Fast EM-Driven Design Optimization of Microwave Filters Using Adjoint Sensitivity and Response Features

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Abstract — We present an algorithm for design optimization of microwave filters utilizing multi-fidelity electromagnetic (EM)-simulation models, adjoint sensitivities, and a trust-region framework as a convergence safeguard. To further speed up the design process, the optimization is performed at the level of suitably selected response features whose dependence on the designable parameters is significantly less nonlinear than that of the original responses (here, *S*-parameters versus frequency). Switching between the EM models of different fidelity is governed by suitably defined convergence criteria. Our approach is demonstrated by a waveguide filter example. A comprehensive numerical comparison with single- and multi-fidelity optimization algorithms (both adjoint-based) is also provided.

Index Terms — Computer-aided design, EM-driven design, filter optimization, adjoint sensitivity, response features.

I. Introduction

Full-wave electromagnetic (EM) analysis allows accurate performance evaluation of microwave structures. However, its computational expense poses problems for automated EM-driven design closure as most optimization methods require many simulations to converge to optimal designs. The issue is critical for complex structures (with longer simulation times) and those with a larger number of adjustable parameters.

A reduction of EM-driven design cost can be achieved by means of surrogate-based optimization (SBO) [1], where most operations are performed on a suitable surrogate, whereas the expensive high-fidelity simulations are only executed for design verification and providing data for further refinement of the surrogate. SBO methods have been extensively developed over the recent years (e.g., [2], [3], [4]), however, due to various practical issues (e.g., assumed implementation complexity, convergence issues [5], etc.) they have not yet been widely accepted by engineering community.

The recent availability of adjoint sensitivity techniques [6], [7] through some commercial EM solvers ([8], [9]) has revived interest in gradient-based optimization. The possibility of obtaining accurate derivative data at small extra overhead allows for substantial reduction of the optimization cost, as noted in the literature (e.g., [10]). As recently demonstrated [11], adjoint-based optimization can be further accelerated when combined with variable-fidelity EM models.

As indicated in [12] it might be advantageous to carry out the design optimization process in the space of suitably selected feature points, whose dependence on the design variables is much less nonlinear than that of the original responses such as S-parameters vs. frequency.

In this paper, we propose an enhancement of the multi-level algorithm with adjoints [11] by feature-based optimization. In each step, a gradient-based algorithm embedded in a trust region framework is utilized. However, unlike [11], the optimization is conducted using response features (except for the first iteration, where the lowest-fidelity model is optimized at the level of the original responses). As demonstrated using a waveguide filter, adjoint-based optimization at the response-feature level allows for up to 40 percent cost reduction compared to the multi-fidelity adjoint-based algorithm [11], and over 70 percent savings compared to direct high-fidelity model optimization (also with adjoints).

II. Multi-Fidelity Adjoint-Based Optimization with Response Features

A. Problem Formulation and EM Models

The problem at hand can be formulated as follows

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

where $\boldsymbol{R}_f(\boldsymbol{x})$ denotes the response vector of a high-fidelity EM-simulated model of the microwave filter of interest (e.g., $|S_{11}|$ and/or $|S_{21}|$ versus frequency); U is an objective function that encodes given performance specifications, while $\boldsymbol{x}$ is an n-dimensional vector of design variables.

In this work, we utilize a family variable-fidelity models $\{\boldsymbol{R}_j\}$, $j = 1, \ldots, K$, all evaluated by the same EM solver. The model $\boldsymbol{R}_{j+1}$ features finer discretization than the model $\boldsymbol{R}_j$, and, consequently, improved accuracy at the expense of longer simulation time. For notational consistency, we assume that $\boldsymbol{R}_K = \boldsymbol{R}_f$. In practice, the number of coarse-discretization models is two or three.

B. Feature-Based Surrogates

Filter responses are highly nonlinear functions of both frequency and geometry parameters. As shown in [12], efficient optimization can be realized using so-called feature points that determine critical parts of the response, potentially responsible for violation of given design specifications. Figure 1 shows a reflection response of an example filter as well as feature points corresponding to passband edges (–20 dB levels) and local response maxima within the passband. Frequency and level locations of these points determine whether the filter satisfies the design specifications, here, defined as $|S_{11}| \leq -20$ dB for 10.4 GHz to 11.6 GHz.

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The feature points of the response vector $\boldsymbol{R}_k(\boldsymbol{x})$ are denoted as $\boldsymbol{p}_k^{\,j}(\boldsymbol{x}) = [f_k^{\,j}(\boldsymbol{x})\ r_k^{\,j}(\boldsymbol{x})]^T$, $j = 1, \ldots, M$, where, f and r are the frequency and magnitude components of the respective point. They can be extracted by simple analysis (screening) of the original S-parameter response. Design speedup when using feature points results from the fact that $\boldsymbol{p}_k^{\,j}(\boldsymbol{x})$ are normally much less nonlinear w.r.t. $\boldsymbol{x}$ than $\boldsymbol{R}_k(\boldsymbol{x})$. The original problem (1) can be reformulated in the feature space as

$$\boldsymbol{x}^* = \arg\min_{\boldsymbol{x}} U_F\left(\boldsymbol{P}_f(\boldsymbol{x})\right) \tag{2}$$

where U_F is the objective function defined for the feature points (equivalent to U for the original response $\boldsymbol{R}_f(\boldsymbol{x})$), and $\boldsymbol{P}_f = [(\boldsymbol{p}_f^{\,1})^T \ldots (\boldsymbol{p}_f^{\,M})^T]^T$ is the vector of aggregated feature points.

C. Optimization Algorithm

The proposed optimization algorithm produces a sequence of approximate solutions to (1), $\boldsymbol{x}^{(j)}$, $j = 0, 1, \ldots, K$, so that

$$\boldsymbol{x}^{(1)} = \arg\min_{\boldsymbol{x}} U(\boldsymbol{R}_1(\boldsymbol{x})) \tag{3}$$

and

$$\boldsymbol{x}^{(j+1)} = \arg\min_{\boldsymbol{x}} U_F(\boldsymbol{P}_j(\boldsymbol{x})) \tag{4}$$

for $j > 1$, i.e., $\boldsymbol{x}^{(j)}$ is an optimum of the jth model $\boldsymbol{R}_j$. Clearly, $\boldsymbol{x}^{(j)} = \boldsymbol{x}^*$. Note that from the second iteration on, optimization is realized in the feature space. We do not use feature-based optimization in the first iteration because the initial design may be far from the optimum, where some of the relevant feature points are not yet present in the original response.

The vector $\boldsymbol{x}^{(j)}$ is obtained in a trust-region algorithm as

$$\boldsymbol{x}^{(1.i+1)} = \arg\min_{\boldsymbol{x}:\|\boldsymbol{x}-\boldsymbol{x}^{(1.i)}\|\le\delta^{(1.i)}} U(\boldsymbol{G}_1^{(i)}(\boldsymbol{x})) \tag{5}$$

and

$$\boldsymbol{x}^{(j.i+1)} = \arg\min_{\boldsymbol{x}:\|\boldsymbol{x}-\boldsymbol{x}^{(j.i)}\|\le\delta^{(j.i)}} U_F(\boldsymbol{H}_j^{(i)}(\boldsymbol{x})) \tag{6}$$

Here, $\boldsymbol{x}^{(j.i)}$, $i = 0, 1, \ldots$, is a series of approximate solutions of (3) (for $j = 1$) and (4) (for $j > 1$); $\boldsymbol{G}_1^{(i)}$ is the 1st-order expansion of $\boldsymbol{R}_1$ at $\boldsymbol{x}^{(1.i)}$ defined as

$$\boldsymbol{G}_j^{(i)}(\boldsymbol{x}) = \boldsymbol{R}_j(\boldsymbol{x}^{(i)}) + \boldsymbol{J}_{\boldsymbol{R}_j}(\boldsymbol{x}^{(j.i)})\cdot(\boldsymbol{x}-\boldsymbol{x}^{(j.i)}) \tag{7}$$

and where $\boldsymbol{H}_j^{(i)}$ is the linear model of the feature vector $\boldsymbol{P}_j$:

$$\boldsymbol{H}_j^{(i)}(\boldsymbol{x}) = \boldsymbol{P}_j(\boldsymbol{x}^{(i)}) + \nabla_{\boldsymbol{P}_j}(\boldsymbol{x}^{(j.i)})\cdot(\boldsymbol{x}-\boldsymbol{x}^{(j.i)}) \tag{8}$$

where $\boldsymbol{J}_{\boldsymbol{R}1}$ is the Jacobian of $\boldsymbol{R}_1$ and $\nabla_{\boldsymbol{P}j}$ is the gradient of $\boldsymbol{P}_j$, both obtained using the adjoint sensitivity technique. The starting point to find $\boldsymbol{x}^{(j)}$ is $\boldsymbol{x}^{(j.0)} = \boldsymbol{x}^{(j-1)}$ (the initial design $\boldsymbol{x}^{(0)}$ is the starting point for optimizing $\boldsymbol{R}_1$). The process of finding the new design $\boldsymbol{x}^{(j.i+1)}$ and updating the search radius $\delta^{(j.i)}$ follows the standard trust region rules [13]. Switching between the models is controlled by the termination condition $\|\, \boldsymbol{x}^{(j.i)} - \boldsymbol{x}^{(j.i-1)} \,\| < \varepsilon_j$, where $\varepsilon_j = M^{(K-j)}\varepsilon$, with ε as the overall termination threshold; here, $\varepsilon = 0.001$, and M is the scaling factor (here, $M = 10$). Thus, the termination condition for optimizing lower-fidelity models is more relaxed than for the higher-fidelity ones (which is sufficient due to the limited accuracy of the lower-fidelity models).

III. Illustration Example

Consider a waveguide filter with nonsymmetrical irises [14] shown in Fig 2. The design variables are $\boldsymbol{x} = [z_1\ z_2\ z_3\ d_1\ d_2\ d_3\ t_1\ t_2\ t_3]^T$. It is implemented in HFSS [9]. We consider three models: the high-fidelity $\boldsymbol{R}_f$ (~115,000 tetrahedral mesh cells, evaluation time about 25 minutes), and two coarse-discretization models: $\boldsymbol{R}_1$ (~2,000 mesh cells, evaluation time 3 minutes), and $\boldsymbol{R}_2$ (~12,000 mesh cells, evaluation time 10 minutes). The design specifications are: $|S_{11}| < -25$ dB for 10.4 GHz to 11.6 GHz. The initial design (cf. Fig. 3) is $\boldsymbol{x}^{(0)} = [12.0\ 14.0\ 14.0\ 14.0\ 12.0\ 11.0\ 1.5\ 3.0\ 2.5]^T$ mm.

The filter was optimized using the algorithm of Section II. Figure 4 shows the difference between $\boldsymbol{R}_1$, $\boldsymbol{R}_2$ and $\boldsymbol{R}_f$ at a selected design on the optimization path. The high-fidelity model response at the final design $\boldsymbol{x}^* = [12.62\ 13.54\ 14.21\ 15.48\ 12.48\ 11.35\ 1.78\ 2.27\ 1.49]^T$ mm is shown in Fig. 3. It can be observed (cf. Table I) that the total optimization cost corresponds to only about 4 evaluations of the high-fidelity model.

For comparison, the filter was optimized using the multi-fidelity adjoints-based algorithm [11]. Also, the high-fidelity model was optimized directly using the trust-region-based algorithm with adjoint sensitivities, equivalent to executing the algorithm of Section II with $K = 1$. While all final designs are of comparable quality, the design costs of the benchmark techniques are 62% and 233% higher, respectively.

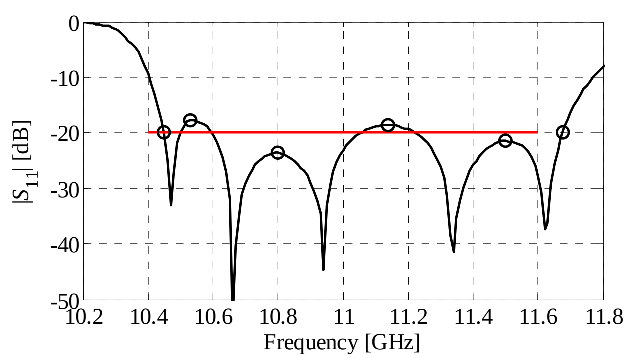

Fig. 1. Return loss of a detuned microwave filter (—) and corresponding response features (o) with design specifications (**—**).

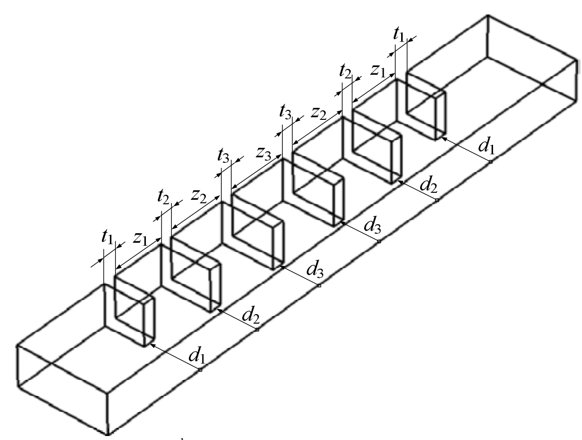

Fig. 2. Geometry of the 5th-order waveguide bandpass filter [14].

IV. Conclusions

A computationally efficient algorithm for design optimization of microwave filters has been proposed. It is based on variable-fidelity EM simulations and adjoint sensitivities, utilizes feature-based optimization, and is embedded in a trust region framework to ensure convergence. As demonstrated by a waveguide filter example, our technique allows considerable savings compared to multi-fidelity gradient search as well as direct optimization of the high-fidelity model (both benchmark methods using adjoints).

Acknowledgements

This work was supported in part by the Icelandic Centre for Research (RANNIS) Grant 130450051, by the Natural Sciences and Engineering Research Council of Canada under Grants RGPIN7239-11, STPGP447367-13, and by Bandler Corporation.

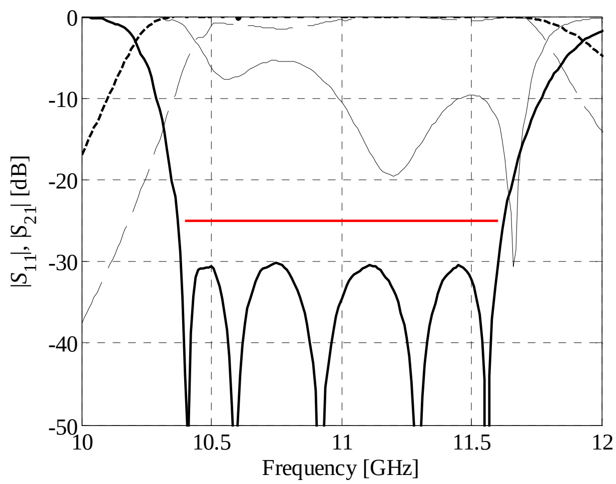

Fig. 3. Fifth-order waveguide filter: responses of the high-fidelity model $\boldsymbol{R}_f$ at the initial (thin lines) and the final (thick lines) designs: $|S_{11}|$ (—) and $|S_{21}|$ (- - -).

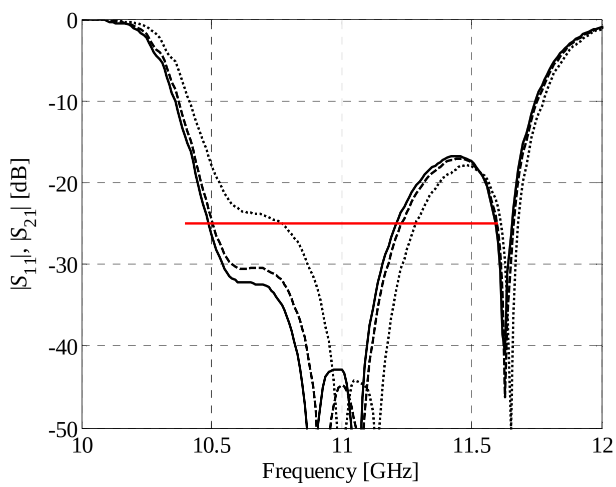

Fig. 4. Fifth-order waveguide bandpass filter: $|S_{11}|$ responses of the models $\boldsymbol{R}_1$ (····), $\boldsymbol{R}_2$ (- - -) and $\boldsymbol{R}_f$ (—) at one of the designs selected design on the optimization path. The plots indicate the differences between the models is meaningful, particularly for lower values of $|S_{11}|$.

Table I. Fifth-order Waveguide Filter: Optimization Results

Algorithm	Optimization Cost: Number of Model Evaluations	CPU Time: Absolute [min]	CPU Time: Relative to $\boldsymbol{R}_f$	max $\lvert S_{11}\rvert$ for 10.4 GHz to 11.6 GHz at Final Design
Multi-Fidelity Feature-Based (This work)	11 × $\boldsymbol{R}_1$	33	1.3	–30.2 dB
	3 × $\boldsymbol{R}_2$	30	1.2	
	2 × $\boldsymbol{R}_f$	50	2.0	
	Total cost:	113	4.5	
Multi-Fidelity Trust-Region$	11 × $\boldsymbol{R}_1$	33	1.3	–29.3 dB
	5 × $\boldsymbol{R}_2$	50	2.0	
	4 × $\boldsymbol{R}_f$	100	4.0	
	Total cost:	183	7.3	
Trust-Region-Based#	15 × $\boldsymbol{R}_f$	375	15.0	–26.6 dB

$ Multi-fidelity trust-region optimization with adjoints [11].
# Trust-region optimization of $\boldsymbol{R}_f$ with adjoints (cf. Section II with $K = 1$).

References

[1] S. Koziel, D. Echeverría-Ciaurri, and L. Leifsson, "Surrogate-based methods," in S. Koziel and X.S. Yang (Eds.) *Computational Optimization, Methods and Algorithms*, Springer, pp. 33-60, 2011.

[2] M.B. Yelten, T. Zhu, S. Koziel, P.D. Franzon, and M.B. Steer, "Demystifying surrogate modeling for circuits and systems," *IEEE Circuits Syst. Magazine*, vol. 12, no. 1, pp. 45-63, 2012.

[3] J.W. Bandler, Q.S. Cheng, S.A. Dakroury, A.S. Mohamed, M.H. Bakr, K. Madsen, and J. Søndergaard, "Space mapping: the state of the art," *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 1, pp. 337-361, Jan. 2004.

[4] J.W. Bandler, "Have you ever wondered about the engineer's mysterious 'feel' for a problem?" *IEEE Canadian Review*, no. 70, pp. 50-60, Summer 2013.

[5] S. Koziel, J.W. Bandler, and K. Madsen, "Quality assessment of coarse models and surrogates for space mapping optimization," *Optimization and Engineering*, vol. 9, no. 4, pp. 375-391, 2008.

[6] J.W. Bandler and R.E. Seviora, "Direct method for evaluating scattering matrix sensitivities," *Electr. Lett.*, vol. 6, no. 24, pp. 773-774, Nov. 1970.

[7] M.H. Bakr and N.K. Nikolova, "An adjoint variable method for time domain TLM with wideband Johns matrix boundaries," *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 2, pp. 678-685, Feb. 2004.

[8] CST Microwave Studio, ver. 2013, CST AG, Bad Nauheimer Str. 19, D-64289 Darmstadt, Germany, http://www.cst.com, 2013.

[9] Ansys HFSS, ver. 14.0 (2012), ANSYS, Inc., Southpointe 275 Technology Drive, Canonsburg, PA 15317.

[10] Y.S. Chung, C. Cheon, I.H. Park, and S.Y. Hahn, "Optimal design method for microwave device using time domain method and design sensitivity analysis-part II: FDTD case," *IEEE Trans. Magn.*, vol. 37, no. 5, pp. 3255-3259, Sep. 2001.

[11] A. Bekasiewicz and S. Koziel, "Efficient multi-fidelity design optimization of microwave filters using adjoint sensitivity," *Int. J. RF and Microwave CAE*, early view, 2014.

[12] O. Glubokov and S. Koziel, "EM-driven tuning of substrate integrated waveguide filters exploiting feature-space surrogates," *Int. Microwave Symp.*, 2014.

[13] A.R. Conn, N.I.M. Gould, and P.L. Toint, *Trust Region Methods*, MPS-SIAM Series on Optimization, 2000.

[14] W. Hauth, R. Keller, U. Papziner, R. Ihmels, T. Sieverding, and F. Arndt, Rigorous CAD of multipost coupled rectangular waveguide components," *in Proc. 23rd European Microw. Conf.*, Madrid, Spain, Sept, 1993, pp. 611-614.