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Bayesian Optimization for Antenna Design via Multi-Point Active Learning

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Abstract— **In recent years, Bayesian optimization (BO) has shown promising results in electromagnetic designs. However, the existing methods only chose one updating point per optimization cycle, which is time-wasting when parallel computation can be used. To address this problem, a new method, called parallel Bayesian optimization (PBO) is presented in this letter. In this method, a multi-point acquisition function was developed to accelerate the solution efficiency of antenna design optimization. For each optimization cycle in PBO, the acquisition function is applied to choose multiple updating points, and then the responses at the updating points are calculated in parallel. The proposed PBO was applied to design an ultra-wideband microstrip antenna. Compared with the state-of-the-art methods, the PBO achieves better optimization results with less calculation time. The measured results of the antenna prototypes further show great potential for solving antenna design optimization problems.**

Index Terms—**Antenna optimization, Bayesian optimization, Gaussian process, Parallel computation, Surrogate model.**

I. Introduction

High fidelity electromagnetic (EM) simulations have been widely applied in modern antenna design process to enhance the accuracy and reliability of the results. The design optimization of antennas is typically realized using high fidelity EM simulations and evolutionary algorithms such as particle swarm optimization (PSO) [1], differential evolution (DE)[2], and so on. However, the algorithms often require a massive amount of CPU time to find the global optima.

In order to address this issue, the surrogate model-based optimization has become more and more attractive in the antenna field. The method employs surrogate models to replace the computationally expensive objective functions (e.g., HFSS model), and the surrogate models lead the search to the global optimum. This optimization strategy includes static surrogate models (SSM) and adaptive surrogate models (ASM). Compared with the SSM which is trained in a preprocessing phase [3], the ASM is gradually updated by using sequential samples to improve the approximation accuracy in the promising regions where the true global optimum probably exists [4,12]. The sample selection (i.e. active learning) in ASM is very important for the automatic optimization design [5]. Bayesian optimization (BO) is an ASM method which can be used for the global optimization of expensive objective functions [6]. Recently, BO was applied to a broadband power amplifier design [7], automated optimization of analog circuits [8] , 3-D integrated circuit design [9], and so on. However, few works utilizes the BO to design antennas except our previous work [10]. Moreover, these BO algorithms produce only one updating point at each iteration, which is time-wasting when parallel computation can be used.

This paper proposes a parallel Bayesian optimization (PBO) method for antenna designs. In this method, the pseudo expected improvement (PEI) criterion is integrated into the BO framework, and it can produce multiple updating points for parallel computation of EM models. The comparisons from an example show that the proposed method can take less iteration and achieve speedup in antenna designs.

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II. Problem Formulation of Antenna Design

Let $\boldsymbol{R}_f(\boldsymbol{x}) = \left[\boldsymbol{R}_f(\boldsymbol{x},\omega_1), \boldsymbol{R}_f(\boldsymbol{x},\omega_2), \cdots, \boldsymbol{R}_f(\boldsymbol{x},\omega_m)\right]$ denote the antenna response (e.g., gain, S11 over a frequency band of interest) of a high-fidelity EM model, $\boldsymbol{x}$ denote a vector of design variables and ω represents the frequency. The antenna design problem can be formulated as:

$$\boldsymbol{x}^* = \arg\min_{\boldsymbol{x}\in\Gamma} y(\boldsymbol{x}) \tag{1}$$

where $\boldsymbol{x}^*$ is the optimum design to be found. $\Gamma = \left\{\boldsymbol{x} \middle| \boldsymbol{x}_l \le \boldsymbol{x} \le \boldsymbol{x}_u\right\}$ is the deign space of interest. $y(\boldsymbol{x})$ is a given objective function which represents the error function of the antenna response $\boldsymbol{R}_f(\boldsymbol{x})$ and desired design specifications. Suppose, if S_{uq} and S_{lq} represent the set of upper and lower specifications, then the error function can be defined as:

$$e_q = \begin{cases} \boldsymbol{R}_f(\boldsymbol{x},\omega_q) - S_{uq} & , \ q \in J_u \\ S_{lq} - \boldsymbol{R}_f(\boldsymbol{x},\omega_q) & , \ q \in J_l \end{cases} \tag{2}$$

where J represent the index sets of the frequency points, ω_q denotes q -th frequency sample.

Utilizing (2), the objective function in (1) can be formulated as either a minimax or a generalized function of e_q [11].

III. Proposed Algorithm

The objective function in (2) is usually solved using a numerical simulator, which causes high computational cost. This section proposes a parallel Bayesian optimization (PBO) algorithm to address this problem.

Given a training data $\{\boldsymbol{X},\boldsymbol{Y}\}$, the surrogate model $\hat{y}(\boldsymbol{x})$ of the objective function $y(\boldsymbol{x})$ is constructed using Gaussian process regression (GPR) [6]. The prediction of the model $\hat{y}(\boldsymbol{x})$ at a new point $\boldsymbol{x}_n$ is a normal distribution $y(\boldsymbol{x}_n): N(\mu(\boldsymbol{x}_n), s(\boldsymbol{x}_n))$ with the mean and variance functions expressed as:

$$\begin{aligned}\mu(\boldsymbol{x}_n) &= \boldsymbol{k}(\boldsymbol{x}_n,\boldsymbol{X})^{\mathrm{T}}\left[\boldsymbol{K}+\sigma_N^2\boldsymbol{I}\right]\boldsymbol{y}\\ s^2(\boldsymbol{x}_n) &= k(\boldsymbol{x}_n,\boldsymbol{x}_n)-\boldsymbol{k}(\boldsymbol{x}_n,\boldsymbol{X})^{\mathrm{T}}\left[\boldsymbol{K}+\sigma_N^2\boldsymbol{I}\right]^{-1}\boldsymbol{k}(\boldsymbol{x}_n,\boldsymbol{X})^{-1}\end{aligned} \quad (3)$$

where $\boldsymbol{I}$ is the identity matrix, and σ_N is the noise deviation. $\boldsymbol{k}(\boldsymbol{x}_n,\boldsymbol{X})$ represents the covariance vector between the new query point $\boldsymbol{x}_n$ and the training dataset $\boldsymbol{X}=[\boldsymbol{x}_1,\boldsymbol{x}_2,\cdots,\boldsymbol{x}_{n-1}]$, $\boldsymbol{K}$ denotes the kernel matrix of the training dataset, and we use a squared exponential covariance function to express its ij-th element $k_{ij}(\boldsymbol{x}_i,\boldsymbol{x}_j)$ in the kernel matrix :

$$k_{ij}(\boldsymbol{x}_i,\boldsymbol{x}_j)=\exp\left(-\boldsymbol{\theta}\left\|\boldsymbol{x}_i-\boldsymbol{x}_j\right\|^2\right) \quad (4)$$

As discussed in [6], the surrogate model $\hat{y}(\boldsymbol{x}_n)$ is first build, and then it is sequentially updated at each iteration by maximizing an acquisition function which selects an updated design point $\boldsymbol{x}_n$. In this work, the expected improvement (EI) is chosen as the acquisition function, because it does not need parameters to configure [6, 10]. Utilizing the EI, the updated point $\boldsymbol{x}_n$ is expressed as:

$$\begin{aligned}&\boldsymbol{x}_n=\arg\max_{\boldsymbol{x}\in\Gamma}\ E(\boldsymbol{x})\\ &E(\boldsymbol{x})=\left(y_{\min}-\hat{y}(\boldsymbol{x})\right)\Phi\left(\frac{y_{\min}-\hat{y}(\boldsymbol{x})}{s(\boldsymbol{x})}\right)+s(\boldsymbol{x})\phi\left(\frac{y_{\min}-\hat{y}(\boldsymbol{x})}{s(\boldsymbol{x})}\right)\end{aligned} \quad (5)$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative density function and probability density function of the normal distribution. $y_{\min}$ is the current best function value in the available data.

However, the existing EI chooses one updating point at each iteration, which is time-wasting when the parallel computing can be used. Therefore, the function in (4) is modified to produce $q(q>1)$ updated points using the PEI function [11]:

$$\boldsymbol{x}_n^q=\arg\max_{\boldsymbol{x}\in\Gamma}\ EI(\boldsymbol{x})\cdot\prod_{i=1}^{q-1}\left[1-\exp\left(-\boldsymbol{\theta}\left\|\boldsymbol{x}-\boldsymbol{x}_n^i\right\|^2\right)\right] \quad (6)$$

where $\boldsymbol{\theta}$ is the same as eq.(4), and it is determined after the surrogate model is built. Therefore, no parameter is needed to be specified by the user when using the PEI criterion.

Utilizing (6), multiple updated points can be chosen per optimization cycle, and then the responses of the points are obtained using parallel computing of simulation models.

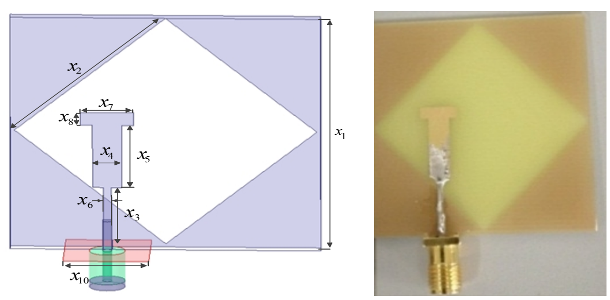
IV. Application Example

This section provides an ultra-wideband microstrip antenna to illustrate the validity of the proposed algorithm. Moreover, the PBO algorithm is compared with three well-known ASM algorithms: SADEA in [12] and traditional BO algorithms with EI function (BO-EI) [6]. The automatic optimization producers are accomplished by combining HFSS 18.0 with Matlab2016b. In the example, the results are computed on a workstation with a quad-core 64 bit Intel(R) Xeon(R) CPU and 128 GB of RAM. The number of initial data is 20, and they are achieved using Latin hypercube design. The maximum iteration number is 100. For the PBO, four updating points are produced at each iteration.

Consider the microstrip antenna in Fig. 1. The antenna is designated to operate on FR4 epoxy dielectric substrate ($\varepsilon_r=4.4, \tan\delta=0.02, h=1.5$ mm). The structure is described by 10 design variables $\boldsymbol{x}=[x_1,x_2,x_3,x_4,x_5,x_6,x_7,x_8,x_9,x_{10}]$, as shown in Fig.1. Table I presents the ranges of the parameters. Their initial values are $\boldsymbol{x}=[38.5,25.2,7.4,1.5,12,3,4,1,9.5,10]$ mm. In this example, a range of 2.5GHz to 15 GHz is considered as the desired bandwidth, and the desired voltage standing wave ratio (VSWR) in the range is defined as $\Gamma(\boldsymbol{x},\omega_i)\le 2$ dB. Following to (2), the objective function in (1) is also formulated as:

$$y(\boldsymbol{x})=\sum_{i=1}^{m}\max\left[\Gamma(\boldsymbol{x},\omega_i)-2,0\right] \quad (7)$$

where $m=251$ is the number of sampling frequency evenly distributed from 2.5 GHz to 15 GHz (0.05 GHz increments).



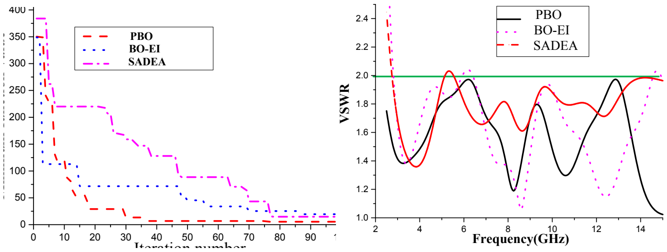
(a) Structural configuration (b) Antenna prototype

Fig. 1. Ultra-wideband microstrip antenna

TABLE I
LOWER AND UPPER BOUNDS OF 10 DESIGN VARIABLES (mm)

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
Lower	30	22	5	0.5	6	1	2	0.5	6.5	5
Upper	40	27	15	6.5	14	6	8	4	12.5	15

Fig. 2 (a) shows the iterative process. Fig.2 (b) presents the comparisons of the optimal return loss. Table II shows the comparisons of the optimal results and computing efficiency. From Fig. 2 (a), it is observed that the convergence speed of the PBO algorithm is faster than other algorithms. Specifically, the overall time required by the PBO amounts to about a half of the one required by SADEA. Compared with the BO-EI algorithm, the computing time required by PBO-PEI algorithm is reduced by 54.11%. In addition, the objective function value found by PBO algorithm is the smallest among the algorithms.



(a) (b)

Fig. 2. Comparisons of design results. (a) Convergence curves of the objective function. (b) Optimal VSWR obtained four algorithms.

TABLE II
COMPARISIONS OF OPTIMIZATION VALUES AND COST

Algorithms	Function values	Iteration number	Times (Hours)
PBO	5.53	36	2400
BO-EI	19.55	87	5230
SADEA	14.79	78	4681

Utilizing the PBO algorithm, the optimized dimensions $\boldsymbol{x}=\left[39.9,25.13,10.54,3.36.8,97,1.7,3.12,3.95,6.66,14.33\right]$ mm are obtained in 36 iterations, and the final antenna design were fabricated and measured. Fig. 1 (b) shows the photograph of the fabricated prototype. Fig. 3 shows the measured and simulated VSWR at different frequency.

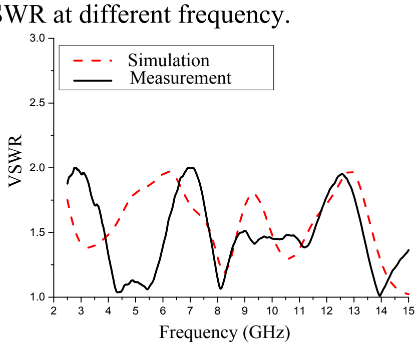
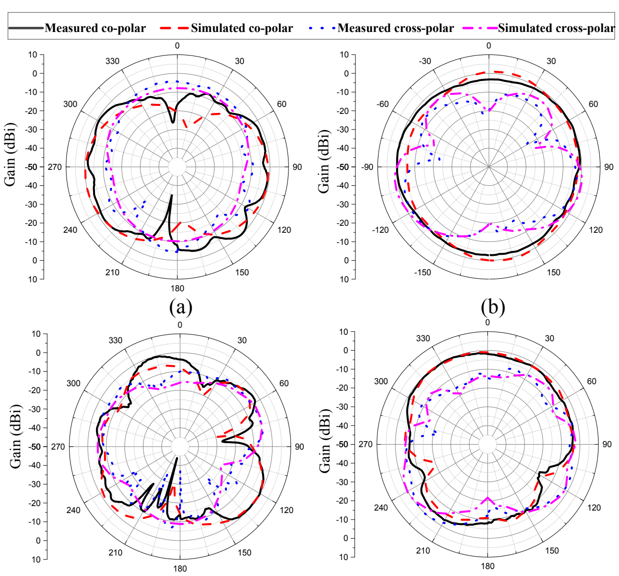


Fig. 3. Comparisons of measured and simulated VSWR.



(c) (d)

Fig.4. Comparisons of measured and simulated radiation patterns. (a) E-plane at 7.5 GHz. (b) H-plane at 7.5 GHz. (c) E-plane at 13.5 GHz. (d) H-plane at 13.5 GHz.

As observed in Fig. 3, the fabricated antenna prototype has a bandwidth range from 2.5 to 15 GHz, which meets the desired design target. Fig.4 presents the comparisons of the simulated and measured radiation patterns of the prototype at 7.5 GHz and 13.5 GHz. As shown in Figs. 3~4, the simulated and measured results are closed, and their differences are due to the fabrication errors of the RF connectors.

V. Conclusion

In this letter, a computationally efficient methodology for automatic design optimization of wideband antennas has been presented. The proposed PBO approach exploits PEI to pick up multiple updating points in each optimization cycle, and then the antenna response at the updating points are automatically calculated using parallel computation of EM models. The proposed method is demonstrated using an ultra-wideband microstrip antenna. Compared with the existing method in antenna design field, the proposed method can take less iteration and achieve speedup in the automated optimization of antenna designs. Numerical results are further confirmed by experimental validation of fabricated antenna prototype.

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