results of test functions show that our algorithm outperforms original MOEA/D, modified MOEA/D (M-MOEA/D), and nondominated sorting genetic algorithm II (NGSA-II) in terms of diversity. Experimental validation of Pareto-optimal planar miniaturized multiband antenna designs is also provided, showing excellent convergence and considerable computational savings compared to those previously published approaches.

1. Introduction

Contemporary antenna usually requires simultaneous handing of multiple objectives. In order to accurately evaluate the antenna response, a high-fidelity electromagnetic (EM) simulation is necessary. However, accurate EM analysis is computationally expensive due to the need of repetitive parameter sweeps, which poses a large challenge for multi-objective antenna design [1,2].

Automated multi-parameter antenna optimization using evolutionary algorithms (EAs) provides a new way for antenna designs because it does not need a prior preference regarding design objectives (which is usually either not obtainable or not desirable). EAs have been successfully applied to multi-objective optimization problems (MOP) related to antenna and array designs, such as genetic algorithm (GA) [3–5], particle swarm optimization (PSO) [6,7], and nondominated sorting genetic algorithm (NSGA) [8]. In these schemes, a MOP is either converted into a single objective optimization problem (SOP) using some composition approaches [3–7], or treated as a whole [8]. In these implementations, a weight vector responses to one search direction in design space so that computational cost could be unendurable due to low searching efficiency. In [9], a multi-objective evolutionary algorithm based on decomposition (MOEA/D) was proposed for solving MOPs. In this algorithm, a MOP is explicitly decomposed into a number of scalar subproblems which can be optimized simultaneously. By using the information of solutions of neighboring subproblems, simultaneous optimization of these decomposed subproblems results in a considerable reduced computational cost. As one of the most popular multi-objective optimization techniques, MOEA/D has been successfully applied to array synthesis [10,11]. However, different from array synthesis, the direct utilization of MOEA/D in the multi-parameter antenna designs may be still difficult if high-fidelity EM simulations are involved. Fortunately, the surrogated-based optimization techniques developed recently by Koziel et al. [1,2,12–15] have proved to be computationally efficient than the traditional EM-driven approaches.

In this work, aiming at improving optimization efficiency and computational cost, we propose an improved MOEA/D algorithm expedited with surrogate-assisted model for fast multi-objective design of multi-parameter antenna structures. In our improved MOEA/D, a diversity detection operator is adopted to judge the level of population diversity and then a mixed population update operation is performed to increase population diversity while preserving beneficial individuals. The performance of our improved MOEA/D is validated by several test functions. Moreover, in order to greatly reduce the computational cost of antenna design process, a hybrid optimization strategy integrating a dynamically updatable surrogate model into the improved MOEA/D is proposed.

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This strategy allows us to obtain a set of Pareto-optimal designs at a very low computation cost. The results of a miniaturized multi-band planar antenna design are also presented, showing the superiority of our approach in terms of computational cost and solution diversity over other reported approaches.

2. Problem formulation

In this section, we briefly describe the formulation of the multi-objective antenna design problem. Generally, the multi-objective design of multi-parameter antenna structures can be stated as a MOP

$$\begin{cases} \min F(\boldsymbol{x}) = (f_1(\boldsymbol{x}),\ f_2(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x}))^T \\ s.t.\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \tag{1}$$

where $f_k(\boldsymbol{x}), k = 1, 2, \ldots, m$ is the kth design objective. A typical objective is to ensure $|S_{11}| < -10$ dB over a certain frequency band of interest, and to minimize the antenna reflection over that band. Also, there might be some other objectives with respect to antenna size, gain, efficiency, and so on. $\boldsymbol{X}$ is a design space, and $\boldsymbol{x} = (x_1, \ldots, x_n)$ is a vector of n design variables defining a particular antenna structure. In multi-objective antenna design, the target is to obtain the Pareto front (PF) [1,2], i.e., multiple designs representing the trade-off between various characteristic of the antenna under consideration.

For multi-objective optimization, any two designs $\boldsymbol{x}$ and $\boldsymbol{y}$ for which $f_k(\boldsymbol{x}) < f_k(\boldsymbol{y})$ and $f_l(\boldsymbol{x}) < f_l(\boldsymbol{y})$ for at least one pair $k \neq l$, are not commensurable, i.e., none is better than the other in the multi-objective sense [1,2]. We define the Pareto dominance relation $\prec$ saying that for the two designs $\boldsymbol{x}$ and $\boldsymbol{y}$, we have $\boldsymbol{x} \prec \boldsymbol{y}$ ($\boldsymbol{x}$ dominates $\boldsymbol{y}$) if $f_k(\boldsymbol{x}) \leqslant f_k(\boldsymbol{y})$ for all $k = 1, 2, \ldots, m$ and $f_k(\boldsymbol{x}) < f_k(\boldsymbol{y})$ for at least one k [1,2,16]. The multi-objective optimization aims to find a representation of a Pareto front $\boldsymbol{X}_p$ (viz. Pareto-optimal set) of the design space $\boldsymbol{X}$, such that for any $\boldsymbol{x} \in \boldsymbol{X}_p$, there is no $\boldsymbol{y} \in \boldsymbol{X}$ for which $\boldsymbol{y} \prec \boldsymbol{x}$ [1,2,16].

3. Design methodology

3.1. Improved MOEA/D

MOEA/D is one of the most popular optimization algorithms in solving MOPs. In MOEA/D implementation, it is necessary to decompose the MOP under consideration [9]. Let $\boldsymbol{\lambda}^1, \ldots, \boldsymbol{\lambda}^N$ be a set of N evenly distributed weight vectors and $\boldsymbol{z}^*$ be the reference point. The problem of the PF approximation in (1) can be decomposed into N scalar optimization subproblems by using several decomposition approaches (e.g., the Tchebycheff approach) and the objective function of the jth subproblem is

$$g^{te}(\boldsymbol{x}|\boldsymbol{\lambda}^j, \boldsymbol{z}^*) = \max_{1 \leqslant i \leqslant M} \{\lambda_i^j |f_i(\boldsymbol{x}) - z_i^*\} \tag{2}$$

where $\boldsymbol{\lambda}^j = (\lambda_1^j, \ldots, \lambda_M^j)$. MOEA/D features excellent optimization efficiency by minimizing all objective functions simultaneously in a single run.

In MOEA/D, the neighborhood size (viz. T in [9]) plays a key role in algorithm performance. A smaller T leads to a good local optimization capability and hence fast convergence. Considering the heavy burden of antenna simulations, a smaller value of T is usually preferred in multi-parameter antenna design. However, a smaller T may result in degraded population diversity and tend to prematurity. Accordingly, it is necessary to develop a scheme to improve diversity for a small value of T. In our proposed algorithm, two improvements are introduced: (a) a diversity detection operator is designed to judge the level of population diversity; (b) population update is performed partially by random disturbance strategy and partially by a nondominated sorting strategy (NDS) in order to improve the diversity while keeping promising individuals. A detailed description of the improvements is given as follows:

3.1.1. Operation (a): diversity detection

Variance can measure how far a set of data are spread out in probability theory and statistics. So, we introduce this concept to measure the degree of aggregation of population. First, we define the fitness variance of population, σ^2, as follows,

$$\sigma^2 = \frac{1}{M}\frac{1}{N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\frac{f_{ij} - f_{iavg}}{f}\right)^2 \tag{3}$$

where $f = \max\{1, \max|f_{ij} - f_{iavg}|\}, (i \in [1, M], j \in [1, N])$, M and N are the number of objectives and population size, respectively; f_{ij} and f_{iavg} are the fitness of the jth individual and the mean fitness of population for the ith objective, respectively. The lower the value of σ^2 is, the more similarities there are among the individuals; and vice versa.

Then by comparing the value of σ^2 with a preset threshold, we can judge whether premature occurs or not. We define the threshold function, $H(t)$, as follows

$$H(t) = H_{\max} - \frac{(H_{\max} - H_{\min}) \times t}{MaxIter} \tag{4}$$

where H_{max} and H_{min} are the maximum and minimum thresholds, respectively; t is the iteration index and $MaxIter$ is the number of total iteration. If the value of σ^2 is smaller than the value of $H(t)$, local optimum will occur. Considering that the population diversity decreases with the number of iteration, a time-variant decreasing threshold function is designed. Specifically, a larger threshold is set at the initial stage of evolution to reduce the possibilities of falling into local minima; while with the increase of the iteration number, a gradually decreased threshold is set to track the state of population accurately.

3.1.2. Operation (b): mixed population update

Let P denote the current population and P_a denote an alternative population which is used for the storage of promising individuals. When local minima occurs, a sub-population P_s consisting of N_r individuals is first selected from the current population randomly

$$N_r = round(q \times N) \tag{5}$$

where q is an alterable re-selection factor, $round$ is a function that rounds to the nearest integer. The duplicate version of sub-population P_s is stored in the alternative population P_a to avoid missing promising individuals in the next operation of random disturbance on P_s.

Then, a random disturbance operator is performed on each individual of the sub-population P_s,

$$\boldsymbol{x}'_k = \boldsymbol{x}_k \times \left(1 + \frac{\lambda}{2}\right) \tag{6}$$

where $\boldsymbol{x}_k$ and $\boldsymbol{x}'_k$ are the previous and updated version of a selected individual k $(k = 1, 2, \ldots, N_r)$, respectively; λ is a random variable with the standard normal distribution in $[0, 1]$. For the remaining $N - N_r$ individuals in P, they will be updated together with the alternative population P_a by a nondominated sorting strategy (NDS) [17]. Then, the updated population can be expressed as

$$P = P_s + NDS((P - P_s) \cup P_a) \tag{7}$$

It can be seen from (7) that both selected individuals with random disturbance and those promising individuals with NDS are applied to the next evolution to increase the population diversity and