# An Aggressive Approach To Parameter Extraction

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Abstract—A novel Aggressive Parameter Extraction (APE) algorithm is presented. Our APE algorithm addresses the optimal selection of parameter perturbations used to increase trust in parameter extraction uniqueness. We establish an appropriate criterion for the generation of these perturbations. The APE algorithm classifies possible solutions for the parameter extraction problem. Two different approaches for obtaining subsequent perturbations are utilized based on a classification of the extracted parameters. The APE algorithm is successfully demonstrated in parameter extraction of an HTS filter model.

### I. INTRODUCTION

Parameter extraction is important in device modeling and characterization. It also plays a crucial role in the Space Mapping (SM) technology [1, 2, 3]. Optimization approaches to parameter extraction often yield nonunique solutions. In SM optimization this nonuniqueness may lead to divergence or oscillatory behavior.

We present an "aggressive" approach to parameter extraction. While generally applicable, the new algorithm is discussed here in the context of SM technology. We assume the existence of a "fine" model that generates the target responses and a "coarse" model whose parameters are to be extracted.

Several authors have addressed nonuniqueness in parameter extraction. For example, Bandler et al. [4] proposed the idea of making unknown perturbations to a

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certain system whose parameters are to be extracted. Later Bandler et al. [5] suggested that multi-point parameter extraction be used to match the first-order derivatives of the two models to ensure a global minimum. The perturbations used in that approach are predefined and arbitrary. The optimality of the selection of those perturbations was not addressed. Recently, a recursive multipoint parameter extraction technique was suggested by Bakr et al. [2]. This approach employs a mapping between the two models to enhance uniqueness.

Our new algorithm aims at minimizing the number of perturbations used in the multi-point parameter extraction process by utilizing the best possible perturbation during each iteration. Consequently, we designate this as an Aggressive Parameter Extraction (APE) algorithm. Each perturbation requires an additional fine simulation which could be very CPU intensive. We classify the different solutions returned by the multi-point extraction process and, based on this classification, a new perturbation that is likely to sharpen the result is suggested.

## II. PARAMETER EXTRACTION

The objective of parameter extraction is to find a set of parameters of a model whose responses match a given set of measurements. It can be formulated as

$$\mathbf{x}_{os}^{e} = arg \left\{ \min_{\mathbf{x}_{os}} \left\| \mathbf{R}_{m} - \mathbf{R}_{os}(\mathbf{x}_{os}) \right\| \right\}$$
(1)

where  $R_m$  is the vector of given measurements,  $R_{os}$  is the vector of circuit responses and  $x_{os}^e$  is the vector of extracted parameters. In the context of SM the fine model response  $R_{em}$ , typically from an electromagnetic simulator, at a certain point  $x_{em}$  supplies the target response  $R_m$ . Fig. 1 illustrates the single point parameter extraction for the two dimensional case. Bakr *et al.* [2] suggested a procedure in which the vector of extracted parameters should satisfy

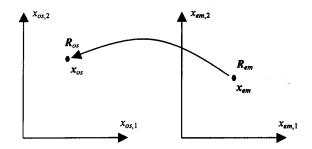


Fig. 1. Illustration of single-point parameter extraction.

$$\mathbf{x}_{os}^{e} = arg \left\{ \min_{\mathbf{x}_{os}} \left\| \left[ \mathbf{e}_{0}^{T} \quad \mathbf{e}_{1}^{T} \quad \cdots \quad \mathbf{e}_{N_{p}}^{T} \right]^{T} \right\| \right\}$$
 (2)

where

$$\boldsymbol{e}_0 = \boldsymbol{R}_{os}(\boldsymbol{x}_{os}) - \boldsymbol{R}_{em}(\boldsymbol{x}_{em}) \tag{3}$$

and

$$e_i = R_{os}(x_{os} + \Delta x_{os}^{(i)}) - R_{em}(x_{em} + \Delta x_{em}^{(i)}),$$
 (4)

where  $i=1, 2, \ldots, N_p$  and  $\Delta x_{os}^{(i)} \in V_p$ , the set of perturbations in the coarse model space where  $|V_p| = N_p$  and  $\Delta x_{em}^{(i)}$  is the corresponding perturbation in the fine model space. The perturbations  $\Delta x_{os}^{(i)}$  and  $\Delta x_{em}^{(i)}$  are related through a matrix B by

$$\Delta x_{os}^{(i)} = \mathbf{B} \Delta x_{em}^{(i)} \tag{5}$$

The matrix B approximates the mapping between the two spaces. It follows that the set V of fine model points utilized for the multi-point parameter extraction is

$$V = \{x_{em}\} \cup \left\{x_{em} + \Delta x_{em}^{(i)} \middle| \forall \Delta x_{os}^{(i)} \in V_p\right\}$$
 (6)

Fig. 2 illustrates the multi-point parameter extraction procedure.

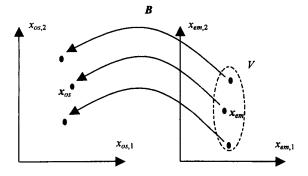


Fig. 2. Illustration of multi-point parameter extraction.

The vector of coarse model responses  $\mathbf{R}$  used to match the two models is given by

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_{os}(\mathbf{x}_{os}) \\ \mathbf{R}_{os}(\mathbf{x}_{os} + \Delta \mathbf{x}_{os}^{(1)}) \\ \vdots \\ \mathbf{R}_{os}(\mathbf{x}_{os} + \Delta \mathbf{x}_{os}^{(Np)}) \end{bmatrix}$$
(7)

The dimensionality of R is  $m_p$ , where  $m_p = (N_p + 1)m$  and m is the dimensionality of both  $R_{os}$  and  $R_{em}$ . Vector  $x_{os}^e$  is labeled locally unique [6] if there exists an open neighborhood of  $x_{os}^e$  containing no other point  $x_{os}$  such that  $R(x_{os}) = R(x_{os}^e)$ . Otherwise, it is labeled locally nonunique. It was shown in [6] that the local uniqueness condition is equivalent to the condition that the Jacobian of the vector of matched responses R has rank n, where n is the dimensionality of  $x_{os}$  and  $x_{em}$ .

# III. THE NEW ALGORITHM

In each iteration of the APE algorithm multi-point parameter extraction is applied using the current set of fine model points to obtain  $x_{os}^e$ . The Jacobian J of R at  $x_{os}^e$  is then evaluated. The rank k of J is then checked. If k < n, the number of extracted parameters, the perturbation taken is obtained by solving the linear system of equations

$$A^T \Delta x = -c \tag{8}$$

where the matrix A is given by

$$A = [G^{(k+1)}g^{(1)}...G^{(n)}g^{(1)}...G^{(n)}g^{(k)}]$$
(9)

and the vector c is given by

$$\boldsymbol{c} = \begin{bmatrix} \boldsymbol{g}^{(k+1)T} \, \boldsymbol{g}^{(1)} \\ \vdots \\ \boldsymbol{g}^{(n)T} \, \boldsymbol{g}^{(1)} \\ \vdots \\ \boldsymbol{g}^{(n)T} \, \boldsymbol{g}^{(k)} \end{bmatrix}$$
(10)

Here  $g^{(i)}$ ,  $i=1,\ldots,k$  is the set of linearly independent gradients of responses in R and  $g^{(i)}$ ,  $i=k+1,\ldots,n$  is the set of gradients of n-k of the newly simulated responses at the point  $x_{os}^e + \Delta x$ .  $G^{(i)}$ ,  $i=k+1,\ldots,n$  is the set of Hessians of the corresponding responses at the point  $x_{os}^e$ . This perturbation attempts to increase the rank of J at  $x_{os}^e$  by at least one.

Otherwise, the perturbation taken by the algorithm is obtained by solving the eigenvalue problem

$$(\boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e})^{T}\boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e}) - \boldsymbol{I})\Delta\boldsymbol{x} = \lambda\Delta\boldsymbol{x}$$
 (11)

This perturbation aims at maximizing the increase in the  $\ell_2$  objective function of the parameter extraction problem at false minima and thus weakens these points as possible solutions to the multi-point parameter extraction problem.

Once the perturbation is determined in the coarse model space, it is mapped to the fine model space and a new fine model point is added to the set of points used for parameter extraction. Multi-point parameter extraction is then repeated using the augmented set of points. The algorithm terminates when the vector of extracted coarse model parameters does not change significantly in two consecutive iterations. A MATLAB [7] implementation of the algorithm is currently used.

## IV. THE HTS FILTER

The fine model for HTS filter [8] (Fig. 3) is simulated as a whole using Sonnet's *em* [9]. The "coarse" model is a decomposed Sonnet version of the fine model. This model exploits a coarser grid than that used for the fine model.

It is required to extract the coarse model parameters corresponding to the fine model parameters given in Table I. The values in this table are the optimal coarse model design obtained using the minimax optimizer in OSA90/hope [10] according to specifications given in [8].

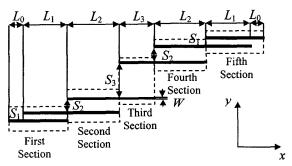


Fig. 3. The HTS filter [8].

We utilized the responses at 15 discrete frequencies in the range [3.967 GHz, 4.099 GHz] in the parameter extraction process.

The algorithm first started by applying single point parameter extraction. The set V contains only the point given in the second column of Table II. The extracted coarse model parameters are given in the second column of Table III The algorithm detected that this extracted point is a locally unique minimum. A new fine model point is then generated by solving the eigenvalue problem (11). A two-point parameter extraction step is then carried out. The points utilized are given in the second and third columns of Table II. The extracted coarse model parameters are given in the third column of Table III. Again the algorithm detected that the extracted coarse model point is locally unique and a new fine model point

TABLE I THE OPTIMAL COARSE MODEL DESIGN FOR THE HTS FILTER

Parameter	Value		
$L_1$	181.00		
$L_2$	201.59		
$L_3$	180.97		
$S_1$	20.12		
$S_2$	67.89		
S <sub>3</sub>	66.85		

All values are in mils

TABLE II
THE FINE MODEL POINTS USED IN THE APE
ALGORITHM FOR THE HTS FILTER

Parameter	$x_f^{(1)}$	$x_f^{(2)}$	$x_f^{(3)}$	$x_f^{(4)}$
$L_1$	181.00	182.55	181.34	179.86
$L_2$	201.59	205.64	205.38	197.74
$L_3$	180.97	183.36	184.20	178.08
$S_1$	20.12	20.05	20.07	20.46
$S_2$	67.89	68.40	68.08	67.35
$S_3$	66.85	67.25	66.98	66.46

All values are in mils

is generated and added to the set of points. The same steps were then repeated for three-point and four point parameter extraction. The points utilized are given in Table II. The results are shown in the fourth and fifth columns of Table III. It is clear that the extracted parameters are approaching a limit. The fine model response and the response at the corresponding extracted

TABLE III
THE VARIATION IN THE EXTRACTED PARAMETERS
FOR THE HTS FILTER

Parameter	1	2	3	4
$L_1$	188.31	179.99	176.67	178.50
$L_2$	197.69	204.52	208.52	206.78
$L_3$	189.72	181.23	178.00	179.09
$S_1$	19.34	17.13	17.21	18.99
$S_2$	52.67	63.44	56.52	57.99
$S_3$	52.06	53.18	53.47	56.77

all values are in mils

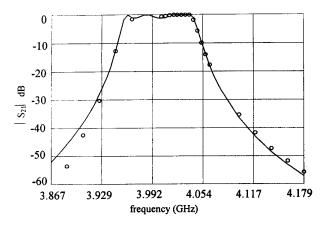


Fig. 4. The fine model response (o) and the corresponding coarse model response (-) at the extracted coarse model point obtained through four-point parameter extraction for the HTS filter. Note that only points in the range 3.967 GHz to 4.099 GHz were actually used.

coarse model point for the last iteration are shown in Fig. 4. Fig. 4 demonstrates that a good match between the responses of both models over a wider range of frequencies than that used for parameter extraction is achieved.

#### V. CONCLUSIONS

An Aggressive Parameter Extraction (APE) algorithm is proposed. Our APE algorithm addresses the optimal selection of parameter perturbations used to improve the sharpness of a multi-point parameter extraction procedure. New parameter perturbations are generated based on the nature of the minimum reached in the previous iteration. We consider possibly locally unique and locally non-unique minima. The APE algorithm continues until the extracted coarse model parameters can be trusted.

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#### REFERENCES

- [1] J.W. Bandler, R.M. Biernacki, S.H. Chen, R.H. Hemmers and K. Madsen, "Electromagnetic optimization exploiting aggressive space mapping," *IEEE Trans. Microwave Theory Tech.*, vol. 43, 1995, pp. 2874-2882.
- [2] M.H. Bakr, J.W. Bandler, R.M. Biernacki, S.H. Chen and K. Madsen, "A trust region aggressive space mapping algorithm for EM optimization," *IEEE Trans. Microwave Theory Tech.*, vol. 46, 1998, pp. 2412-2425.
- [3] J.W. Bandler, R.M. Biernacki, S.H. Chen, P.A. Grobelny and R.H. Hemmers, "Space mapping technique for electromagnetic optimization," *IEEE Trans. Microwave Theory Tech.*, vol. 42, 1994, pp. 2536-2544.
- [4] J.W. Bandler, S.H. Chen and S. Daijavad, "Microwave device modeling using efficient ℓ<sub>1</sub> optimization: a novel approach," *IEEE Trans. Microwave Theory Tech.*, vol. MTT-34, 1986, pp. 1282-1293.
- [5] J.W. Bandler, R.M. Biernacki and S.H. Chen, "Fully automated space mapping optimization of 3D structures," *IEEE MTT-S Int. Microwave Symp. Dig.* (San Francisco, CA), 1996, pp. 753-756.
- [6] J.W. Bandler and A.E. Salama, "Fault diagnosis of analog circuits," Proc. IEEE, vol. 73, pp. 1279-1325, 1985.
- [7] MATLAB<sup>®</sup> Version 5.0, The Math. Works, Inc., 24 Prime Park Way, Natick, MA 01760, 1997.
- [8] J.W. Bandler, R.M. Biernacki, S.H. Chen, W.J. Gestinger, P.A. Grobelny, C. Moskowitz and S.H. Talisa, "Electromagnetic design of high-temperature superconducting filters," Int. J. Microwave and Millimeter-Wave Computer-Aided Engineering, vol. 5, 1995, pp. 331-343.
- [9] em<sup>M</sup>, Sonnet Software, Inc., 1020 Seventh North Street, Suite 210, Liverpool, NY 13088, 1997.
- [10] OSA90/hope<sup>™</sup> Version 4.0, formerly Optimization Systems Associates Inc., P.O. Box 8083, Dundas, ON, Canada, L9H 5E7, 1997, now HP EEsof Division, 1400 Fountaingrove Parkway, Santa Rosa, CA 95403-1799.