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PERMEABILITY MEASUREMENT OF FERROMAGNETIC MATERIALS IN MICROWAVE FREQUENCY RANGE USING SUPPORT VECTOR MACHINE REGRESSION

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Abstract—A new method based on supported vector regression (SVR) approach is proposed for permeability measurement. The microstrip transmission-line is used as measurement cell, and supported vector machine (SVM) is introduced to extract permeability of ferromagnetic materials. Experiment results show that thanks to SVM's good ability of generalization, permeability of ferromagnetic materials can be extracted accurately and easily.

1. INTRODUCTION

Ferromagnetic materials exhibit much higher level of saturation magnetization. They are now found numerous applications in high-speed electronics and microwave devices, such as M-RAMs, planar inductors, filters, electromagnetic interference supressors and giant magneto impedance sensors. Different applications require ferromagnetic material with different properties, and the permeability spectrum of ferromagnetic materials are among the most important factors determining the suitability of the materials for the applications and the performances of the devices made from the materials [1–3]. A number of techniques have been developed which have the potential to be applied for the permeability measurement of ferromagnetic materials [4–6]. Microstrip transmission method which doesn't need complex sample facture technology is a broadband measuring method for permeability measurement, but because the microstrip is an open structure, it hard to measure the actual permeability of the material directly [7].

Recently, Vapnic's SVM theory has been applied successfully for classification and regression problems [8–10]. SVM solves a constrained quadratic optimization problem, and it is based on statistical learning theory that gives the possibility to control the model's complexity and hence, to control its generalization ability. The advantage over other approaches like artificial neural-network (ANN), SVM is approach based on structural risk minimization (SRM) principle, which consists of minimizing a trade-off between the model's complexity and the generalization ability [11]. The modeling is usually called the SVM regression tasks which support vector regression (SVR). Through using SVR, one can determine the actual permeability of the ferromagnetic material.

In this paper, S-parameters of the microstrip transmission-lines with material samples are obtained by using a commercially available full-wave electromagnetic simulator (Ansoft HFSS); transmission constant (γ) and character impedance (Z_c) were deduced from the S-parameter. Then effective permeability was derived from the transmission constants and character impedances. At last, SVR was used to construct the model between actual permeability and effective permeability, and the actual permeability of the material was extracted from the effective permeability. The result suggest that SVR can extract the permeability of material accurately and easily.

2. MEASUREMENT CELL

A significant advantage of our method consists of using a microstrip cell, the production of which does not require a complex technology. The material under test is used as microstrip substrate, and upper strip and ground plane were respectively added in the two sides of it (see Figure 1). The scattering parameters of the cell are measured and constitutive magnetic parameters of the material are extracted.

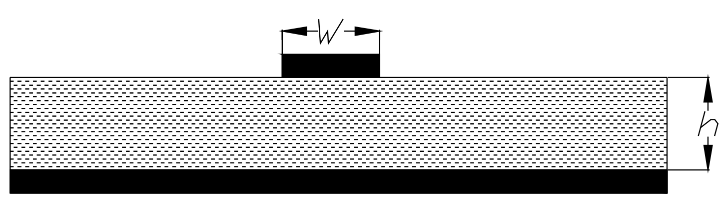

Figure 1. The microstrip cell of material sample.

3. BASIC THEORIES OF PERMEABILITY MEASUREMENT

S-parameter of the under test network is shown as (1):

$$S = \begin{pmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{pmatrix} \tag{1}$$

The network is symmetrical and reciprocal, so $S_{11} = S_{22}$ and $S_{12} = S_{21}$, and the S-matrix can be exchanged into A-matrix as:

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \tag{2}$$

The values of a, b, c, d can be obtained from the S-parameter as:

$$a = d = \frac{1}{2}\left[\frac{1 - S_{11}^2}{S_{21}} + S_{21}\right] \tag{3}$$

$$b = \frac{1}{2}\left[\frac{(1 + S_{11})^2}{S_{21}} - S_{21}\right] \tag{4}$$

$$c = \frac{1}{2}\left[\frac{(1 - S_{11})^2}{S_{21}} - S_{21}\right] \tag{5}$$

The normalized A-matrix of the transmission-line is:

$$\begin{pmatrix} ch\gamma l & \dfrac{Z_c}{Z_0} sh\gamma l \\ \dfrac{Z_0}{Z_c} sh\gamma & ch\gamma l \end{pmatrix} \tag{6}$$

where l is the length of microstrip transmission-line, γ is the transmission constant, Z_c is the characteristic impedance of the microstrip transmission-line, and Z_0 is the characteristic impedance of the test system.

By comparing (5) with (6), we can obtain the value of γ and Z_c [12].

On the other hands, γ and Z_c can be expressed as:

$$\gamma = \alpha + j\beta = \gamma_0 \sqrt{\mu_{reff}\varepsilon_{reff}} \tag{7}$$

$$Z_c = Z_0^0 \sqrt{\frac{\mu_{reff}}{\varepsilon_{reff}}} \tag{8}$$

where

$$\gamma_0 = j\frac{2\pi}{\lambda_0} \tag{9}$$

$$Z_0^0 = \begin{cases} 60\ln\left(\dfrac{8h}{W}+\dfrac{h}{4W}\right), & \dfrac{W}{h}\le 1 \\ \dfrac{120\pi}{\dfrac{W}{h}+1.393+0.667\ln\left(\dfrac{W}{h}+1.444\right)}, & \dfrac{W}{h}>1 \end{cases} \tag{10}$$

and

$$\tilde{\gamma} = \frac{\gamma}{\gamma_0} = \sqrt{\mu_{reff}\varepsilon_{reff}} \tag{11}$$

$$\tilde{Z}_c = \frac{Z_c}{Z_0^0} = \frac{\mu_{reff}}{\sqrt{\mu_{reff}\varepsilon_{reff}}} \tag{12}$$

where W is the width of upper strip, h is the height of the substrate, as shown in Figure 1, μ_{reff} is the effective permeability of the material, ε_{reff} is the effective permittivity of the material, γ_0 is the transmission constant of microstrip with air substrate, and Z_0^0 is the characteristic impedance of microstrip with air substrate. So ε_{reff} and μ_{reff} can be obtained from:

$$\varepsilon_{reff} = \tilde{\gamma}/\tilde{Z}_c \tag{13}$$

$$\mu_{reff} = \tilde{\gamma} * \tilde{Z}_c \tag{14}$$

For ferromagnetic materials, sometimes their permeability is important; in this paper, the permeability of it was measured to prove that this measurement method is correct. The μ_{reff} can be obtained from (14), but because part of electromagnetic field is outside the actual microstrip substrate, the effective permeability is not equal to the actual permeability of the material, so one must extract the actual permeability from the effective permeability.

4. SUPPORT VECTOR REGRESSION MODEL

Similar to the artificial neural network (ANN) model, SVR estimates the non-linear function that encodes the fundamental interrelation between a given input and its corresponding output data that is acquired from EM simulation also define training data. This developed model then can be used to predict outputs for given inputs that were not included in the training data.

In this paper, the actual permeability is computed as the output. The operation frequency (f) and the effective permeability are used as the SVR model input parameters. The width of the upper strip (W) is set at 0.2 mm, and the height of substrate (h) is set at 0.5 mm. The operation frequency is from 1 GHz to 10 GHz, and the permeability range of the materials under test is set from 1 to 10.

LIBSVM-matlab code was used to implement SVR model. It computes a very efficient sequential minimal optimization (SMO) type decomposition method to solve the SVR problems. υ-SVM regression based on radial basis function (RBF) kernel function has been considered in our regression experiments. The RBF kernel is shown as follows [11, 13]:

$$K(x, x_i) = \exp\left(-r \cdot \|x - x_i\|^2\right). \tag{15}$$

where r is a constant defining the kernel width.

Before running LIVSVM code, we need to determine some SVR parameters including the constant defining of kernel function (r), tolerance of termination criterion (ε), the penalty parameter (C) and the constant ν. $\nu \in [0, 1]$ is the parameter to control the number of support vectors. After performing many experiments with different variable values, the variables were fixed as: $\varepsilon = 0.0001$, $\nu = 0.5$, $C = 1000$, and r with the default value of $1/k$, k means the number of SVR model input parameters.

Furthermore, the quality of each model is evaluated as its prediction accuracy, measured by mean squared error (MSE) and the linear correlation coefficient (R).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2. \tag{16}$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \overline{x})^2 \sum_{i=1}^{N}(y_i - \overline{y})^2}}. \tag{17}$$

x_i is the value of material permeability, y_i is the value of SVR predicted and N is the number of validation data. $\overline{x}$ is the mean value of material permeability and $\overline{y}$ is the mean value of ν-SVR predicted.

The extract step is that:

1) Set the permeability of material, run simulation and calculate effective permeability from S-parameters to obtain training data.
2) Use SVR to structure the model between actual permeability and effective permeability.

3) Predict the permeability through the model. By comparing the predicted value with set value, one can determine the precision of the model.

In practice, one can easily obtain the S-parameters of the measurement cell by using vector network analyzer, and through using the structured SVR model, one can get the permeability of the material accurately.

5. RESULTS

The plot of the SVR model predicted permeability is compared to the training dataset and is shown in Figure 2. The more the points are concentrated around the diagonal line, the better the prediction is. To illustrate the prediction ability, the predicted values by direct prediction are plotted against the test dataset as depicted in Figure 3. Summary of MSE and R are shown in Table 1. As can be seen from the results, excellent agreement between the predicted value of SVR model and the set value can be arrived.

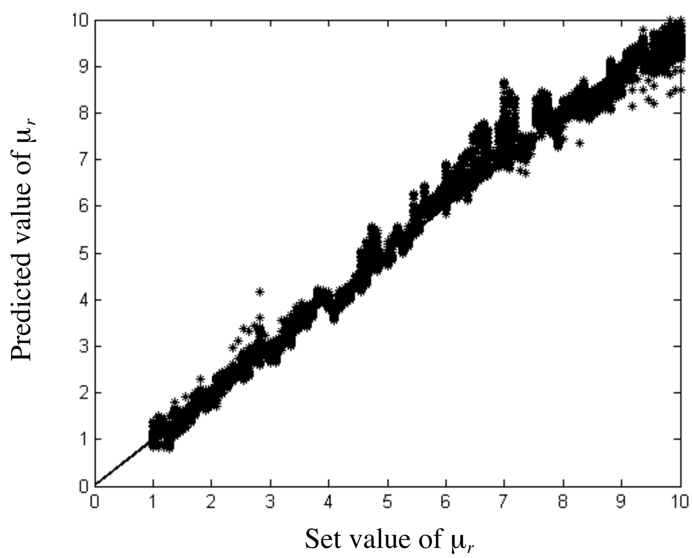

Figure 2. Plot of real part of permeability we set and SVR computed training data.

Two groups of permeability are also extracted in the frequency range from 1 GHz to 10 GHz. As shown in Figure 4 and Figure 5, the predicted values agreed with the set values in the full interested frequency range very well.

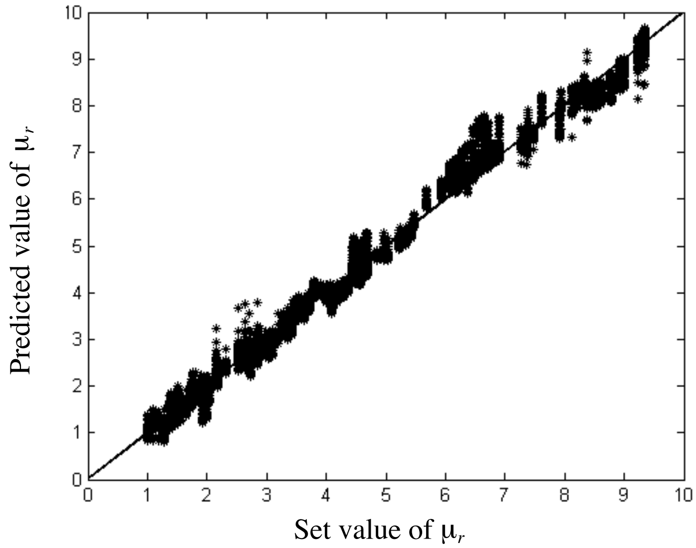

Figure 3. Plot of real part of permeability we set and SVR computed testing data.

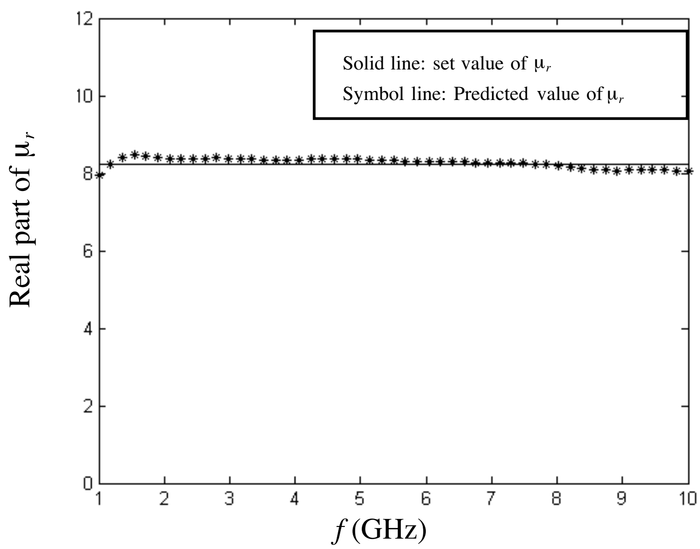

Figure 4. Plot of values of computed SVR.

Table 1. MSE and correlation coefficient (R) of the training data and testing data.

Data	Training data	Testing data
MSE	0.0908531	0.0577988
R	0.986836	0.989927

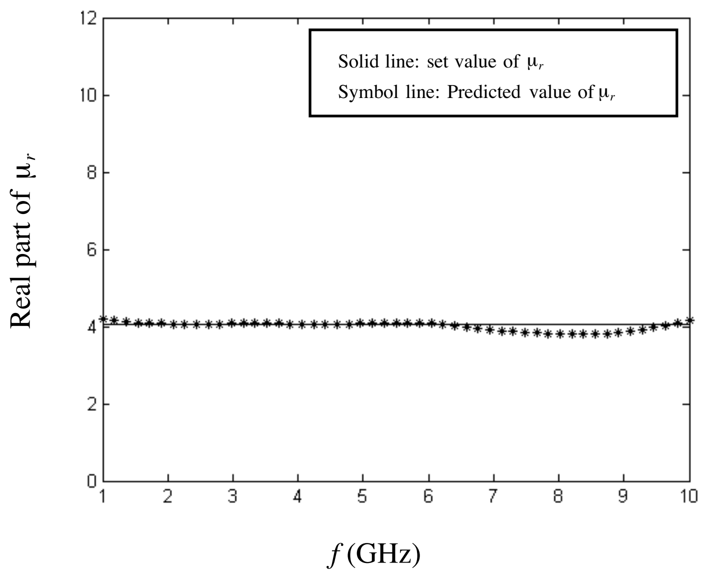

Figure 5. Plot of values of computed SVR.

6. CONCLUSIONS

In this paper, ferromagnetic material permeability measurement problem has been reformulated as regression estimation. SVR is introduced to extract the actual permeability of ferromagnetic materials. Microstrip transmission-line is used as measurement cell, and the formulations for calculating effective permeability are also deduced. It has been shown that excellent agreement between the predicted value of SVR model and the set value is achieved. By using SVR, the actual permeability of magnetic material can be extracted accurately.

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REFERENCES

1. Ledieu, M. and O. Acher, "New achievements in high-frequency permeability measurements of magnetic materials," *Journal of Magnetism and Magnetic Materials*, 144–150, 2003.
2. Vincent, D., et al., "A new broad-band method for magnetic thin-film characterization in the microwave range," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 53, No. 4, 1174–1180, April 2005.
3. Liu, Y., et al., "Broadband complex permeability characterization of magnetic thin films using shorted microstrip transmission-line perturbation," *Review of Scientific Instruments*, Vol. 76, 063911.1–063911.8, 2005.
4. Wang, Y. and M. N. Afsar, "Measurement of complex permittivity of liquids using waveguide techniques," *Progress In Electromagnetics Research*, PIER 42, 131–142, 2003.
5. Mahmoud, S. F., "Surface wave character on a slab of metamaterial with negative permittivity and permeability," *Progress In Electromagnetics Research*, PIER 51, 127–137, 2005.
6. Baudry, D., A. Louis, and B. Mazari, "Characterization of the open-ended coaxial probe used for near-field measurements in EMC applications," *Progress In Electromagnetics Research*, PIER 60, 311–333, 2006.
7. Maricevic, Z. A. and T. K. Sarkar, "Analysis and measurements of arbitrarily shaped open microstrip structures," *Progress In Electromagnetics Research*, PIER 15, 253–301, 1997.
8. Vapnik, V., *The Nature of Statistical Learning Theory*, Springer-Verlag, New York, 1995.
9. Chu, W., C. J. Ong, and S. S. Keerthi, "An improved conjugate gradient scheme to the solution of least squares SVM," *IEEE Trans. Neural Network*, Vol. 6, No. 2, 498–501, March 2005.
10. Shevade, S. K., S. S. Keerthi, C. Bhattacharyya, and K. R. K. Murthy, "Improvements to the SMO algorithm for SVM regression," *IEEE Trans. Neural Network*, Vol. 11, No. 5, 1188–1193, Sept. 2000.

11. Bermani, E., A. Boni, A., A. Kerhet, and A. Massa, "Kernels evaluation of SVM based-estimators for inverse scattering problems," *Progress In Electromagnetics Research*, PIER 53, 167–188, 2005.
12. Tian, B. N., et al., "Researches on transmission/reflection method for material electromagnetic parameters measurements," *Chinese Journal of Radio Science*, Vol. 16, No. 1, 57–60, March 2001.
13. Xia, L., et al., "Modeling of 3D vertical interconnect using support vector machine regression," *IEEE Microwave and Wireless Components Letters*, Vol. 16, No.12, 639–641, December 2006.