Optimization for RF Coupling and Interference Reduction of Devices in Complex Systems

E. S. Siah[1], T. Ozdemir[1], J. L. Volakis[1], P. Y. Papalambros[2]
[1]Radiation Laboratory, EECS Dept.,
[2]ODE Laboratory, MEAM Dept.,
University of Michigan, 1301 Beal Ave
Ann Arbor, MI 48109-2122, USA
e-mail: esiah@eecs.umich.edu, volakis@eecs.umich.edu

R. W. Wiese
General Motors Corporation
GM Proving Grounds, Mail Code 483-340-111
3300 GM Rd.
Milford, MI 48380, USA
e-mail: richard.w.wiese@gm.com

Abstract: In recent years, evolutionary optimization methods such as genetic algorithms have become increasingly popular in EM optimization problems. However, these methods tend to have slow convergence bounds and further, they do not yield a deterministic optimal solution. In this paper, we propose a new method of using Kriging meta-modeling in conjunction with the divided rectangles (DIRECT) global optimizer to yield a global optimum solution. DIRECT yields a deterministic answer with a fast convergence bound and inherits both local and global optimization properties. This proposed hybrid optimization routine is applied here to two examples dealing with electromagnetic coupling reduction. One of them deals with minimizing coupling to sensors from antenna radiation on automobiles. The other example focuses on multi-sensor optimization subject to RF coupling constraints.

Keywords: Optimization, Kriging, Fast Multipole Method, Method of Moments, EMC/EMI

Introduction

Recent developments with fast algorithms like the multilevel fast multipole moment method (MLFMM) and the fast hybrid finite-element boundary-integral (FE-BI) method have significantly reduced the length of simulation time. Consequently, applying numerical optimization schemes with EM based solver codes is now a distinct possibility. Previous work in design has primarily focused on optimizing specific problems [1-2] using evolutionary schemes like genetic algorithms (GA) [3], neural nets [4] and physically modeled processes like simulated annealing (SA) [5].

The GA is a relatively robust, stochastic based global optimization algorithm modeled after the Darwinian process of natural selection to produce the best fit design. As such, it lacks efficiency in its optimization routine and requires hundreds or thousands of solver evaluations.

SA is a stochastic global optimization algorithm that models after the physical process of annealing, defined as a thermal process for obtaining low-energy states of a solid in a heat bath. SA suffers from the same drawbacks as GA in that the convergence is slow and the optimized solution is not unique or deterministic. In addition, the performance of SA depends on the initialization of certain parameters used within SA and this discourages the use of this optimization routine.

In this paper, we propose the use of a hybrid global optimization scheme that converges quickly and yields a deterministic optimized solution. This hybrid scheme involves the use of Kriging meta-modeling [6] to interpolate between certain data points for predicting the intermediate points and incorporates the use of divided rectangles (DIRECT) as the global optimizer. The DIRECT algorithm is a derivative free, global algorithm that guarantees a deterministic and unique solution [7]. In addition, DIRECT has the added benefit of possessing both local and global optimization properties. Hybridizing the DIRECT search algorithm with Kriging meta-model parameters has the added benefit of producing an efficient global optimizer that converges quickly. The above attributes of the hybrid optimizer makes it ideal for optimizing complex, large scaled EM structures within an acceptable time frame.

The theory and the pertinent aspects of Kriging meta-modeling and the DIRECT optimizer will be explained first. Two examples will then be presented. In the first example, the hybrid optimizer will be used to minimize electromagnetic coupling from an antenna to the pins of a chip located within a resonant cavity housed within the chassis of an automobile. To achieve it, an improved version of the hybrid optimizer has been utilized. The Kriging model is initially created using a sparsely meshed solution space and this model is continually improved upon with the current data point at the end of that optimization iteration. In addition, the flexibility of the hybrid optimizer is improved by allowing DIRECT to optimize on other parameters within the Kriging meta-model, thus allowing the user to change the emphasis the optimizer has on local searching. In the second example, the same optimization scheme will be applied to determine maximum excitations that can be applied to the ports on a harness (running over the floor of the automobile body) given the maximum allowable interference with an FM antenna printed on the back glass of the automobile.

Optimization Methods

The interaction between the optimizer and the EM analyzer code can be seen in Fig 2. As can be seen, the overall convergence rate depends on both the convergence rates of the optimizer as well as the analyzer code. Our aim is to use an efficient global optimizer which utilizes a statistical model in its search for a global minimum solution with local searching properties in conjunction with fast electromagnetic solvers to design large scaled electromagnetic structures. The statistical model used is derived from Kriging interpolation meta-modeling while the global optimizer employed is the DIRECT algorithm.

Kriging Interpolation Meta-modeling

Interpolation among the sampled data points can be accomplished using polynomial fitting or using least squares fit. However, these methods exhibit highly oscillatory curve fitting at locations between the sampled data points. On the other hand, Kriging interpolation functions and neutral networks exhibit much less oscillations and have been shown to provide better fitting in multi-dimensional domains [6]. Kriging is a special form of interpolation function that uses the correlation between neighboring points to determine the overall function at any arbitrary point. The concept of utilizing Kriging as interpolation functions originated in the 1960s, where it was first used to analyze mining data. Kriging interpolation modeling relies on the decomposition, for a single dimension:

$$Y(x) = f(x) + \varepsilon(x) \tag{1}$$

in which Y(x) is a random variable on the x variable. Y(x) is the interpolated function predicted by the Kriging algorithm representing an approximation to the true function *f*(x) whereas ε(x) is the error deviation. Polynomial and least squares interpolation functions regard ε(x) as independent. Here, the Kriging meta-model assumes that ε(x) is not independent and obeys a zero mean Gaussian process. For a kth dimension problem, the Kriging meta-model can be represented as:

$$Y(\bar{x}) = f(\bar{x}) + \varepsilon(\bar{x}) = \sum_{j=1}^{k} \beta_j f_j(\bar{x}) + Z(\bar{x}) \qquad (2)$$

where $f_j(\bar{x})$ are the interpolating basis functions, β_j are the corresponding coefficients and $\bar{x}$ is a vector containing the optimization variables. As mentioned above, $Z(\bar{x})$ is the zero mean Gaussian distributed error function that models the uncertainty in $Y(\bar{x})$. The covariance of this error function is modeled as

$$Cov\left(Z(\bar{w}), Z(\bar{x})\right) = \sigma_z^2 R(\bar{w},\bar{x}) \qquad (3)$$

$$R(\bar{w},\bar{x}) = \prod_{d=1}^{k} e^{-\theta^d \left|w^d - x^k\right| p^d} \qquad (4)$$

for which σ_z^2 is a scale factor known as the process variance that can be tuned to fit the given data and $R(\bar{w},\bar{x})$ is the spatial correlation function (SCF). The vector $\bar{w}$ refers to the vector of given data points while the vector $\bar{x}$ refers to the desired point in the kth dimension. The value of θ in (4) determines the influence of the surrounding data point on the predicted data point, with larger values indicating a smaller degree of influence and thus a weaker covariance value. The *p* parameter in (4) is a smoothing function and the superscripts *d* and *k* in equation (4) refer to one of the k dimensions in the multi-dimensional model. Before the application of the Kriging algorithm, the values of σ_z^2, θ and *p* are determined from an auxiliary optimization problem where the difference between the function values of the predicted and the given data points is minimized. For this instance, gradient based SQP, SLP and any other optimization algorithms can be used within DIRECT algorithm as described below.

The DIRECT Algorithm

The DIRECT optimization algorithm [7] is a derivative free, global algorithm that yields a deterministic and unique solution. Its attribute of possessing both local and global properties makes it ideal for fast convergence. The divided rectangles (DIRECT) functions primarily by subdividing the entire design space into hyper-rectangles, or hyper-cubes for multi-dimensional problems. At each iteration step, DIRECT selects and subdivides the set of hyper rectangles (hyper cubes) that are most likely to produce the lowest objective function. This decision is based upon the Lipschitizian Optimization theory, specifically the manipulation of the Lipschitizian constant. Mathematically, the Lipschitizian constant K satisfies

$$\left|f(\bar{x}_1) - f(\bar{x}_2)\right| \le K \left\|\bar{x}_1 - \bar{x}_2\right\| \qquad \bar{x}_1, \bar{x}_2 \in domainR \qquad (5)$$

where the points $\bar{x}_1$ and $\bar{x}_2$ lie within the entire design space and $f(\bar{x})$ refers to the objective function for the optimization problem. Within DIRECT, all possible values of the Lipschitizian constant K are used such that larger values of K are employed for global optimization followed by smaller K values to perform local optimization to achieve convergence. Thus, the convergence process is greatly sped up and the optimization algorithm achieves both local and global searching properties. An illustration of a single dimensional optimization by DIRECT is shown in figure 1. At the first iteration, DIRECT samples the center of the design space, subdivides the domain into two and samples at the center of the sub-domains during the next iteration. The domain with the lower sampled objective function is further sub-divided and the center points within the new sub-domains are further sampled. This is iterated until the termination criterion has been met. Such a global process of sub-dividing the domains and sampling at their centers is mathematically guaranteed to obtain the optimum point provided the Lipschitizian constant is chosen to be greater than the largest gradient of the objective function. In choosing from all possible values for this constant, DIRECT has sufficient resolution to capture the largest change of the objective function gradient and thus obtain the most optimal point. The multi-dimensional optimization process of the DIRECT algorithm can be easily extended to multi-dimensional applications. For multivariate DIRECT optimization, the algorithm follows the steps:

Step 1: Place the entire design space into a unit hyper cube. Anoint c_1 to be the center of the hyper cube and sample $f(c_1)$. Set $f_{\min} = f(c_1)$.

Step 2: Identify the set R of potentially optimal cubes.

Step 3: Choose a cube R_j within the set R.

Step 4: Sample the center of cube R_j and determine which cube is suitable to be further sub-divided into cubes. Update $f_{\min}$.

Step 5: Set $R = R - R_j$. If $R \neq 0$, go to step 3.

Step 6: Terminate if goal is met or if number of iterations has exceeded.

For further information on DIRECT, the reader is referred to [7].

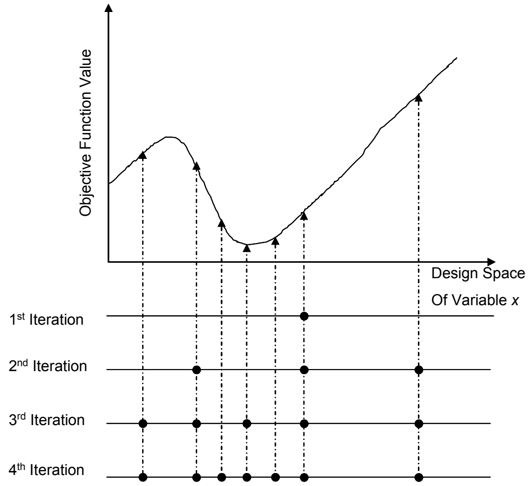

Figure 1. Flow chart of the hybrid optimizer: superego.

Hybrid Optimizer

The concept of creating the kriging meta-model using a design of experiments (DoE) on the entire design space may be inefficient as it maps both potentially good as well as bad domains within the design space. To avoid this, an initial sparse sampling is used to map the design space in creating the Kriging meta-model. At the end of each optimization iteration, the information on the current design iterate is used to update the Kriging meta-model. In this way, it endows the Kriging meta-model with an *adaptively* improving characteristic and reduces the number of iterations required for convergence. The program flow of this improved hybrid optimization algorithm is shown in Figure 2.

The flexibility of the hybrid optimizer is further improved by defining the sampling criteria. The hybrid optimizer optimizes for the minimum objective function, which is in turn defined by the infill sampling criteria.

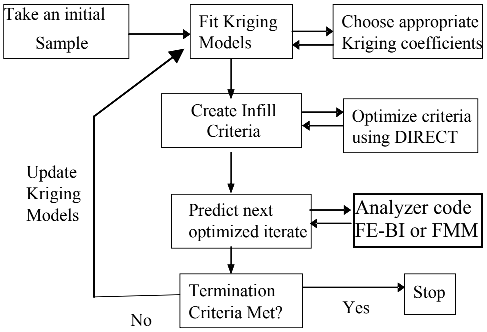

Figure 2. Flow chart of the improved hybrid optimizer: SuperEGO and the Analyzer code.

Here, we will define two different sampling criteria: the regional extreme sampling criteria and the minimum objective function criteria. The regional extreme criterion is mathematically defined as:

$$W = Y(\bar{x}) + \left(f_{\min} - Y(\bar{x})\right)\Phi(z) + \sigma\phi(z) \qquad (6)$$

In this, Φ is defined as the cumulative distribution function, ø is the probability distribution function of the spatial correlation function (SCF) shown in (4), $f_{\min}$ is the current minimum objective function value and $Y(\bar{x})$ refers to the current value of the objective function. The objective function and the SCF values are in turn obtained from the Kriging meta-models. Thus, in this infill sampling criterion, the hybrid optimizer minimizes both the objective function values as well as the covariance of the SCF, giving it an added emphasis on local searching properties in addition to the local properties of the DIRECT algorithm. The minimum objective function sampling criterion simply allows DIRECT to minimize the objective function values.

In essence, the improved hybrid optimizer (SuperEGO) starts off with a sparse sampling of the design domain and derives the Kriging meta-model through an auxiliary optimization with DIRECT. It continues with the optimization process based on the sampling criterion chosen, where DIRECT is used for predicting the next iterate. This is in turn used by the fast electromagnetic analysis module to carry out the expensive evaluation of the objective function. At the end of this optimization iteration, the iterate is used to update the Kriging meta-model. Continuously updating the Kriging meta-model at every iteration provides fast convergence.

RF Coupling Minimization

Example 1: Antenna–Electronics Coupling

The antenna position at the rear of an automobile is optimized, with the objective of minimizing the EM coupling at the 40 pins located around the periphery of the chip. The chip is located inside a cavity with a small opening as shown Figure 3(a). The optimization is performed at 700MHz, which is the resonance frequency of the cavity. The antenna consists of a pair of crossed magnetic slots with orthogonal phase excitation to generate a circularly polarized incident field. We expect a significant amplification of the incident antenna field within the cavity [8]. For optimization, the chosen objective function is defined as

$$F(x,y,z) = \frac{\sum_{i=1}^{40} \left|E_i^{total}\right|^2}{\sum_{i=1}^{40} \left|E_i^{inc}\right|^2} \qquad (7)$$

where E_i^{total} refers to the total and is the complex field amplitude measured at the location of the i^{th} pin in the presence of the automobile and the cavity whereas E_i^{inc} refers to the incident field and is the complex field amplitude measured at the location of the i^{th} pin when there is nothing but free-space.

For this optimization problem, there are 3 variables and 6 inequality constraints pertaining to planes confining the spatial volume at the rear of the automobile (design domain). The analyzer code used for this problem is the multilevel fast multipole moment method (MLFMM) with curvilinear basis functions in MoM [8]. The automobile is modeled with curvilinear biquadratic elements to reduce geometry error and problem size. An initial mesh of the automobile is shown in Figure 3(b) with about 36,000 unknowns. The electromagnetic simulation took about 2 hours to complete on an SGI computer. The automobile model has about 36000 unknowns and solves in about 2 hours in an SGI computer platform. The hybrid optimizer was started with a sparse initial set of 18 samples points located randomly within the design domain. The objective function value and the covariance of the SCF of the Kriging meta-model are first determined for the initial 18 sample points uniformly chosen within the defined spatial volume.

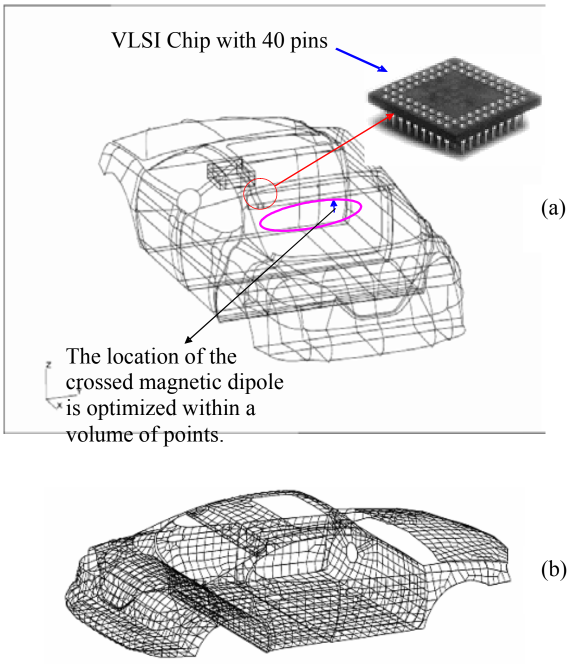

Figure 3. (a) Geometry of the antenna location optimization (within purple region) on an automobile for minimal EM coupling from the source antenna to 40 pins on a VLSI chip, (b) Quadrilateral surface mesh of the automobile.

The convergence history for the optimizer is given in Figure 4. It is seen that the hybrid optimizer converged in less than 40 iterations. During the initial optimization steps, the regional extreme sampling criterion is used within the optimization problem to examine the effect of adding local searching properties. Additional local searching properties can cause the optimizer to get stuck at a local minimum. To avoid such traps, the sampling criterion has been changed such that the hybrid optimizer has a reduced emphasis on the local searching properties. This resulted in the hybrid optimizer searching through other local minima and a convergence rate of tens of iterations. This is in contrast to GA and SA, which take up to hundreds of iterations to converge.

The optimization yielded an antenna position at x = 24.19753 mm, y = -421.773 mm and z = -34.6448 mm for an objective function value of F(x,y,z) = 0.122057. Given that the antenna at the center of the automobile yields F(x,y,z) = 13.3025, it can be concluded that the hybrid optimizer has produced an optimal solution that reduced the coupling by as much as 20.37dB. In addition, the optimal solution for this optimizer is a deterministic answer and no additional runs of the optimizer are needed (unlike GA).

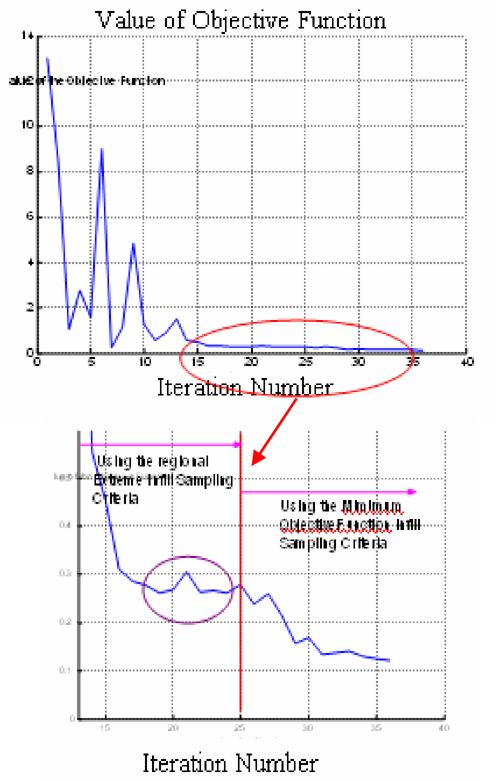

Figure 4. Convergence rate.

Example 2: Harness–FM Antenna Coupling

Figure 5(a) shows the CAD model of another automobile. In this case, a pseudo harness (with a heat shield) has been placed just above the floor of the car as shown. Each port on the harness (there are a total of four) is independently driven by a sensor. The goal is to optimize the complex amplitude of each sensor output voltage so that the resulting average field magnitude along the length of the FM antenna (printed on the back glass) is between 9.7 and 9.8 μV/m. The problem has 4 variables (the sensor output voltages) and 4 inequality constraints: $0 \le |V_{1,2}| \le 150$ μV and $100 \le |V_{3,4}| \le 200$ μV. The objective function for this problem is given by

$$\langle F\rangle = \left|\frac{\sum_{j=1}^{4}\sum_{i=1}^{M}E_{ij}^{ANT}}{M}\right| - 9.75x10^{-6} \qquad (8)$$

Where E_{ij}^{ANT} are the complex electric field amplitude at the i^{th} sample point at the antenna location and M=16.

The same optimizer as in the first example was used here as well. The convergence history is shown in Figure 6(b) and the resulting optimum driving voltages are $V_1 = 69.53e^{j0}$ μV, $V_2 = 22.58e^{j18.68}$ μV, $V_3 = 174.10e^{j15.13}$ μV, $V_4 = 157.01e^{j15.02}$ μV.

Conclusion

It was demonstrated that the hybridization of the DIRECT optimizer with Kriging metamodeling resulted in significant improvement in the convergence rate. This allowed for the solution of rather complex and large scale practical optimization problems. This new optimizer has the additional flexibility of allowing the user to change the emphasis of local searching upon the backdrop of global searching within the design space. The proposed optimizer was used for minimizing EM coupling from antenna to electronic devices and from harness to antennas inside an automobile. In both examples, the entire automobile model (metallic parts only) was included in the EM analysis made possible by the employment of FMM. Further, the use of the hybrid optimizer allowed for convergence in tens of iterations while avoiding local minima.

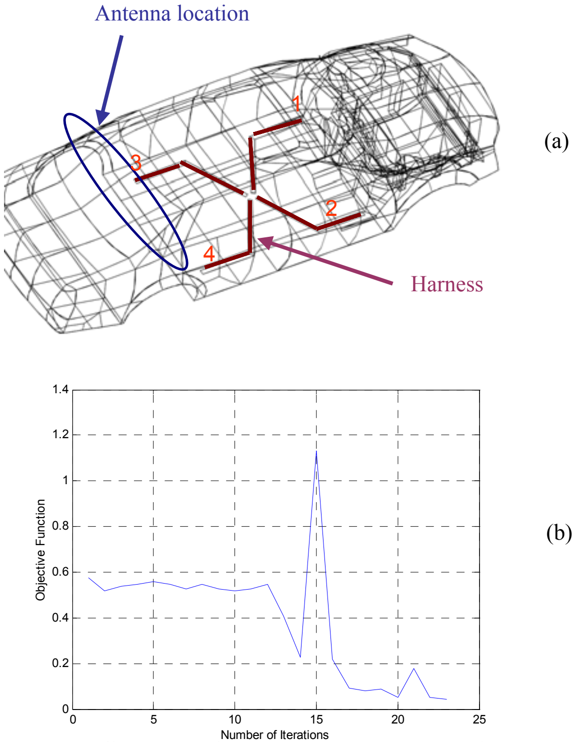

Figure 5. (a) Geometry of the harness-antenna coupling reduction problem, (b) convergence data resulting from optimization.

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