Application of Artificial Neural Networks to Broadband Antenna Design Based on a Parametric Frequency Model

Youngwook Kim, *Student Member, IEEE*, Sean Keely, Joydeep Ghosh, *Fellow, IEEE*, and Hao Ling, *Fellow, IEEE*

***Abstract*—An artificial neural network (ANN) is proposed to predict the input impedance of a broadband antenna as a function of its geometric parameters. The input resistance of the antenna is first parameterized by a Gaussian model, and the ANN is constructed to approximate the nonlinear relationship between the antenna geometry and the model parameters. Introducing the model simplifies the ANN and decreases the training time. The reactance of the antenna is then constructed by the Hilbert transform from the resistance found by the neuromodel. A hybrid gradient descent and particle swarm optimization method is used to train the neural network. As an example, an ANN is constructed for a loop antenna with three tuning arms. The antenna structure is then optimized for broadband operation via a genetic algorithm that uses input impedance estimates provided by the trained ANN in place of brute-force electromagnetic computations. It is found that the required number of electromagnetic computations in training the ANN is ten times lower than that needed during the antenna optimization process, resulting in significant time savings.**

***Index Terms*—Artificial neural network, broadband antenna, Gaussian model, genetic algorithm, Hilbert transform, particle swarm optimization.**

I. Introduction

THE design of broadband antennas is a computationally intensive task, especially when a frequency-domain electromagnetic (EM) simulator is used. Moreover, when an optimization method such as a genetic algorithm [1] is used in the design process, the antenna characteristics must be computed for thousands of hypothetical antennas over a broadband of frequencies in order to evaluate the relative merit of each configuration.

In order to substitute the computationally intensive EM simulation, artificial neural networks (ANNs) [2], [3] have been suggested as attractive alternatives [4]. An ANN can be suitable for modeling high-dimensional and highly nonlinear problems. When properly trained with reliable learning data, a neuromodel is computationally more efficient than an exact EM simulator, and more accurate than a model based on approximate physics. Thus, the neural network approach has been explored in the design of microwave components and circuits such as microstrip lines [5], spiral inductors [6], HEMT [7], filters [8], and mixers [9]. In the antenna community, ANN has been applied to beamforming [10] and direction-finding [11] for arrays, as well as to microstrip antenna design [12]. However, the use of ANN for very broadband antennas with multiple resonances has not been extensively researched yet.

Typically, when the ANN is used for antenna design, the antenna geometry parameters and the frequency are regarded as inputs to the ANN, while the output is the antenna input impedance. This approach has been very successful for narrow-band antenna design. However, when the ANN is used in this manner in the broadband case, the number of hidden units will increase drastically as the number of oscillations in the impedance versus frequency graph increases. Increasing the number of hidden units requires longer training time. Furthermore, it can lead to a high chance of reaching a local minimum, resulting in unsuccessful training. Recently Lebber *et al.* reported an ANN implementation to predict the antenna gain, bandwidth, and polarization for a broadband patch antenna [13]. However, the method does not calculate the impedance variations over a wide frequency band. This approach cannot obtain quantities such as number of resonances.

In this paper, we *indirectly* use a neural network for predicting the input impedance of a broadband antenna via a parametric frequency model. The input resistance of the antenna is first parameterized by a Gaussian model [14]. The Gaussian parameters are then estimated for the different training antennas, and a neural network is trained to describe the relationship between the antenna geometry and the Gaussian parameters, as shown in Fig. 1. By introducing the parametric model, the resulting ANN operates in a much less complex solution space. This leads to a smaller network size, faster training time, and more robust convergence of the training process. For the training method, a hybrid scheme combining the gradient descent method and a particle swarm optimization [15] is utilized. Once the network for the input resistance is in place, the input reactance is generated by the Hilbert transform [16]. This proposed technique is valid when the band of interest is broad and the resonant frequencies of the antenna are distinct.

The resulting neural model is next exploited for antenna optimization. In this paper, we use the loop-based broadband antenna structure reported in [17] as an example. The antenna has

Manuscript received February 28, 2006; revised October 13, 2006. This work was supported by the Texas Higher Education Coordinating Board under the Texas Advanced Technology Program and the National Science Foundation Major Research Instrumentation Program.

Y. Kim, J. Ghosh, and H. Ling are with the Department of Electrical and Computer Engineering, University of Texas at Austin, Austin, TX 78712 USA (e-mail: ykim5@ece.utexas.edu).

S. Keely is with the Department of Physics, University of Texas at Austin, Austin, TX 78712 USA (e-mail: skeely@mail.utexas.edu).

Digital Object Identifier 10.1109/TAP.2007.891564

seven geometric parameters: the lengths and heights of its three rectangular tuning arms and the radius of the antenna wire. The antenna structure is optimized for broadband operation via a genetic algorithm (GA) that uses the input impedance predicted by the ANN over a broad frequency range and over the range of antenna geometries being considered by the GA. The performance of the ANN in terms of accuracy and computational savings is evaluated in this application against a brute-force electromagnetic computation.

This paper is organized as follows. Section II presents the Gaussian model and its parameter estimation. In Section III, the structure of the neural network is described, and the training method and their results based on the example broadband antenna are discussed. Section IV presents the optimization of the antenna using the resulting neural network. Conclusions are given in Section V.

II. Gaussian-Based Frequency Model for Input Resistance

The input impedance of a broadband antenna usually contains multiple resonances within the band of interest. A direct approximation of this characteristic by a neural network may lead to a large number of hidden units and is prone to failure. Furthermore, the drastic change in reactance at the resonant frequency can be difficult for the ANN to learn. In order to simplify the problem, we embed a suitable physical principle into the network so as to constrain the solution space.

We choose to model the resistance by a sum of Gaussians. The Gaussian model is simple and relatively insensitive to parameter errors. Furthermore, modeling only the resistance behavior leads to a reduced network size, improved training time, and better chance of successful training. Once the broadband resistance is modeled, the reactance can be recovered via the Hilbert transform. A Gaussian model to approximate the frequency dependent resistance envelope of a symmetric resonator can be represented as

$$\mathrm{Re}(Z(f)) = \left(\sum_k c_k \cdot e^{\left(-\frac{(f-b_k)^2}{a_k}\right)}\right) + d. \tag{1}$$

Here, $Z(f)$ is the impedance function; a_k, b_k, and c_k are coefficients of the model; and d is a bias.

This Gaussian expansion is naturally encoded as a radial basis function (RBF) with one input and one output [18]. The coefficients are searched by the gradient descent method, introducing one Gaussian at a time in a procedure similar to the resource allocation network of Platt [19]. It can be shown that, using this method, the Gaussian will, at every update, move into an approximation of the previous training step's Gaussian-target product. This is exploited to let each basis function settle into an approximation of a single resonance by ensuring that the initial width of the Gaussian is large and subtracting from the target curve each already placed Gaussian. This method consistently yields good results with a minimal number of Gaussians.

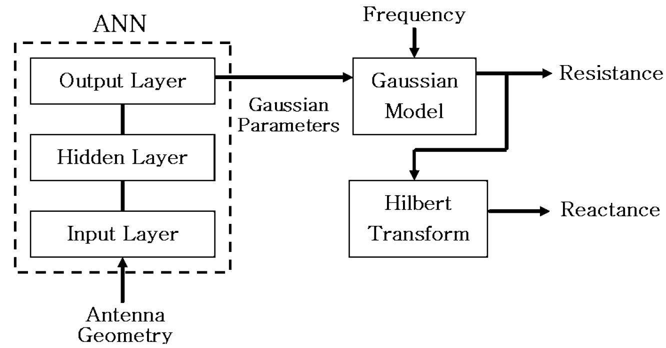


Fig. 1. Impedance prediction network.

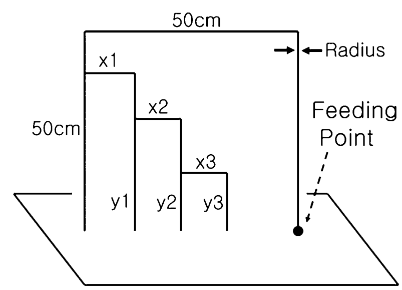


Fig. 2. Antenna shape and parameters.

III. Artificial Neural Net Structure

An artificial neural network is next constructed to model the complex relationship between the antenna geometry and the Gaussian model parameters. For modeling the antenna geometry, the multilayered perceptron (MLP) is utilized. The MLP is a known universal approximator and has been extensively used in microwave applications [20]. The suggested network system is illustrated in Fig. 1.

A broadband antenna for automobiles, reported earlier in [17], is considered as an example. It is a loop structure with three tuning arms as presented in Fig. 2. The structure has seven geometric parameter variables: the lengths and heights of its three rectangular tuning arms and the radius of the antenna wire. The frequency range of interest is in the ultra-high-frequency (UHF) band from 170 to 650 MHz. The MLP takes the seven geometric parameters as inputs and produces all of the means, variances, and amplitudes of the Gaussian model as outputs. The number of modeled Gaussians is set to six, giving 19 free parameters to specify the frequency dependency including the bias.

The MLP consists of an input layer, a hidden layer, and an output layer. The hyperbolic tangent is employed as an activation function, and a linear output layer is used. Bias is added to the input and the hidden layer. Two hundred fifty hidden units and 19 output units are used, where the 19 outputs represent the mean, variance, and amplitude for each of the six Gaussians, plus a single number indicating the bias amount. The total number of weights in the net is 6769. The normalized range of inputs to the ANN is from 0 to 50, and that of output is from 0 to 500.

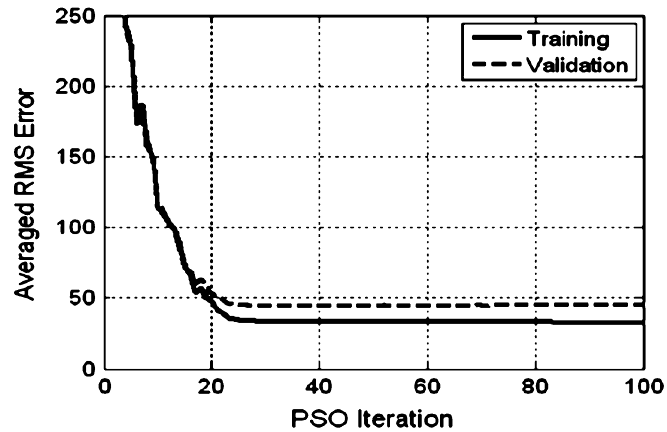
The constructed MLP is trained by three strategies: i) gradient descent, ii) particle swarm optimization (PSO), and iii) hybrid gradient descent and PSO. For network training, a data set of 270 antenna configurations is generated and the corresponding Gaussian parameters are estimated. The numerical electromagnetic code (NEC) is used for the EM simulation. From the data set, 135 samples are selected as training data and the remaining 135 are used as validation data. All of the training data are input into the ANN one after the other, and the cumulative averaged root mean square (rms) error of the output is regarded as the cost function.

First, we apply the gradient descent by error back propagation (EBP) to train the ANN. EBP propagates error backwards through the network to allow the error derivatives for all weights to be efficiently computed [21]. When the training is performed, the rms errors of both the training and validation processes decrease with increasing iterations. In the parameter space, the averaged rms error of the training approaches 33.7 and that of the validation approaches 44.8 after 5000 epochs.

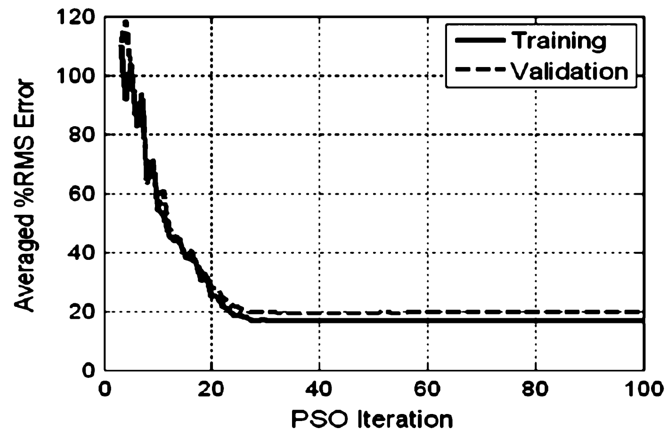
One potential drawback of the gradient descent is that it is a local search method, and its performance can be strongly affected by the initial guess. The PSO algorithm has been tried for training neural networks with good reported performance for simple networks [22], [23]. Here we implement a PSO to train the 6769 weights in the net. One hundred particles are introduced, and they are iterated 150 times. To limit the search space for the parameters to a physically possible range, the damping wall is employed [24]. The PSO is initiated with random numbers and training is performed. The averaged rms error of training approaches 132.1, and that of validation approaches 134.2 in the parameter space. Clearly, the PSO performs poorly in comparison to the gradient descent. We believe this is due to the very huge parameter space (6769) in our problem.

To improve the training with the PSO, we also try using the results of the gradient descent to initialize the PSO. Gradient descent already finds a relatively good solution, so the PSO is expected to find a better answer near the gradient descent solution in the complex cost surface, which may contain many local minima. The evaluated cost of the PSO with the gradient descent as initial guess starts at 33.7. However, in order to show how the particles move close to the given solution, the second best cost is plotted in Fig. 3 until the PSO finds a better solution than the gradient descent. After defeating the gradient descent result, the best cost is selected for the plot. The final averaged rms error of training is 32.4, and that of validation is 43.5, which are lower than the errors from the gradient descent. Shown in Fig. 3(b) is the %rms error of the input resistance as constructed from the Gaussian model. The final %rms error of training is 16.4%, and that of validation is 19.1%.

Fig. 4(a) and (b) shows, respectively, a sample from the training data set and a sample from the validation data set. The dashed curves are predicted by the ANN, and the solid curves are the true resistance calculated by NEC. It can be observed that the resistance from the neural net matches fairly well with the true value.



(a)



(b)

Fig. 3. The error from PSO with the initial guess from gradient descent, (a) the averaged rms error of parameters and (b) the averaged %rms error of resistance.

IV. Broadband Antenna Optimization Using ANN

The performance of the trained ANN is evaluated through an antenna optimization process. A GA is used to optimize the considered broadband antenna structure. In the process of the GA, the antenna impedances are generated by the trained ANN rather than by an EM simulator, as depicted in Fig. 5. The resistance is calculated using the trained neural network, and the reactance is derived from the Hilbert transform. The three lengths and three widths of the tuning arms and the wire radius are optimized within a 50 by 50 cm^2 area. The cost function of the GA is defined as the average voltage standing-wave ratio (VSWR) in the frequency range from 170 to 220 and from 470 to 650 MHz to cover UHF analog television and digital video broadcasting. Each generation of the GA consists of 100 chromosomes, and the replacement rate and the mutation rate are 70% and 5%, respectively [17].

The broadband antenna is optimized after 31 iterations. The best cost function in the GA process using the trained ANN is 1.6. The heights and widths of the side arms of the optimized antenna are 35.4 by 12.0 cm^2, 28.4 by 5.6 cm^2, and 12.6 by 12.8 cm, and the wire radius is 0.49 mm. The impedance of the resulting antenna from the ANN is plotted against the exact impedance calculated by NEC for the same optimized geometry

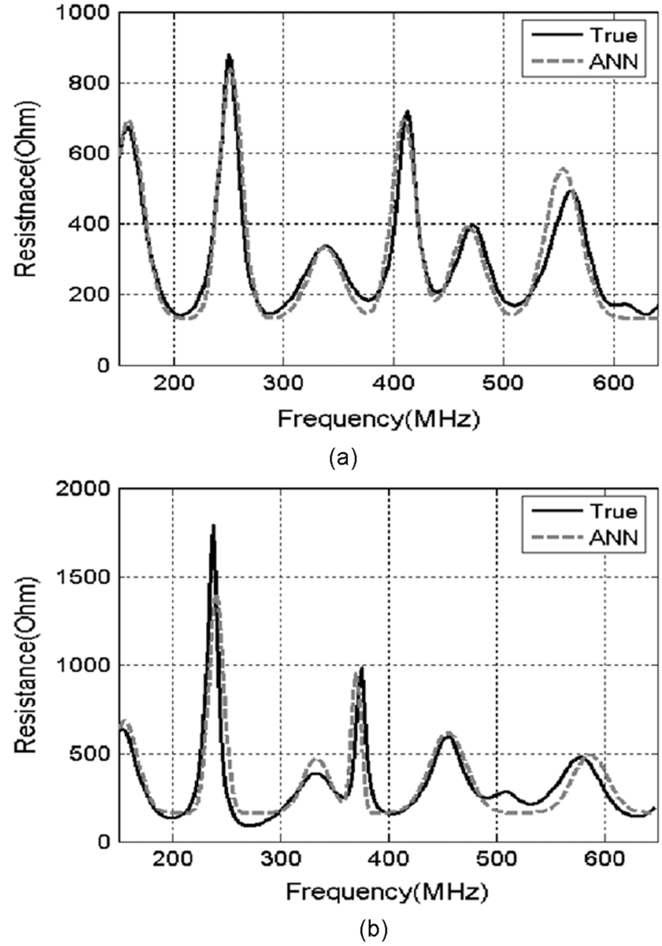


Fig. 4. Prediction of resistance by the ANN: (a) %rms error $= 13.14\%$ and (b) %rms error $= 24.16\%$.

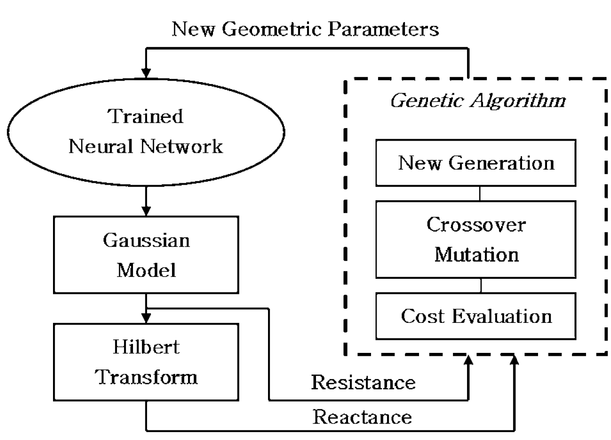


Fig. 5. Genetic algorithm with the ANN.

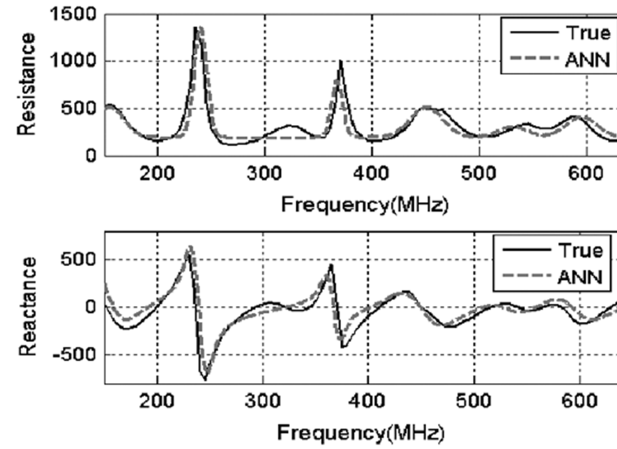


Fig. 6. Resistance and reactance of the optimized antenna.

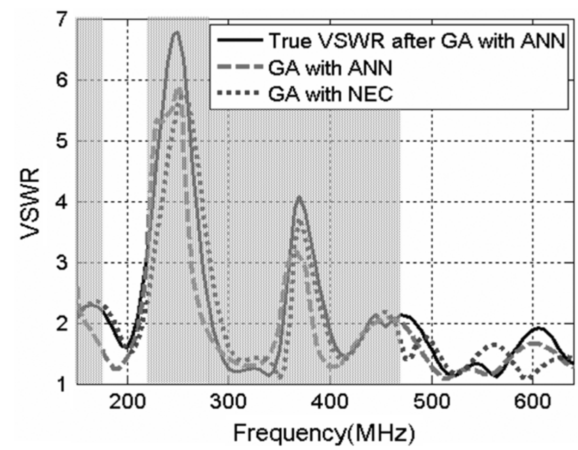


Fig. 7. VSWR of the optimized antenna.

in Fig. 6. The ANN result agrees fairly well with the NEC calculation. Their corresponding VSWR curves are plotted in Fig. 7. The dashed curve is the "GA with ANN" result and the solid curve is the true VSWR of the optimized design as calculated by NEC. The averaged VSWR as computed by NEC is 1.63 in the band of interest (the unshaded regions in the plot).

In order to gauge the performance of the developed ANN, the considered antenna is optimized again by the GA, this time using brute-force calculations by NEC for all the cost function evaluations. The GA converges after 29 iterations. The best cost in the optimization process is 1.64. Due to the difference in the exact NEC calculation and the ANN prediction, the GA this time converges to a slightly higher optimized cost and a different optimized antenna configuration. In Fig. 7, we plot the VSWR of this optimized antenna configuration as the dotted curve. We observe that the performance of the "GA with NEC" antenna is comparable to that of the "GA with ANN" antenna.

Note that during the GA optimization using the brute-force approach, the NEC simulation must be carried out for all 2900 different antenna geometries. Using the developed neural network, however, NEC is employed only 270 times for the generation of the training and validation data sets. This is a 10.7-fold reduction in the number of EM calculations as compared to the brute-force method.

As another example, we optimize the antenna again using the ANN in a different frequency band from 320 to 650 MHz. The averaged VSWR of the final converged design is 1.66 as predicted by the ANN and 1.72 as calculated by NEC. The GA optimization is also done via brute force using NEC for all the EM calculations. The averaged VSWR of the final converged design is 1.62. In this case, the reduction in the number of EM calculations is found to be 11.8.

V. Conclusion

In this paper, an ANN-based system has been proposed to predict the input impedance of a broadband antenna. The input resistance of the antenna was first parameterized by a Gaussian model over a broad band of frequencies and the ANN was then constructed to approximate the nonlinear relationship between the antenna geometry and the model parameters. Introducing the model simplified the construction and training of the ANN, resulting in robust performance. The neural network was trained by using particle swarm optimization as a local search procedure seeded with an initial guess from the gradient descent learning. The reactance of the antenna was then constructed by the Hilbert transform. To test the performance of the resulting ANN, a loop antenna with multiple tuning arms was optimized by a GA, whereby the developed ANN system was used for the cost function evaluations. The performance of the ANN was compared with that of a direct approach, in which the cost function evaluation was done using the EM simulator. It was found that the ANN approach led to a tenfold reduction in the number of required EM simulations and was still able to maintain an acceptable level of accuracy. This indicates that a parametric frequency model used in conjunction with an ANN forms an effective framework for the design and evaluation of very broadband antennas. While the Gaussian model is found to perform adequately, other frequency models such as the rational function model may lead to even better performance. This topic is currently under investigation.

References

[1] R. L. Haupt, "An introduction to genetic algorithms for electromagnetics," *IEEE Antennas Propag. Mag.*, vol. 37, pp. 7–15, Apr. 1995.

[2] C. Bishop, *Neural Networks for Pattern Recognition*. Oxford, U.K.: Oxford Univ. Press, 1995.

[3] Q. Zhang, K. C. Gupta, and V. K. Devabhaktuni, "Artificial neural networks for RF and microwave design—From theory to practice," *IEEE Trans. Microwave Theory Tech.*, vol. 51, pp. 1339–1350, Apr. 2003.

[4] A. Patnaik, D. E. Anagnostou, R. Mishra, C. G. Christodoulou, and J. C. Lyke, "Applications of neural networks in wireless communications," *IEEE Antennas Propag. Mag.*, vol. 46, pp. 130–137, Jun. 2004.

[5] J. Li and Z. Bao, "Neural network models for the coupling microstrip line design," in *Proc. IEEE Int. Conf. Syst.*, Oct. 2003, vol. 5, pp. 4916–4921.

[6] A. Ilumoka and Y. Park, "Neural network-based modeling and design of on-chip spiral inductors," *Proc. 36th Southeastern Symp. Syst. Theory*, pp. 561–564, 2004.

[7] S. Lee, B. A. Cetiner, H. Torpi, S. J. Cai, J. Li, K. Alt, Y. L. Chen, C. P. Wen, K. L. Wang, and T. Itoh, "An X-band GaN HEMT power amplifier design using an artificial neural network modeling technique," *IEEE Trans. Electron Devices*, vol. 48, pp. 495–501, Mar. 2001.

[8] A. S. Ciminski, "Artificial neural networks modeling for computer-aided design of microwave filter," in *Proc. 14th Int. Conf. Microw., Radar, Wireless Commun.*, May 2002, vol. 1, pp. 95–99.

[9] J. Xu, M. C. E. Yagoub, R. Ding, and Q. Zhang, "Neural-based dynamic modeling of nonlinear microwave circuits," *IEEE Trans. Microwave Theory Tech.*, vol. 50, pp. 2769–2780, Dec. 2002.

[10] Z. He and Y. Chen, "Robust blind beamforming using neural network," *Proc. Inst. Elect. Eng. Radar, Sonar, Navig.*, vol. 147, pp. 41–46, Feb. 2000.

[11] S. Jha and T. Durrani, "Direction of arrival estimation using artificial neural networks," *IEEE Trans. Syst., Man, Cybern.*, vol. 21, pp. 1192–1201, Sep. 1991.

[12] R. K. Mishra and A. Patnaik, "Designing rectangular patch antenna using the neurospectral method," *IEEE Trans. Antennas Propag.*, vol. 51, pp. 1914–1921, Aug. 2003.

[13] S. Lebbar, Z. Guennoun, M. Drissi, and F. Riouch, "Compact and broadband microstrip antenna design using a geometrical-methodology-based artificial neural network," *IEEE Antennas Propag. Mag.*, vol. 48, pp. 146–154, Apr. 2007.

[14] D. Xu, L. Yang, and Z. He, "Overcomplete time delay estimation using multi-Gaussian fitting method," in *IEEE Int. Workshop VLSI Design Video Tech.*, May 2005, pp. 248–251.

[15] J. Robinson and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," *IEEE Trans. Antennas Propag.*, vol. 52, pp. 397–407, Feb. 2004.

[16] A. E. Gera, "Linking resistance and reactance via Hilbert transforms," *Proc. 17th Conv. Electr. Electron. Eng. Israel*, pp. 141–144, Mar. 1991.

[17] Y. Kim, Y. Noh, and H. Ling, "Design of ultra-broadband on-glass antenna with a 250 Ω system impedance for automobiles," *Electron. Lett.*, vol. 40, pp. 1566–1568, Dec. 2004.

[18] P. J. Radonja, "Radial basis function neural networks: In tracking and extraction of stochastic process in forestry," *Proc. 5th Seminar Neural Network Appl. Electr. Eng. (NEUREL 2000)*, pp. 81–86, Sep. 2000.

[19] J. Platt, "A resource allocating network for function interpolation," *Neural Computat.*, vol. 3, pp. 213–225, 1991.

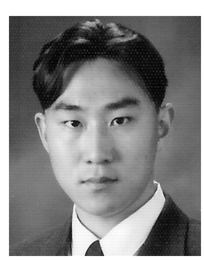
[20] A. Patnaik and R. K. Mishra, "ANN techniques in microwave engineering," *IEEE Micro*, vol. 1, pp. 55–60, Mar. 2000.

[21] S. Makram-Ebeid, J.-A. Sirat, and J.-R. Viala, "A rationalized error back-propagation learning algorithm," in *Proc. Int. Joint Conf. Neural Netw.*, Jun. 1989, vol. 2, pp. 373–380.

[22] V. G. Gudise and G. K. Venayagamoorthy, "Comparison of particle swarm optimization and backpropagation as training algorithms for neural networks," *Proc. IEEE Swarm Intell. Symp.*, pp. 110–117, Apr. 2003.

[23] E. A. Grimaldi, F. Grimacca, M. Mussetta, and R. E. Zich, "PSO as an effective learning algorithm for neural network applications," in *Proc. Int. Conf. Computat. Electromagn. Appl.*, Nov. 2004, pp. 557–560.

[24] T. Huang and A. S. Mohan, "A hybrid boundary condition for robust particle swarm optimization," *IEEE Antennas Wireless Propag. Lett.*, vol. 4, pp. 112–117, 2005.



Youngwook Kim (S'01) was born in Seoul, Korea, in 1976. He received the B.S. degree in electrical engineering from Seoul National University in 2003 and the M.S. degree in electrical and computer engineering from the University of Texas at Austin in 2005, where he is currently pursuing the Ph.D. degree.

His research interests include developments of fast optimization algorithm for antenna design, equivalent circuit modeling of broadband antennas, DOA estimation, and through-walls human tracking.

Sean Keely received the B.Sc. degree in physics from the University of Nevada, Reno, in 2003. He is currently pursuing the M.Sc. degree in physics from the University of Texas, Austin.

His interests include applications of short pulse lasers, numerical simulation, and the use of approximate operators in simulations.

Joydeep Ghosh (S'87–M'88–SM'02–F'06) received the B.Tech. degree from IIT, Kanpur, in 1983 and the Ph.D. degree from the University of Southern California, Los Angeles, in 1988.

He is currently the Schlumberger Centennial Chair Professor of Electrical and Computer Engineering at the University of Texas (UT), Austin. He teaches graduate courses on data mining, artificial neural networks, and Web analytics. He joined the UT-Austin Faculty in 1988. He is the Founder-Director of the Intelligent Data Exploration and Analysis Lab. His research interests lie primarily in intelligent data analysis, data mining and web mining, adaptive multilearner systems, and their applications to a wide variety of complex engineering and artificial intelligence problems. He has published more than 200 refereed papers and 30 book chapters, and has coedited 18 books. His research has been supported by the NSF, Yahoo!, Google, ONR, ARO, AFOSR, Intel, IBM, Motorola, TRW, Schlumberger, and Dell, among others. He has been a plenary/keynote speaker on several occasions such as ANNIE'06, MCS 2002, and ANNIE'97. He also serves on the Program Committee of several top conferences on data mining, neural networks, pattern recognition, and Web analytics every year. He has widely lectured on intelligent analysis of large-scale data. He has been a Co-organizer of workshops on high-dimensional clustering (ICDM 2003; SDM 2005), Web analytics (SIAM International Conference on Data Mining—SDM2002), Web mining (SDM 2001), and parallel and distributed knowledge discovery (KDD-2000). He has been a Consultant or Advisor to a variety of companies, from successful startups such as Neonyoyo and Knowledge Discovery One to large corporations such as IBM, Motorola, and Vinson & Elkins.

Dr. Ghosh received the 2005 Best Research Paper Award from the UT Co-op Society and the 1992 Darlington Award given by the IEEE Circuits and Systems Society for the best paper in the areas of CAS/CAD, as well as nine other best paper awards over the years. He was Conference Cochair of Computational Intelligence and Data Mining (CIDM'07), Program Cochair for the SIAM International Conference on Data Mining (SDM'06), and Conference Cochair for Artificial Neural Networks in Engineering (ANNIE) from 1993 to 1996 and 1999 to 2003. He is Founding Chair of the Data Mining Technical Committee of the IEEE CI Society. He was voted the Best Professor by the Software Engineering Executive Education Class of 2004.

Hao Ling (S'83–M'86–SM'92–F'99) was born in Taichung, Taiwan, R.O.C., on September 26, 1959. He received the B.S. degree in electrical engineering and physics from the Massachusetts Institute of Technology, Cambridge, in 1982 and the M.S. and Ph.D. degrees in electrical engineering from the University of Illinois at Urbana-Champaign in 1983 and 1986, respectively.

He joined the Faculty of the University of Texas at Austin in 1986, where he is currently a Professor of electrical and computer engineering and holder of the L. B. Meaders Professorship in Engineering. During 1982, he was with the IBM T. J. Watson Research Center, Yorktown Heights, NY, where he conducted low-temperature experiments in the Josephson Department. He participated in the Summer Visiting Faculty Program in 1987 at the Lawrence Livermore National Laboratory, Livermore, CA. In 1990, he was an Air Force Summer Fellow with Rome Air Development Center, Hanscom Air Force Base, MA. His principal area of research is in computational electromagnetics. During the past two decades, he has actively contributed to the development and validation of numerical and asymptotic methods for characterizing the radar cross section from complex targets. His recent research interests also include radar signal processing, antenna design, and propagation channel modeling.

Dr. Ling was a recipient of the National Science Foundation Presidential Young Investigator Award in 1987 and the NASA Certificate of Appreciation in 1991, as well as several teaching awards from the University of Texas.