Parametric Inversion of 2-D Dielectric Rough Surface Based on SVM

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Abstract— The inverse scattering of the geometric parameters with the 2-D rough surface is studied in this paper. Relative parameters are estimated by means of a regression technique based on the use of support vector machines (SVM). The Radar Cross-Section (RCS) is used as feature value, after a proper training procedure, the proposed method is able to reconstruct the parameters of the rough surface. Numerical results are provided for the validation of the approach.

1. INTRODUCTION

Inverse scattering is one of the most challenging problems in electromagnetic field due to its nonlinear and probabilistic characteristics. However, it is still gaining a considerable amount of attention because of its numerous applications in civil areas as well as military areas. In the past, the inversion techniques that have been proposed are mainly based on the numerical inversion of the integral scattering equations in the spatial domain or on iterative minimization technique. Unfortunately, these methods often require a great amount of computational resources and long CPU time. Recent years, techniques based on the use of Machine Learning Methods (MLM) such as neural networks (NNs) and support vector machines (SVM) have been proposed to solve inverse scattering problems.

SVM is based on the Structural Risk Minimization Principle (SRMP) and Statistical Learning Theory (SLT), the solution of which is global optimal. A lot of specialists have already performed inverse scattering researches to detect the buried target by the use of SVM. In this paper, numerical solution based on method of moment (MoM) is used to compute scattering field, then with the help of support vector regression (SVR), we establish the inverse scattering model to reconstruct the parameters of the rough surface.

2. INVERSE SCATTERING MODEL

Generally, research on inverse scattering problem usually measure the scattered field containing scatterer characteristic information such as geometric size, physical material at first. Then we obtain the estimated value of the scattered field by the SVR process. In this paper, we acquire the scatterer information (RCS in this passage) by MoM.

SVR theory can be simply stated as following. Given several training samples ($\{X_i, y_i\}$; $i = 1, 2, \ldots, n$; $X_i \in R^n$; $y_i \in R$). X_i may be the RCS value while y_i may be the unknown properties of the surface or the target in this passage. By training the samples we can find a function that have a maximum fixed error ε for all the samples from the training set, at the same time, the function should be as smooth as possible in order to reduce the effects on the estimated values caused by the perturbation of the input data. This function as follow

$$\Phi(X) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(X_i, X) + b \tag{1}$$

N is the number of support vector, while functional parameters (α_i, α_i^*, b) are unknown quantities and must be chosen in order to minimize the distance between the values predicated by the function and the samples. Besides, nonlinear transformation function k is a kernel function. Function (1) also contain structural parameters (ε, C, γ^2). Parameter C is called penalty factor which measures the trade-off between the training error rate and the model complexity. γ^2 is square of the standard deviation when Gaussian function serve as the kernel function. The ε is called insensitive loss function which is defined as

$$\varepsilon(X, y) = \begin{cases} 0 & \text{if } |y - \Phi| \le \varepsilon \\ |y - \Phi| - \varepsilon & \text{others} \end{cases} \tag{2}$$

3. NUMERICAL RESULTS

In order to assess the effectiveness of the SVM approach, several numerical simulations have been performed.

We reconstruct the root-mean-square (rms) height δ and relevant length ℓ of the surface in this paper. The kernel function used for SVM here is a radial kernel, which is given by

$$K(X_i, X) = e^{(-|X_i - X|^2/\gamma^2)} \tag{3}$$

Simplified model of the problem illustrated as Figure 1. A random rough surface (length $L = 10\lambda_0$) generated by Monte Carlo method divides the region into two parts (air-soil). A tapered wave with HH polarized uniform (frequency $f = 300\,\text{MHz}$) illuminating the air-soil interface in the x-z plane (with incident angle $\theta = 30°$). Region below the rough surface is filled by dielectric substance of known dielectric property ($\varepsilon_2 = 2 - 0.2j$ $\mu_2 = \mu_0$), while μ_0 is the magnetic permeability of the vacuum. Five observation points of different direction($\theta_s = i\pi/6$; $i = 1, 2, 3, 4, 5$) are used to measure the scattered field.

The RCS of the target used as samples, RCS at the observation points are calculated by MoM. We calculate 50 different rough surfaces to avoid the randomness of the rough surface. Then we obtain 100 training samples ($\delta_i = 0.025\lambda_0 + (i-1)\Delta x$, $i = 1, 2, \ldots, 10$, $\Delta x = 0.0075\lambda_0$; $\ell_i = 0.5\lambda_0 + (i-1)\Delta y$, $i = 1, 2, \ldots, 10$, $\Delta y = 0.1\lambda_0$) and 81 test samples ($\delta_i = 0.0255\lambda_0 + (i-1)\Delta x$, $i = 1, 2, \ldots, 9$, $\Delta x = 0.0075\lambda_0$; $\ell_i = 0.51\lambda + (i-1)\Delta y$, $i = 1, 2, \ldots, 9$, $\Delta y = 0.1\lambda_0$).

After the training phase, we acquire the structural parameters of the SVM regression. Then we use the test samples mentioned above to evaluate the precision of the SVM. The reconstruction of both the root-mean-square (rms) height δ and relevant length ℓ are shown in Figures 3 and 4

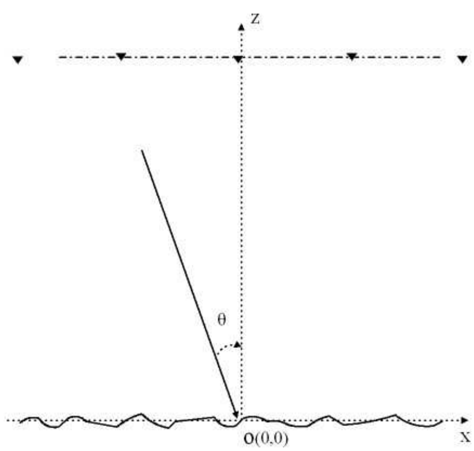

Figure 1: Cross section of the 2-D dielectric rough surface.

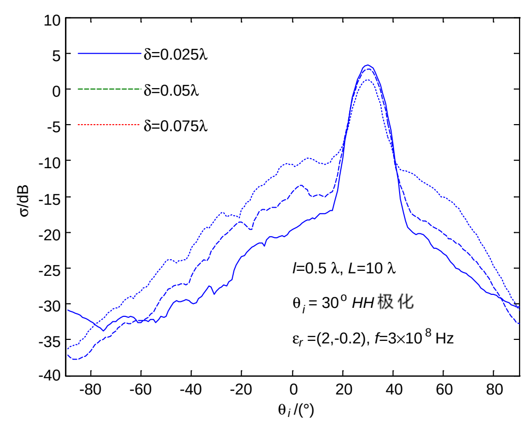

Figure 2: RCS with different δ.

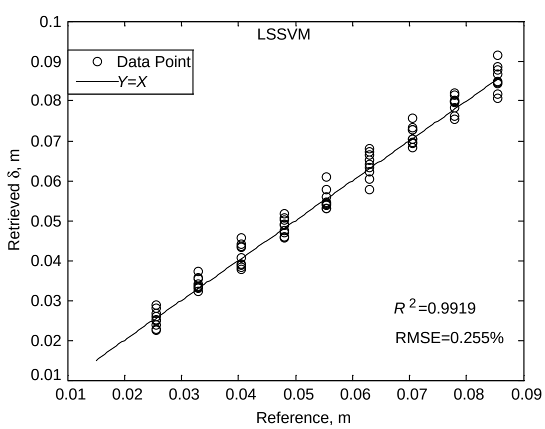

Figure 3: Estimation of the root-mean-square height δ.

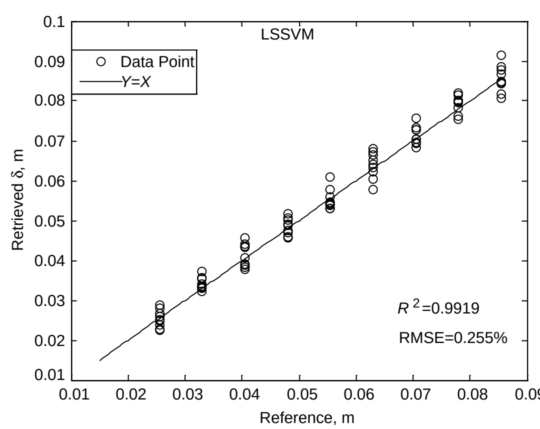

Figure 4: Estimation of the relevant length ℓ.

Table 1.

	δ	ℓ
R^2	0.9919	0.9959
RMSE	0.255%	2.376%

comparison with the reference, respectively. The correlation coefficient (R^2) between the retrieved and reference of the surface parameters and root-mean-square error (RMSE) are shown in the Table 1. Our retrieval result is very encourage.

We also found that the algorithm had multi solution problem for several references that produced large estimation errors. Figure 4 shows that the deviation will increase when the relevant length exceed within limits. This is probably because the RCS changes acute when ℓ get larger, but our sampling interval is not small enough.

4. CONCLUSION

In this paper, several observations points are set to acquire the scattered field, then we calculate the RCS at the points by MoM, finally, geometric parameters reconstruction of the random rough surface shallow buried cylinder is achieved with the help of SVM theory. The training of SVM requires the solution of a constrained quadratic optimization problem, this is a key point of the proposed approach which allows to overcome the typical drawbacks as overfitting or local minima (compared with NNs). Numerical results show the validity and veracity of SVM approach. Future work will be focused on the use of SVM to 3-D target buried beneath a rough surface.

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