SPACE MAPPING OPTIMIZATION OF MICROWAVE CIRCUITS EXPLOITING SURROGATE MODELS

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ABSTRACT

A powerful new Aggressive Space Mapping optimization algorithm is presented. It draws upon recent developments in both surrogate-based optimization and microwave device neuromodeling. Our surrogate formulation (new to microwave engineering) exploits, in a novel way, a linear frequency-space mapping. This is a powerful approach to severe response misalignments.

INTRODUCTION

We present a novel Aggressive Space Mapping algorithm for microwave circuit optimization. It integrates, for the first time, two distinct optimization approaches: Space Mapping (SM) optimization [1] and surrogate-based optimization [2]. Both approaches aim at efficiently optimizing an accurate and time-intensive "fine" model, e.g., a full-wave electromagnetic simulator. SM exploits the existence of a less accurate but fast "coarse" model. It formulates the design problem as a system of nonlinear equations. On the other hand, surrogate-based optimization, new to the microwave arena, exploits an approximate model iteratively in solving the original design problem.

Our algorithm combines both approaches. The original design problem is solved using an approximate surrogate model. This model is a convex combination of a mapped coarse model and a linearized fine model. The accuracy of the surrogate model is improved in every iteration.

Recent developments in Space Mapping-based Neuromodeling (SMN) [3] exploit frequency-sensitive mappings. We integrate this concept, in a novel way, with SM optimization. In each iteration, a linear frequency-space mapping is exploited in constructing the mapped coarse model. During the optimization iterates, the coarse and fine models are simulated over different sets of frequencies. The algorithm is demonstrated through the design of a high temperature superconducting (HTS) filter [4].

SPACE MAPPING OPTIMIZATION VS. OPTIMIZATION VIA SURROGATES [1, 2]

We denote the fine model responses at a point $\boldsymbol{x}_f \in \Re^{n\times 1}$ and frequency ω by $\boldsymbol{R}_f(\boldsymbol{x}_f, \omega) \in \Re^{Nr\times 1}$. These responses may include the real and imaginary parts of S_{11}, etc. The response vector $\boldsymbol{R}_f(\boldsymbol{x}_f) \in \Re^{m\times 1}$ denotes the responses over all the N_ω simulation frequencies where $m=N_r N_\omega$. The original design problem is

$$\boldsymbol{x}_f^* = arg\left\{ \min_{\boldsymbol{x}_f} U(\boldsymbol{R}_f(\boldsymbol{x}_f)) \right\} \qquad (1)$$

where U is the objective function and $\boldsymbol{x}_f^*$ is the optimal fine model design. Solving (1) using direct optimization methods can be prohibitive due to the model's intensive simulation time.

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SM optimization exploits the existence of a fast but less accurate "coarse" model of the circuit. We denote by $\boldsymbol{x}_c \in \Re^{n\times 1}$ and $\boldsymbol{R}_c(\boldsymbol{x}_c) \in \Re^{m\times 1}$ a coarse model point and the corresponding response, respectively. SM establishes a mapping $\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_f)$ between the two spaces such that $\boldsymbol{R}_f(\boldsymbol{x}_f) \approx \boldsymbol{R}_c(\boldsymbol{x}_c)$ [1]. The space-mapped design $\overline{\boldsymbol{x}}_f$ is a solution of the nonlinear system

$$\boldsymbol{f}(\boldsymbol{x}_f) = \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* = \boldsymbol{0} \qquad (2)$$

where $\boldsymbol{P}(\boldsymbol{x}_f)$ is approximated through Parameter Extraction (PE) and $\boldsymbol{x}_c^*$ is the optimal coarse design.

Previous SM-based optimization algorithms solve (2) iteratively. Let $\boldsymbol{x}_f^{(i)}$ be the *i*th iterate in the solution of (2). The original ASM algorithm utilizes a quasi-Newton step. Our TRASM algorithm minimizes $\left\| \boldsymbol{f}(\boldsymbol{x}_f^{(i+1)}) \right\|$ using least squares within a trust region.

Here, a time-intensive model is optimized using a "surrogate" model. We denote the surrogate model in the *i*th iteration by $\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f) \in \Re^{m\times 1}$. The step taken is obtained by solving

$$\boldsymbol{h}^{(i)} = arg\left\{ \min_{\boldsymbol{h}^{(i)}} U(\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)})) \right\},\ \left\| \boldsymbol{h}^{(i)} \right\| \le \delta^{(i)} \qquad (3)$$

where $\delta^{(i)}$ is the trust region size. The point $\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}$ is then validated using fine model simulation. It is accepted if it improves the desired fine model objective function. Otherwise, the accuracy of $\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f)$ should be improved using fine model validations. Additional fine model simulations may be generated to improve the surrogate model in certain directions of the parameter space.

OUR SURROGATE MODEL

In the *i*th iteration, our algorithm utilizes a surrogate model expressed as a convex combination between a linearized fine model (LFM) and a mapped coarse model (MCM) $\boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f)$. It is given by

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f) = \lambda^{(i)} \boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f) + (1-\lambda^{(i)})(\boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) + \boldsymbol{J}_f^{(i)} \Delta \boldsymbol{x}_f),$$
$$\lambda^{(i)} \in [0,1] \qquad (4)$$

where $\boldsymbol{J}_f^{(i)} \in \Re^{m\times n}$ is an approximation to the Jacobian of fine model responses at $\boldsymbol{x}_f^{(i)}$ and $\Delta \boldsymbol{x}_f = \boldsymbol{x}_f - \boldsymbol{x}_f^{(i)}$. The parameter $\lambda^{(i)}$ determines which of the models LFM or MCM is favored.

The MCM utilizes the linear frequency-space mapping

$$\boldsymbol{R}_f(\boldsymbol{x}_f, \omega_j) \approx \boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f, \omega_j) = \boldsymbol{R}_c(\boldsymbol{P}^{(i)}(\boldsymbol{x}_f, \omega_j), P_\omega^{(i)}(\boldsymbol{x}_f, \omega_j)),\ j=1, 2, \ldots, N_\omega \qquad (5)$$

where

$$\begin{bmatrix} \boldsymbol{P}^{(i)}(\boldsymbol{x}_f, \omega_j) \\ P_\omega^{(i)}(\boldsymbol{x}_f, \omega_j) \end{bmatrix} = \begin{bmatrix} \boldsymbol{B}^{(i)} & \boldsymbol{s}^{(i)} \\ \boldsymbol{t}^{(i)T} & \sigma^{(i)} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{x}_f \\ \omega_j \end{bmatrix} + \begin{bmatrix} \boldsymbol{c}^{(i)} \\ \gamma^{(i)} \end{bmatrix}, \qquad (6)$$

The parameters $\boldsymbol{B}^{(i)} \in \Re^{n\times n}$, $\boldsymbol{s}^{(i)} \in \Re^{n\times 1}$, $\boldsymbol{t}^{(i)} \in \Re^{n\times 1}$, $\boldsymbol{c}^{(i)} \in \Re^{n\times 1}$, $\sigma^{(i)} \in \Re^{1\times 1}$ and $\gamma^{(i)} \in \Re^{1\times 1}$ are the mapping parameters. ω_j is the *j*th simulation frequency, *j*=1, 2, …, N_ω. Here, a fine model point $\boldsymbol{x}_f$ and frequency ω_j correspond to a coarse point $\boldsymbol{P}^{(i)}(\boldsymbol{x}_f, \omega_j)$ and frequency $P_\omega^{(i)}(\boldsymbol{x}_f, \omega_j)$.

The mapping parameters of (6) are obtained so that the MCM approximates the fine model over a region of fine model parameters and frequency. They are obtained by the optimization procedure

$$[\boldsymbol{B}^{(i)}, \boldsymbol{s}^{(i)}, \boldsymbol{t}^{(i)}, \sigma^{(i)}, \boldsymbol{c}^{(i)}, \gamma^{(i)}] = arg\left\{ \min_{\boldsymbol{B}, \boldsymbol{s}, \boldsymbol{t}, \sigma, \boldsymbol{c}, \gamma} \left\| \begin{bmatrix} \boldsymbol{e}_1^T & \boldsymbol{e}_2^T & \cdots & \boldsymbol{e}_{N_p}^T \end{bmatrix}^T \right\| \right\} \qquad (7)$$

$$\boldsymbol{e}_k = \boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f^{(k)}) - \boldsymbol{R}_f(\boldsymbol{x}_f^{(k)})\ \ \forall\, \boldsymbol{x}_f^{(k)} \in V^{(i)} \qquad (8)$$

where $V^{(i)}$ is a set of fine model points whose cardinality is $\left|V^{(i)}\right| = N_p$ and $\boldsymbol{e}_k \in \Re^{m\times 1}$. $V^{(i)}$ is mainly composed of a subset of previously simulated points. It contains points that are

within an α-neighborhood of $\boldsymbol{x}_f^{(i)}$ and sufficiently cover this neighborhood. Additional points may be simulated by the algorithm. This occurs if the algorithm fails to make a successful iteration and the previously simulated fine points do not adequately cover the α-neighborhood.

THE ALGORITHM

The *i*th iteration of the algorithm proceeds as follows. First, the set $V^{(i)}$ is constructed. The mapping parameters are then estimated using the optimization procedure (7)-(8). The step $\boldsymbol{h}^{(i)}$ is obtained by solving (3), where the surrogate model is given by (4). Notice that (3) utilizes only coarse model simulations and can be solved by traditional optimization methods.

$\boldsymbol{h}^{(i)}$ is accepted if it improves the objective function. Otherwise, it is rejected. The parameters $\boldsymbol{J}_f^{(i)}$, $\delta^{(i)}$ and $\lambda^{(i)}$ are updated in each iteration. Broyden's formula [5] is used to update $\boldsymbol{J}_f^{(i)}$. Initially, we set $\boldsymbol{J}_f^{(1)} = \boldsymbol{J}_c^*$, the Jacobian of the coarse model response at $\boldsymbol{x}_c^*$. The trust region $\delta^{(i)}$ is updated based on how the actual reduction r_a in U matches the predicted reduction r_p. The ratio

$$\rho = \frac{r_a}{r_p} = \frac{U(\boldsymbol{R}_f(\boldsymbol{x}_f^{(i)})) - U(\boldsymbol{R}_f(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}))}{U(\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f^{(i)})) - U(\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}))} \quad (9)$$

is thus evaluated at the end of each iteration. If $\rho \geq 0.75$, the surrogate model has good accuracy and we set $\delta^{(i+1)} = \pi_1 \delta^{(i)}$, $\pi_1 > 1.0$. If $\rho \leq 0.10$, we set $\delta^{(i+1)} = \pi_2 \delta^{(i)}$, $0 < \pi_2 < 1.0$. Otherwise, we set $\delta^{(i+1)} = \delta^{(i)}$. $\lambda^{(i)}$ is updated to favor the more accurate model, either the LFM or the MCM. It is initialized by $\lambda^{(1)} = 1$. The actual update utilized is

$$\lambda^{(i+1)} = \frac{\left\| \boldsymbol{E}_l^{(i)} \right\|}{\left\| \boldsymbol{E}_l^{(i)} \right\| + \left\| \boldsymbol{E}_m^{(i)} \right\|} \quad (10)$$

where $\boldsymbol{E}_m^{(i)} = \boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}) - \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)})$ and $\boldsymbol{E}_l^{(i)} = \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) + \boldsymbol{J}_f^{(i)} \boldsymbol{h}^{(i)} - \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)})$ define the prediction error using the MCM and the LFM, respectively. The algorithm terminates if n+1 consecutive unsuccessful iterations are carried out or if $\left\| \boldsymbol{h}^{(i)} \right\|$ becomes sufficiently small. One iteration of the algorithm is shown in Fig. 1.

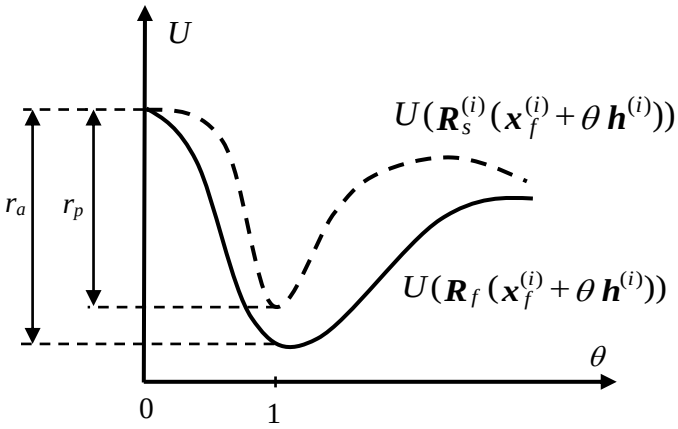

Fig. 1. Illustration of the *i*th iteration of the algorithm.

THE HTS FILTER

We consider the design of an HTS filter [4] (see Fig. 2). The design specifications are

$|S_{21}| \leq 0.05$ for $\omega \leq 3.967$ GHz and

$$4.099 \text{ GHz} \leq \omega \quad (11)$$

$|S_{21}| \geq 0.95$ for 4.008 GHz $\leq \omega \leq$ 4.058 GHz (12)

The design parameters are L_1, L_2, L_3, S_1, S_2 and S_3. We take L_0 = 50 mil and W = 7 mil. The coarse model exploits the empirical models of microstrip lines, coupled lines and open stubs available in OSA90/hope [6]. The fine model employs Sonnet's ***em*** [7] through Empipe [6].

The fine model is simulated at 16 frequency points. We utilize the real and imaginary parts of both S_{11} and S_{21} in the optimization procedure (7)-(8). The initial trust region is $\delta^{(1)} = 0.20 \left\| \boldsymbol{x}_c^* \right\|_\infty$. The interpolation option of Empipe is disabled to make the simulation time per sweep feasible. The grid dimensions in the x and y directions are 1.0 and 1.75 mils, respectively. The substrate dielectric constant is 23.425. The metal and the substrate are both assumed lossless.

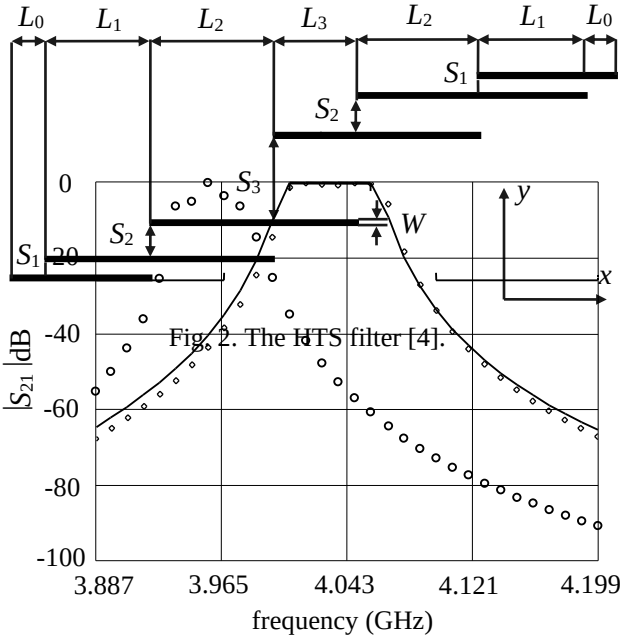

Fig. 2. The HTS filter [4].

Fig. 3. Results for the HTS filter; The optimal coarse response (—), the initial fine response (o) and the final fine model design (◊).

Starting from the snapped optimal coarse design [L_1, L_2, L_3, S_1, S_2, S_3]= [188, 198, 189, 22.75, 99.75, 112] mils, the final design [188, 192, 187, 22.75, 78.75, 91] mils is reached in only 7 iterations, comprising only 7 fine model sweeps. The initial and final responses are shown in Fig 3.

CONCLUSIONS

We present a breakthrough algorithm for efficient optimization of microwave circuits. The algorithm integrates, for the first time, SM optimization with optimization via surrogates. It exploits a novel surrogate formulation in the form of a convex combination of a mapped coarse model and a linearized fine model. The MCM model utilizes, in a novel way, a frequency-space mapping. During optimization, the coarse and fine models are simulated over different frequency ranges. The algorithm is successfully illustrated through the design of a microwave filter.

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