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Far-field Surrogate Model of Flexible Antennas Based on Vector Spherical Harmonics and Neural Network

Guoqing Hou[1], Jinxin Du[2*, 4], Christophe Roblin[3], Xue-Xia Yang[4]

[1]School of Mechatronic Engineering and Automation, Shanghai University, 200444 Shanghai, China;
[2*]Sino-European School of Technology, Shanghai University, 200444 Shanghai, China; email: jinxin_du@shu.edu.cn;
[3]Departement of Communication and Electronics, Télécom Paris & Institut Polytechnique de Paris (IPP), 91120 Palaiseau, France;
[4]Shanghai Institute for Advanced Communication and Data Science, Key Laboratory of Specialty Fiber Optics and Optical Access Networks, Shanghai University, 200444 Shanghai, China;

***Abstract*-To speed up the stochastic modeling of the far-field (FF) electric field of flexible antennas, a novel method combining vector spherical harmonics (VSH) and neural network (NN) is proposed to construct efficient and effective surrogate models. First, we use VSH to parsimoniously representing the antenna's FF electric field vector with a limited number of modes; then, we use NN to map between the input variables and the VSH mode coefficients. We proposed an improved successive halving (ISH) algorithm to optimize the selection of hyperparameters when constructing the NN model. The results show that compared with the polynomial chaos expansion (PCE) model, the prediction error of the NN model has been reduced by 39.22% at the same modeling cost.**

***Keywords*-surrogate model, neural network, hyperparameter optimization, flexible antennas**

I. INTRODUCTION

Nowadays, flexible antennas are becoming a key component for the widely implemented wireless body area networks (WBANs) [1]. Different from their rigid counterparts, wearable flexible antennas operate in fluctuating environments, as a result, their radiation characteristics are easily affected by various types of deformations, temperature or humidity changes and other factors. Efficiently characterizing the electromagnetic (EM) performance of flexible antennas is of prominent importance for evaluating the quality of service (QoS) of WBAN scenarios.

Statistical or stochastic modeling, which regards the flexible antenna as an uncertain "black-box" and build antenna surrogate models based on pre-acquired samples, is a very effective approach. Without being exhaustive, we can mention the polynomial chao expansion (PCE) methods and its variants [2-4], Gaussian process regression [5], support vector machine (SVM) [6], and artificial neural network (NN) [7-8]. However, these attempts were mainly focused on some of the antenna key performance indicators, such as resonance frequency, reflection coefficient, input impedance, bandwidth, etc., but not on the complete far-filed (FF) radiation, that's to say, the FF electric field vector. Recently, with the massive deployment of multi-in multi-output (MIMO), ultra-wideband, and beamforming techniques, the demand of accurate FF surrogate model explodes.

Another key issue for antenna stochastic modeling is that the collection of pre-acquired samples usually relies on time-consuming full-wave EM simulators, such as CST or HFSS, which is unaffordable for complex antenna designs. How to take full advantage of the pre-acquisition to maximize the model accuracy, or to maintain enough accuracy with minimized the pre-acquisition cost, is always a major challenge.

In our previous study [9], we proposed a modeling method based on vector spherical harmonics (VSH) and PCE to build FF surrogate models for flexible antennas. However, the model accuracy was not effectively optimized. The purpose of this work is to further exploit the same pre-acquired samples. We propose a novel modeling method combining VSH and NN to build antenna FF surrogate model. An improved successive halving (ISH) algorithm is introduced to optimize the selection of NN hyperparameters. The feasibility of the proposed method is verified on a flexible textile antenna, and the results show that the new model helps to reduce the average prediction error (in term of the realized gain) from 0.51 dB to 0.31 dB compared with the PCE model, which is a reduction of nearly 39%.

II. MODELING METHODOLOGY

The FF electric field vector $\mathbf{E}^{\infty}(f,\mathbf{r})$ of the flexible antenna can be expressed by its equivalent antenna transfer function (ATF) $\boldsymbol{\mathcal{H}}(f,\hat{\mathbf{r}})$:

$$\boldsymbol{\mathcal{H}}(f,\hat{\mathbf{r}}) = \frac{re^{jkr}}{a_1(f)}\sqrt{\frac{4\pi}{\eta_0}}\cdot\mathbf{E}^{\infty}(f,\mathbf{r}) \tag{1}$$

where a_1 is the incident wave at the port of antenna, η_0 is the impedance in free space, $\hat{\mathbf{r}}=(\theta,\varphi)$ is the unit radial vector, k is the wave number, and $j=\sqrt{-1}$.

It is quite difficult to build a surrogate model for this vector function directly, so we divide the modeling process into two steps. First, the ATF is expanded using VSH expansion to obtain a parsimonious expression; and then we use NN to model the coefficients of the discrete modes of this expansion.

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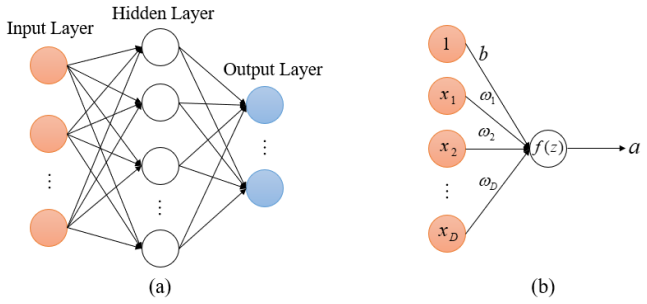


Figure 1. NN structure (a) Feed-forward neural network (b) Neuron structure

A. *Parsimonious Expression of the FF Electric Field*

The VSH is an orthogonal basis on the Hilbert space formed by the square-integrable vector functions defined on the unit sphere, which can expand any vector-valued function under the spherical coordinates into a linear combination of VSH modes. Therefore, the ATF of the antenna disturbed by input variables $\boldsymbol{X}$ can be expressed as:

$$\mathcal{H}(\boldsymbol{X},\hat{\mathbf{r}}) = j\sum_{q=1}^{Q}(-j)^{\mathrm{mod}(q,2)}H_q(\boldsymbol{X})\hat{\boldsymbol{\psi}}_{\lceil q/2\rceil}(\hat{\mathbf{r}}) \tag{2}$$

where $\boldsymbol{X}$ represents the random disturbance, $\hat{\boldsymbol{\psi}}_q(\hat{\mathbf{r}})$ are a set of orthogonal bases of vector-valued spherical functions in L^2 space; $H_q(\boldsymbol{X})$ are the mode coefficients to be determined, and Q the truncation order of the VSH expansion.

So far, we have provided a parsimonious representation of the ATF as a linear combination of a finite number of VSH modes, and the problem of modeling the FF electric field vector of the antenna is converted into the problem of modeling these VSH mode coefficients.

B. *Neural Network Model and Hyperparameter Optimization*

NN has powerful fitting ability and not complex layout. The NN consists of one input layer, one output layer, and several hidden layers, each layer composed of many neurons. Figure 1. (a) shows a classical feed-forward neural network, from which it can be seen that each neuron in the hidden layer receives the output of the previous layer as its input, and after a series of operations, sends its output to the next layer. Figure 1. (b) shows the transfer function of a typical neuron, in which z is the weighted sum of the input variables x, and named as the net input,

$$z = \sum_{d=1}^{D}\omega_d x_d + b \tag{3}$$

where ω_d is the weight and b is the bias.

The net input z, after a nonlinear function f called active function, yields the activity value a.

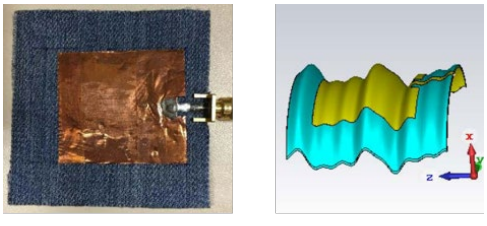
NN contains a large number of weight and bias parameters, and is generally trained by empirical risk minimization. For example, for regression problems, the mean square error (MSE) is generally used as the loss function (LF), and an optimization algorithm is used to find the best weights and bias that minimizes the LF value. This process is not easy, because a large number of hyperparameters need to be adjusted during the training, including learning rate, number of hidden layers, number of neurons, batch-size, initial parameters of weight and bias, activation function, optimizer, etc.

A fast and effective algorithm for optimizing hyperparameters is successive halving (SH) [10]. The idea of this algorithm is simple: given a budget, divide it equally among each hyperparameter configuration, evaluate their performance and eliminate the worst half. Looping these steps until only one configuration remains. However, this algorithm has a drawback, which has particular negative effect when used for hyperparameter selection in NN training. Specifically, hyperparameter configurations with larger learning rate tend to obtain lower LF value at the beginning, but it does not necessarily mean that they perform better when given more training budget, as oscillations may arise that fail to converge. In other words, those configurations that start with poor performance and are eliminated may also get better performance when given more training budget. We make some improvements to SH (ISH) to avoid jumping to "premature" conclusions.

The ISH algorithm is described as follows. First, it selects 1/3 of the configurations each round; then, it selects 1/4 of the remaining configurations according to the LF value, where smaller LF value leads to higher possibility of being chosen. This would not introduce extra burden during the training iterations compared to the conventional SH algorithm, but is capable to effectively alleviate the drawbacks of the latter to some extent.

Algorithm: Improved Successive Halving

Initialization: training budget B, hyperparameter configurations H
Process:
While len(H) > 1:
  $e = B$ / len(H)
  For i = 1, 2, …, len(H):
    train the NN model e epochs with the $H[i]$
    calculate the error MSE_i on the validation set
  End For
  sort H according to increasing MSE value
  $H1 = H$[0: len(H) / 3], $H_{rest} = H$[len(H) / 3: len(H)]
  Randomly select 1/4 of H_{rest} and assign it to $H2$
  $H = H1 + H2$
End While



(a) (b)

Figure 2. (a) Flexible textile antenna (b) Antenna under bending and crumpling

III. Application to a Textile Antenna

To verify the effectiveness of our proposed modeling method, we applied it to build FF surrogate model for a soft textile patch antenna, and compared it with the PCE model.

A. Design of the Textile Antenna

Figure 2. shows the textile antenna presented in [9], which consists of a thin layer of denim and two thin copper sheets. Supposing that in the realistic WBAN environment, the antenna undergoes random disturbances such as bending, crumpling, permittivity variation (due to the humidity for example), and operating frequency (due to dynamic frequency selection). Please refer to [9] for more details. Finally, five independent random parameters are used as the input of the model, and their variability ranges are shown in Table I.

Table I
Input Parameters of the Model

Random parameter	Unit	Range
κ	mm^{-1}	[0, 1/30]
C	mm	[0, 5]
s	-	[1, 1/0.6]
ε_r	-	[1.6, 1.9]
f	Ghz	[2.4, 2.5]

B. Construction of the Neural Network Model

First, a parsimonious expression for the ATF is obtained by using the VSH expansion. We chose the same truncation order as in [9], resulting in 48 dominant VSH modes, which account for 99.9% of the total radiated power.

Then, we chose the appropriate hyperparameters for the NN model by applying the ISH algorithm. As a rule of thumb, we set the batch size to 16, the optimizer is Adam, and the activation function is Elu. The remaining hyperparameters are determined by the ISH algorithm. We also use *k*-fold verification to save the modeling cost. We use the number of hidden layers as a parameter to be determined, the range is [5, 6, 7, 8], and the number of neurons per layer is three times the number of layers. The range of learning rate is [0.0006, 0.001, 0.003, 0.006]. The weights and bias are also generated randomly for several times to avoid falling into the trap of extremely bad starting point. The final choice of ISH is a NN structure with 8 hidden layers and learning rate of 0.003.

Finally, we set the epochs to 1000, and use the selected hyperparameter configuration to train the NN model. The number of samples in the training set and the test set are 700 and 2000, respectively. When training epoch iterates to 730, the LF value of the NN model reaches the minimum, yielding the best model parameters. Then the VSH mode coefficients predicted by the NN model were inversely transformed to obtain the antenna FF electric field vector.

We use a representative indicator called average gain error to evaluate the performance of the surrogate model. Basically, this indicator is the largest absolute difference between the realized gain of the initial FF and the predicted FF by the surrogate model (please refer to [9] for the definition). As shown in Table II, the NN model has an average gain error 0.2 dB less than that of the PCE model presented in [9] on the training set, which is a reduction of 39.22%. Moreover, on the test set, the NN model did not show obvious overfitting phenomenon at all.

Table II
Comparison between NN model and PCE model

Model	Modeling cost	Training set error	Test set error
PCE	700	0.51dB	0.53dB
NN	700	0.31dB	0.33dB

IV. Conclusion

We proposed a new modeling method based on VSH and NN for building surrogate models for the FF radiation of flexible antennas. The selection of NN hyperparameters are automatized and optimized by using an improved SH algorithm. Compared with the existing PCE model, the established NN model can significantly reduce the prediction error. The surrogate model can be utilized for antenna optimization purpose, or combined with channel models to enable end-to-end radio link assessment.

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