

Modelling and Optimization of Metamaterial Antennas using Kernel Machine Approach

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Abstract

This research work is concerned with the application of Gaussian process regression kernel machine learning approach in modelling a metamaterial antenna. MATLAB Graphical user interface (GUI) was used to randomly select two frequency points within the range $2.5\text{GHz} \leq f \leq 3\text{GHz}$ and ten points in the range $3\text{GHz} \leq f \leq 3.6\text{GHz}$ respectively. The training and test inputs generated for the model were standardized along with the frequency of operation. The rand function in MATLAB was used to generate ten sets of values between 0 and 1. The lowest negative log likelihood value gotten was -1.9762. This value is produced by the gp model with an initial hyper parameter value set at 0.1386. The model likelihood value is -13.8155. The model is capable of predicting optimal antenna responses for any new set of input data associated with the modelled metamaterial antennas.

Keywords: Metamaterial, Kernel machine, Antenna, Optimization, Electromagnetic

Introduction

The modelling, analysis, and design of antennas and multitude of other electromagnetic (EM) devices utilized in Radio frequency, Microwave and Optical communications, Radar and Signal processing etc. have been heavily dependent on numerical methods (the Method of Moments) [1], (the Finite Element Method (FEM) [2,3], Finite Discrete Time Domain [4], and hybrid techniques [3] and their attendant algorithms, solvers and software's, i.e. the so called full-wave analysis which includes the use of the Numerical Electromagnetic Code (NEC) [5], the COMSOL software and the ANSOFT HFSS and lately the CST Microwave Studio.

Within the past few decades, these methods have also been applied to the modelling and development of antennas and electromagnetic devices made of artificial or man-made/engineered materials (Electromagnetic Band Gap Structures/High Impedance Surfaces, Artificial Magnetic Conductors, Frequency Selective Surfaces, and Double Negative Materials) all collectively known under the term Metamaterials [6,7,8], which exhibit certain anomalous properties such as negative permeability and permittivity

leading to negative indices of refraction, reverse Doppler effect, reverse Vavilov-Cerenkov radiation, Support of backward waves (antiparallel phase and group velocities), Super resolution imaging and planar slab lensing.

Antennas and Microwave devices made with these materials inculcate superior qualities involving improved electromagnetic compatibility due to reduced coupling (elimination of surface waves), enhanced gain, radiation and impedance characteristics and miniaturization. However, the use of metamaterials for the design and construction of antennas and EM devices has led to an increased complexity in material and structural compositions. As such, modelling and design with full-wave analysis techniques have been observed to be too time consuming especially in antenna optimization scenarios, where several full-wave simulations will have to be run for a complicated antenna structure or a single unit cell of a metamaterial microstructure. Thus for such applications, full-wave analysis becomes prohibitively expensive and uneconomical [9, 10, 11].

Consequently, the need for the rapid and optimal design of complex antenna/EM structures in general and metamaterial antennas in particular has of recent shifted the attention of

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the EM and antenna engineering community to the use of statistical methods and machine learning techniques (mostly based on Artificial Neural Networks, Gaussian Process Modelling and Support Vector Machines) [12,13,14], in conjunction with CAD tools for the modelling and design of antennas and EM devices.

The research work involves the application of the Gaussian Process Regression kernel machine learning (GPML) approach to model a metamaterial Antenna. In particular, the GPML toolbox version 4.0 which runs on a MATLAB platform will be used to develop two models for the responses (real and imaginary parts of the reflection coefficient) of a high impedance surface antenna based on certain input characteristics (wire length and spacing of wires) and frequency of operation.

Literature Review

Gao and Wang in [15] developed an efficient EM trained artificial Neural Network (ANN) for Coplanar Waveguide (CPW) components to calculate S parameters of Electromagnetic Band-Gap (EBG) circuits involving an EBG band stop filter and EBG resonator. The agreement between the model and experimental results shows that the NN model was very effective for the analysis of this type of circuits. The NN modelling and design of EBG'S was taken a step further in [16] where a novel neuro-computational model based on ANN was used for the modelling and analysis of a rectangular waveguide and a parallel plate waveguide structure. The proposed ANN model gave results in excellent agreement with measured results available in the literature. In addition, the technique had the ability to generalize for new variables of input parameters and frequency ranges.

As an alternative to ANN modelling, Villiers and Jacobs in [9] proposed the use of a structured supervised learning technique for modelling a CPW-fed slot antenna input characteristics based on a standard Gaussian Process (GP) regression model. The method was used to model S- parameter input characteristics against frequency for a CPW-fed second resonant slot dipole, while an approximation method for large datasets was applied to an ultra-wideband (UWB) slot with U-shaped tuning stub. The results obtained based on predictions had an accuracy comparable to the target moment-method-based full wave simulations- While the slot dipole exhibited a normalized root mean squared error of 0.50%, the UWB antenna had an error below 1.8%. It was also pointed out that the GP regression methodology had various inherent benefits which includes the need to learn only a handful of hyper parameters and training errors that were effectively zero for noise-free observations.

Along the same lines with the GP Regression model, Liu

and Ji in [10] proposed an automated computation system for large scale design of metamaterials (MTMs) utilizing a computer model emulation technique (CME) that generates a forward mapping from the MTMs particle's geometric dimension to the corresponding EM response. In [11] it was shown that the CME technique was based on a Bayesian nonparametric model, namely Gaussian Process mixture, which is approximately expressed in a closed form Drude-Lorentz type model. This GP mixture model was illustrated as having the ability to tackle non-stationarities and discontinuities in the mapping function. The models inference was carried out via a Markov chain process relying on Gibbs sampling and the experimental results demonstrated that the proposed approach was highly efficient in facilitating rapid design of MTMs with accuracy.

The fundamentals and applications of another alternative and efficient approach for antenna design based on machine learning was expertly expounded by Martinez-Ramon and Christodoulou in [17] - the so called Support Vector Machine (SVM) approach. This technique has been proved to have superior performances in a large variety of real world applications due to their generalization abilities and robustness against noise and interferences. This novel technique was applied to antenna array processing and in particular non-linear beam forming and parameter design for arrays. In accordance with [17], G. Angiuilli, et.al in [18] describes how microwave devices and antennas can be modelled via the Support Vector Regression Machine approach by first taking into account the short comings of the ANN modelling scheme- these include lack of definite and effective methods for the determination of the number of hidden layers and hidden nodes in ANN models, difficulties with generalization and the production of models that over fit the data. Emphasis were laid on the Structural Risk Minimization Principle embodied in the SVM model which enables it to partially overcome the above mentioned short comings of the ANN model.

Finally, it will suffice to say that the research work carried out presently is geared towards utilizing a kernel machine learning (Gaussian Process Modelling) approach in conjunction with CAD tools for a more time efficient and cost effective (as compared to entire full-wave analysis) modelling and optimization of a patch antenna.

Materials and method

The high impedance surface antenna was created via the CST software and is depicted in figure1 below:

In the figure above, L is the wire length, S is the spacing between wires, W is the width/diameter of the wires and t depicts the thickness of the substrate or ground plane.

The following simulations were carried out in CST with respect to the antenna:

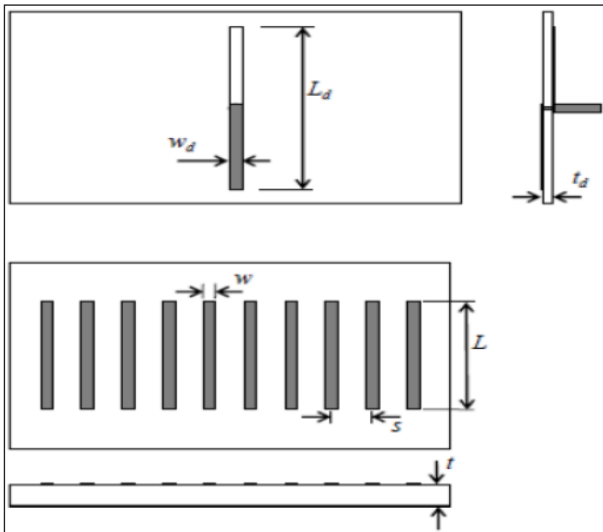


Figure 1. High impedance surface antenna

Design Space

$34\text{mm} \leq L_d \leq 42\text{mm}$

$5\text{mm} \leq s \leq 7\text{mm}$ (distance between strips on AMC surface)

Frequency range

$2.5\text{ GHz} \leq f \leq 3.6\text{ GHz}$ (1021 points)

Training data

50 geometries generated using Latin Hypercube Sampling (1021 frequency points per geometry)

Test data

20 LHS geometries, not included amongst the training geometries (1021 frequency points per geometry)

The above data was stored in .txt files as follows:

Geometry dimensions in mm

new24.050_020.rs6.txt (first 50: training geometries; rest: test geometries)

CST Re(S11) and Im(S11) responses

new24_S11R_050_020.txt (first 50: training; rest: test)

new24_S11I_050_020.txt (first 50: training; rest: test)

In order to initiate the modelling of the antenna in the GPML frame work, the first step involves reading in the above generated data into the MATLAB platform; this is achieved by developing the following MATLAB codes.

Response.m : This code reads in the data stored in the files new24_S11R_050_020.txt (first 50: training; rest: test) and new24_S11I_050_020.txt (first 50: training; rest: test) into the MATLAB environment. The MATLAB arrays generated are then stored as S11R and S11I. In addition, the file Response2.m is utilized to extract the responses from the frequencies and store them in the arrays SR- for

Re(S11) and SI- for Im(S11).

Dimension1.m: This code reads in the data for the geometrical dimensions new24.050_020.rs6.txt (first 50: training geometries; rest: test geometries) and stores the contents in the array 'X'. These input dimensions in conjunction with frequency are standardized in the MATLAB file standardization.m.

Generation of Training Data

In order to generate training data from the responses Re(S11) and Im(S11), the first column of S11R which contains the frequency points are plotted against the 50 columns of SR and SI to produce 50 plots each for both the real and imaginary responses respectively.

The MATLAB Graphical User Interface (GUI) is then used to randomly select 2 frequency points within the range $2.5\text{GHz} \leq f \leq 3\text{GHz}$ and 10 points in the range $3\text{GHz} \leq f \leq 3.6\text{GHz}$ respectively. An example of such graphs is shown in figures 2 & 3 below:

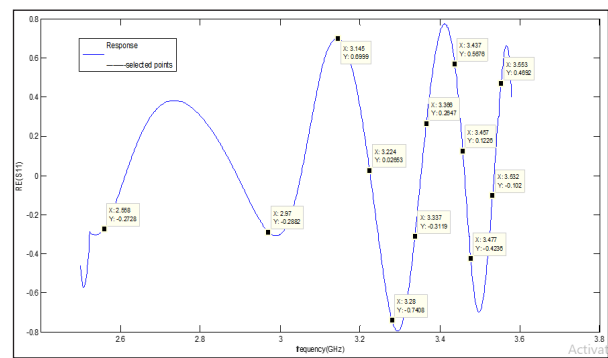


Figure 2. Re(S11) response with selected training points

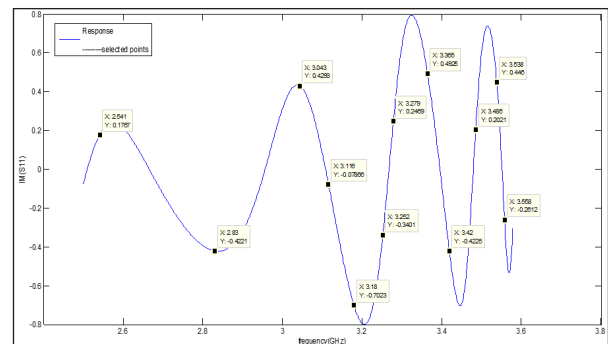


Figure 3. Im(S11) response with selected training points

The real and imaginary responses plotted without the target points are produced by the codes plotnewRE.m and plotnewIM.m respectively, the resulting figures are saved as FigRE.fig and FigIM.fig respectively. The complete sets of plots with the target points are stored in the folders named realfigs.m for the real part of the responses and imfigs.m for the imaginary part of the responses.

Inputs (Training And Test) And Responses (Training And Test)

The training and test inputs for the model are generated in MATLAB file Dimension1.m and are then standardized along with the frequency of operation in the MATLAB file named standardization.m. The file, 'xtr' stands for the array that stores the training inputs and 'xst' stands for the array that stores the test inputs. Also, the arrays fre_train and fim_train contain the real and imaginary training frequency while the array ftest contains the test frequency. Finally, the arrays ftr_real, ftr_im, fts-real and fts_im contains the standardized versions of the imaginary and real training and test frequencies. The training responses are generated in MATLAB file named trainRESPONSE.m, within the file, the array yre_train stores the real part of the training responses while the array yim-train stores the imaginary part of the training responses. The test responses are generated in MATLAB file named testRESPONSE.m, within the file, the array yre_test stores the real part of the test responses while the array yim-test stores the imaginary part of the test responses.

GP Model

The model for the real and imaginary responses are given in the MATLAB files gpreal.m and gp_im.m. In the files, the training and test inputs are provided and the mean function, covariance function, likelihood function and method of inference are specified. The likelihood initial hyper parameter value is at $\log(1e-6)$. The rand function in MATLAB was used to generate 10 sets of values between 0 and 1. These values were utilized as the covariance function initial hyper parameter values.

Table 1. Initial covariance hyper parameter values

0.7513	0.8407	0.3517
0.2551	0.2543	0.8308
0.5060	0.8143	0.5853
0.6991	0.2435	0.5497
0.8909	0.9293	0.9172
0.9593	0.3500	0.2858
0.5472	0.1966	0.7572
0.1386	0.2511	0.7537
0.1493	0.6160	0.3804
0.2575	0.4733	0.5678

The initial covariance hyper parameter values are given in the table 1 above. While the resulting values of the negative log marginal likelihood are given in table 2 below.

From table 2 above it can be inferred that the lowest negative log likelihood is -1.9762.

Table 2. Resulting negative log marginal likelihood values

-0.2860	-0.1735	-1.0450
-1.3661	-1.3692	-0.1854
-0.6812	-0.2054	-0.5356
-0.3580	-1.4126	-0.5984
-0.1155	-0.0733	-0.0864
-0.0416	-1.0498	-1.2525
-0.6029	-1.6266	-0.2781
-1.9762	-1.3819	-0.2828
-1.9018	-0.4845	-0.9665
-1.3567	-0.7480	-0.5660

This value is produced by the gp model with an initial hyper parameter value set at 0.1386.

The model likelihood value is -13.8155.

Summary and Conclusion

The field of Electromagnetics and antenna design is replete with and heavily dependent on full-wave simulations in order to carry out the optimal design of antennas and electromagnetic devices. Contemporarily, the CST Studio Suite is one of the choice software for electromagnetics design. Basically, the software package comprises of the CST Microwave Studio, CST particle studio, CST Mphysics Studio, CST design Studio, CST PCB Studio and CST Cable Studio. Of particular interest in the present work is the CST Microwave Studio which is a specialized tool for the fast and accurate 3 dimensional electromagnetic simulation of high frequency problems. Along with a broad range of applications, it offers shorter development cycles, virtual prototyping before physical trials and optimization in place of experimentation. Consequently, CST microwave studio was used in the initial preliminary design of the proposed patch antenna which operates in the GHz range (center frequency of 3GHz), with dimensions in millimeters. In terms of construction, the antenna consist of a one dimensional (1D) high impedance surface (HIS) comprised of uniformly spaced parallel wires of annealed copper with lengths slightly less than $\frac{\lambda}{2}$ around the resonance frequency

References

1. RF Harrington. Field Computation by Moment Methods, Macmillan, New York, 1968.
2. Silvester PP, Ferrari RL, Finite Elements for Electrical Engineers, Cambridge University Press. New York, 1983.
3. Jin J, The Finite-Element Method in Electromagnetics, Wiley, New York, 1993.
4. A. Taflove, SC Hagness (Eds.). Computational Electrodynamics: The Finite-Difference Time-Domain

- Method, Artech House, Boston, 2005.
5. GJ Burke, AJ Poggio, "Numerical Electromagnetics Code (NEC)-method of moments," Technical Document 116, Naval Ocean Systems Centre, San Diego, CA, September 6, 1982.
 6. G Eleftheriades, KG Balmain, Negative-Refraction Metamaterials: Fundamental Principles and Applications, New York: Wiley, 2006.
 7. D Sievenpiper, High-impedance electromagnetic surfaces, Ph.D. dissertation, Department of Electrical Engineering, University of California, Los Angeles, 1999.
 8. CA Balanis (Ed.). Modern Antenna Handbook, Wiley, New York, 2008.
 9. J.P De Villiers, J.P Jacobs. "Gaussian process modelling of CPW-fed slot antennas," Progress in Electromagnetics Research 2009; 98: 233-249.
 10. B. Liu, and C. Ji, "Automated Metamaterial Design with Computer Model Emulation and Bayesian Optimization," Article in Applied Mechanics and Materials Journal, August 2014.
 11. B. Liu, C. Ji. "Bayesian Nonparametric Modelling for Rapid Design of Metamaterial Microstructures," International Journal of Antennas and Propagation, 2014.
 12. VN Vapnik, The Nature of Statistical Learning Theory. New York: Springer, 1995.
 13. CM Bishop. Neural Networks for Pattern Recognition. Oxford: Oxford University Press, 1995.
 14. RO Duda, PE Hart, DG Stork. Pattern Classification, 2nd ed. New York: Wiley 2001.
 15. C. Gao, Y. Wang. "Analysis of EBG Structures Implemented on CPW Components by Using EM-ANN Models," Antennas and Propagation Society International Symposium, 2002. IEEE. 16-21 June 2002.
 16. E.Q. Fernandes, H. da Fonseca Silva, A.G. D'Assuncao, and M.A. Barbosa de Melo, "Neuro Modelling of Microwave waveguides with EBG Structures," Proceedings SBMO/IEEE MTT-S IMOC 2003.
 17. M.M. Raman, C. Christodoulou. Support Vector Machines for Antenna Array Processing and Electromagnetics. Synthesis Lectures on Computational Electromagnetics: Morgan and Claypool Publishers. 2006.
 18. G. Angiulli, M. Cacciola, M. Versaci. "Microwave devices and Antenna Modelling by Support Vector Regression Machines," Electromagnetic Field Computation, 2006 12th Biennial IEEE Conference 30 April-3 May 2006.

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