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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 algorithm terminates if the extracted parameters can be trusted. It is illustrated using full-wave electromagnetic simulations of microwave transformers and filters. The APE algorithm is successfully applied to parameter extraction of an HTS filter.

SUMMARY

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.

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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 certain system whose parameters are to be extracted. Later Bandler *et al*. [5] suggested that a 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 multi-point parameter extraction technique was suggested by Bakr *et al*. [3]. This approach employs a mapping between the two models to enhance uniqueness.

Our new algorithm aims at minimizing the number of perturbations used in a 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 circuit 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.

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

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

where $\boldsymbol{R}_m$ is the vector of given measurements, $\boldsymbol{R}_{os}$ is the vector of circuit responses and $\boldsymbol{x}_{os}^{e}$ is the vector of extracted parameters. In the context of SM the fine model response $\boldsymbol{R}_{em}$, typically from an electromagnetic simulator, at a certain point $\boldsymbol{x}_{em}$ supplies the target response $\boldsymbol{R}_m$. Bakr *et al*. [3] suggested a procedure in which the vector of extracted parameters should satisfy

$$\boldsymbol{x}_{os}^{e} = arg\left\{\min_{\boldsymbol{x}_{os}} \left\| \begin{bmatrix} \boldsymbol{e}_0^{\,T} & \boldsymbol{e}_1^{\,T} & \cdots & \boldsymbol{e}_{N_p}^{\,T} \end{bmatrix}^T \right\| \right\} \tag{2}$$

where $\boldsymbol{e}_0 = \boldsymbol{R}_{os}(\boldsymbol{x}_{os}) - \boldsymbol{R}_{em}(\boldsymbol{x}_{em})$ and $\boldsymbol{e}_i = \boldsymbol{R}_{os}(\boldsymbol{x}_{os} + \Delta\boldsymbol{x}_{os}^{(i)}) - \boldsymbol{R}_{em}(\boldsymbol{x}_{em} + \boldsymbol{B}^{-1}\Delta\boldsymbol{x}_{os}^{(i)})$, i=1, 2, . ., N_p and $\Delta\boldsymbol{x}_{os}^{(i)} \in V_P$, the set of perturbations in the coarse model space where $|V_p| = N_p$. The matrix $\boldsymbol{B}$ 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 $V = \{\boldsymbol{x}_{em}\} \cup \left\{ \boldsymbol{x}_{em} + \boldsymbol{B}^{-1}\Delta\boldsymbol{x}_{os}^{(i)} \,\middle|\, \forall\, \Delta\boldsymbol{x}_{os}^{(i)} \in V_p \right\}$.

Classification of Extracted Parameters

It follows from (2) that the vector of coarse model responses $\boldsymbol{R}$ used to match the two models is given by

$$\boldsymbol{R} = \begin{bmatrix} \boldsymbol{R}_{os}(\boldsymbol{x}_{os}) \\ \boldsymbol{R}_{os}(\boldsymbol{x}_{os} + \Delta\boldsymbol{x}_{os}^{(1)}) \\ . \\ . \\ \boldsymbol{R}_{os}(\boldsymbol{x}_{os} + \Delta\boldsymbol{x}_{os}^{(N_p)}) \end{bmatrix} \tag{3}$$

The dimensionality of $\boldsymbol{R}$ is m_p, where $m_p=(N_p+1)m$ and m is the dimensionality of both $\boldsymbol{R}_{os}$ and $\boldsymbol{R}_{em}$. Vector $\boldsymbol{x}_{os}^{e}$ is labeled locally unique [6] if there exists an open neighborhood of $\boldsymbol{x}_{os}^{e}$ containing no other point $\boldsymbol{x}_{os}$ such that $\boldsymbol{R}(\boldsymbol{x}_{os}) = \boldsymbol{R}(\boldsymbol{x}_{os}^{e})$. 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 $\boldsymbol{R}$ has rank n.

The Locally Nonunique Case

Assume that a locally nonunique minimum was obtained and that the rank of the Jacobian $\boldsymbol{J}$ of $\boldsymbol{R}$ at $\boldsymbol{x}_{os}^{e}$ is k where $k < n$. We suggest a perturbation $\Delta\boldsymbol{x}$ that attempts to increase the rank of $\boldsymbol{J}$ at this minimum by at least one. This is achieved by imposing the condition that the gradients of n–k of the coarse model responses generated by the new coarse model point $\boldsymbol{x}_{os}^{e} + \Delta\boldsymbol{x}$ be normal to a linearly independent set of gradients of cardinality k of the responses in the vector $\boldsymbol{R}$ at the point $\boldsymbol{x}_{os} = \boldsymbol{x}_{os}^{e}$. It can be shown that the perturbation $\Delta\boldsymbol{x}$ satisfying this condition can be obtained by solving the system

$$\boldsymbol{A}^T \Delta\boldsymbol{x} = -\boldsymbol{c} \tag{4}$$

where the matrix $\boldsymbol{A}$ is given by

$$\boldsymbol{A} = \left[\boldsymbol{G}^{(k+1)}\boldsymbol{g}^{(1)} \,.\, .\boldsymbol{G}^{(n)}\boldsymbol{g}^{(1)} \ldots.. \boldsymbol{G}^{(n)}\boldsymbol{g}^{(k)}\right] \tag{5}$$

and the vector $\boldsymbol{c}$ is given by

$$\boldsymbol{c} = \begin{bmatrix} \boldsymbol{g}^{(k+1)T}\boldsymbol{g}^{(1)} \\ . \\ \boldsymbol{g}^{(n)T}\boldsymbol{g}^{(1)} \\ . \\ \boldsymbol{g}^{(n)T}\boldsymbol{g}^{(k)} \end{bmatrix} \tag{6}$$

Here $\boldsymbol{g}^{(i)}$, i = 1, . ., k is the set of linearly independent gradients and $\boldsymbol{g}^{(i)}$, i = k+1, . ., n is the set of gradients of n–k of the newly simulated responses at the point $\boldsymbol{x}_{os}^{e} + \Delta\boldsymbol{x}$. $\boldsymbol{G}^{(i)}$, i = k+1, . ., n is the set of Hessians of the corresponding responses at the point $\boldsymbol{x}_{os}^{e}$. The proof of (4) is omitted here for brevity.

The Locally Unique Case

If the minimum obtained by the multi-point parameter extraction is a locally unique minimum we still have to ensure that this is the true solution to the extraction problem. Assume that there exist two locally unique minima $\boldsymbol{x}_{os}^{e,1}$ and $\boldsymbol{x}_{os}^{e,2}$ for the multi-point parameter extraction problem obtained using a set of perturbations V_p. Assume also that a perturbation of $\Delta\boldsymbol{x}$ is sought. This perturbation results in deviations of the coarse model responses at the two minima

$$\Delta\boldsymbol{R}_1 = \boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e,1})\Delta\boldsymbol{x} \quad \text{and} \quad \Delta\boldsymbol{R}_2 = \boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e,2})\Delta\boldsymbol{x} \tag{7}$$

where $\boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e,1})$ and $\boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e,2})$ are the Jacobians of the coarse model responses at the two points $\boldsymbol{x}_{os}^{e,1}$ and $\boldsymbol{x}_{os}^{e,2}$, respectively. We impose the condition that the difference between the ℓ_2 norms of these two response deviations be maximized subject to a certain trust region size. It can be shown that the perturbation $\Delta\boldsymbol{x}$ is obtained by solving the eigenvalue problem

$$(\boldsymbol{J}_{os}(\boldsymbol{x}_{os}^{e,1})^T \boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,1}) - \boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,2})^T \boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,2}))\Delta\boldsymbol{x} = \ l\Delta\boldsymbol{x} \quad (8)$$

This perturbation aims at maximizing the increase in the ℓ_2 objective function of the parameter extraction problem at false minima and thus weaken these points as possible solutions to the multi-point parameter extraction problem. The perturbation formula (8) is not suitable for practical implementation. Once a locally unique minimum is reached the Jacobian of the coarse model responses can be readily obtained at this point. However, there is no available information about the Jacobian of the coarse model responses at other locally unique minima that may exist. In such a case, the only reasonable assumption that can be made about the other minima is that the matrix $\boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,2})^T \boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,2})$ in (8) is the identity. This implies that no *a priori* assumption is made about the curvature at the other minimum. It follows that $\Delta\boldsymbol{x}$ should be an eigenvector of the matrix $\boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,1})^T \boldsymbol{J}_{os}\ (\boldsymbol{x}_{os}^{e,1})$.

The perturbation determined by (4) or (8) is a suggested perturbation in the coarse model space. The new fine model point that should be added to the set of fine model points used for the multi-point parameter extraction is obtained by mapping the perturbation obtained in the coarse model space back to the fine model space using the matrix ***B***, which is assumed to be given. This matrix is taken to be the identity if no information is available about the mapping between the two spaces.

The APE Algorithm

In each iteration of the APE algorithm multi-point parameter extraction is applied using the current set of fine model points. The Jacobian ***J*** at $\boldsymbol{x}_{os}^{e}$ is then evaluated. The rank of ***J*** is then checked to determine whether the solution is locally unique or not. If it is locally nonunique the perturbation given by (4) is evaluated. Otherwise, the perturbation given by (8) is evaluated. 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 and multi-point parameter extraction is 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.

A 10:1 Impedance Transformer [8]

Designable parameters are taken as the characteristic impedances of the two transmission lines while the two lengths of the transmission lines are kept fixed at their optimal values (quarter wavelength). The coarse model utilizes nonscaled parameters while a synthetic "fine" model scales each of the two impedances by a factor of 1.6. We use OSA90/hope [9] for all simulations.

We applied the APE algorithm to extract coarse model parameters corresponding to the fine model responses evaluated at $[2.26277 \quad 4.52592]^T$. This point is the optimal coarse model design according to the specifications in [8]. The responses used are the reflection coefficients calculated at 11 equally spaced frequencies in the range 0.5 GHz ≤ f ≤ 1.5 GHz. First, we applied single point parameter extraction. The responses are shown in Fig. 1. The corresponding contours of the ℓ_2 objective function of the parameter extraction problem are shown in Fig. 1(b). We note three locally unique minima for the extraction problem. The APE algorithm generates a new perturbation using (8). The set of fine model points utilized in the two-point parameter extraction is

$$V = \left\{ [2.26277 \quad 4.52592]^T, [1.49975 \quad 4.76634]^T \right\} \tag{9}$$

The fine model response for each point in the set V in (9) and the response at the corresponding extracted coarse model point are shown in Fig. 2. The corresponding ℓ_2 contours of the two-point parameter extraction problem are shown in Fig. 2(c). We note two locally unique minima. The algorithm generates a third perturbation using (8). The set of fine model points utilized in the three-point parameter extraction is

$$V = \left\{ [2.26277 \quad 4.52592]^T, [1.49975 \quad 4.76634]^T, [3.02024 \quad 4.26855]^T \right\} \tag{10}$$

The fine model response for each point in the set V in (10) and the response at the corresponding extracted coarse model point are shown in Fig. 3. The corresponding contours of the ℓ_2 objective function of the three-point parameter extraction are shown in Fig. 3(d). This figure shows that the false minimum is weakened. The vector of extracted coarse model parameters approaches a limit and thus the APE algorithm terminates. The variation in extracted parameters is given in Table I.

The HTS Filter [10]

The fine model for HTS filter (Fig. 4) is simulated as a whole using Sonnet's ***em*** [11]. 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. The physical parameters of the coarse and fine models are given in Table II.

It is required to extract the coarse model parameters corresponding to the fine model parameters given in Table III. The values in this table are the optimal coarse model design obtained using the minimax optimizer in OSA90/hope according to specifications given in [10]. 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 IV. The extracted coarse model parameters are given in the second column of Table V. Fig. 5 shows the fine model response at the given fine model point and the response at the extracted coarse model point.

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 (8). A two-point parameter extraction step is then carried out. The points utilized are given in the second and third columns of Table IV. The extracted coarse model parameters are given in the third column of Table V. Fig. 6 shows the fine model response at the two utilized fine model points and the corresponding responses at the extracted coarse model points, respectively. Again the algorithm detected that the extracted coarse model point is locally unique and a new fine model point 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 IV. The results are shown in the fourth and fifth columns of Table V. It is clear that the extracted parameters are approaching a limit. The fine model responses and the responses at the corresponding extracted coarse model points for the last two iterations are shown in Figs. 7 and 8, respectively. Fig. 8(a) 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.

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 nonunique minima. The APE algorithm continues until the extracted coarse model parameters can be trusted.

References

[1] 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.

[2] 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.

[3] 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 MTT-S Int. Microwave Symp. Dig.* (Baltimore, MD), 1998, pp. 1759-1762.

[4] J.W. Bandler, S.H. Chen and S. Daijavad, "Microwave device modeling using efficient ℓ_1 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® Version 5.0, The Math. Works, Inc., 24 Prime Park Way, Natick, MA 01760, 1997.

[8] J.W. Bandler, "Optimization methods for computer-aided design," *IEEE Trans. Microwave Theory Tech.*, vol. MTT-17, 1969, pp. 533-552.

[9] *OSA90/hope*™ 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.

[10] 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.

[11] ***em***™ , Sonnet Software, Inc., 1020 Seventh North Street, Suite 210, Liverpool, NY 13088, 1997.