Research on Geophysical Modeling Using Extreme Learning Machine for Scatterometer

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Abstract--Using the quantitative geophysical model function (GMF) between the radar backscatter coefficient and the sea surface wind speed, wind direction, radar parameters and environmental parameters, the wind vector can be retrieved from backscattering measurement. In this paper, Extreme learning machine (ELM) approach is used to develop a unified GMF respectively using the simulated training data-set generated by the empirical GMF CMOD5.N and the wind data gained from the ASCAT. Analysis indicates that the method based on extreme learning machine showing a good inversion result compared with CMOD5.N with high accuracy. The new method provides a novel feasible way for future surface wind field inversion.

Introduction

Scatterometer also known as active strabismal microwave sounding unit, which is a kind of non-imaging satellite radar sensor. Sea surface roughness information is obtained by measuring the scatterometer backscatter, thus the wind vector can be retrieved. In order to get the wind information using multiple measurements of normalized radar cross sections σ^0, we need a good understanding of the relationship between the measurements and ocean wind field, which we called the geophysical model function (GMF). Due to a lack of sufficiently accurate theory to describe the relationship between short sea waves and wind vectors, the wind retrieval is mainly through some empirical models [1]. A number of different empirical models of wind retrieval have been made for particular scatterometer instruments, e.g. SASS-1/2, NSCAT-1/2 and QSCAT-1 models for Ku-band sensors, and CMOD series for C-band [2]. Most established empirical models using statistical methods requires a lot of observations which are sometimes difficult to obtain in a short time, and it is expensive. Therefore, the study of new geophysical model function construction method, making full use of insufficient space borne scatterometer observations for wind retrieval is important [3] .

Guangbin Huang et al. 2006 proposed a new learning algorithm called extreme learning machine (ELM) for single-hidden layer feed forward neural networks (SLFNs) which is much faster than conventional popular learning algorithms for feedforward neural networks [4]. In this paper, we build a new unified geophysical model using both simulated data of empirical model CMOD.5N and ASCAT wind products based on this new method. The experimental results show that the new model produces good agreement to the traditional empirical model.

The outline of the paper is as follows. Section 2 describes the theory of geophysical model function and extreme learning machine; Section 3 details the use of extreme learning machine for modeling processes; Section 4 shows the experiments and analysis; Finally, conclusions are given in Section 5.

Related Work

A. The geophysical model function

The geophysical model is also known as the ocean surface electromagnetic backscattering model which describes the function between the scatterometer backscatters σ^0 and sea surface winds vectors.

Given the fixed value of wind speed, incidence and the polarization, the backscatter σ^0 can be computed by giving an azimuth $\emptyset_R$ based on the empirical model. Currently, the general expression of the CMOD series models is:

$$\sigma^0 = b_0(1 + b_1 \cos \emptyset + b_2 \cos 2\emptyset)^{1.6} \tag{1}$$

Where σ^0 is the normalized radar cross sections, $\emptyset$ is the wind direction (which is a function of azimuth $\emptyset_R$), and b_0, b_1, b_2 are functions of wind speed, wind direction and incidence[5,6].

B. Extreme learning machine theory

Extreme learning machine (ELM) is a learning algorithm for single-hidden layer feedforward neural networks (SLFNs) which randomly chooses hidden nodes and analytically determines the output weights of SLFNs [4]. ELM only need to set the nodes of the hidden layer, and during the execution of the algorithm does not need to adjust the input weights and the network hidden element, and generates a unique optimal solution. It also shows a better generalization performance than the traditional learning algorithm.

ELM modeling

The training method of ELM is quite similar to the neural network, given the input feature vector and the target vector based on specific problem, and we just need to set the number of hidden layer node. The modeling procedure of geophysical model using ELM consists of the following steps: First, we need to select the training samples, and make the normalization; Then, take the wind speed V, azimuth ϕ and incidence angle θ as input, the correspondent normalized radar cross sections σ^0 as target, set the hidden layer node and thus we can make the training; The third step is to use a number of test data as the input, use the trained model to get an output and compare with the target to evaluate the accuracy. The structure of the process is given in Fig. 1.

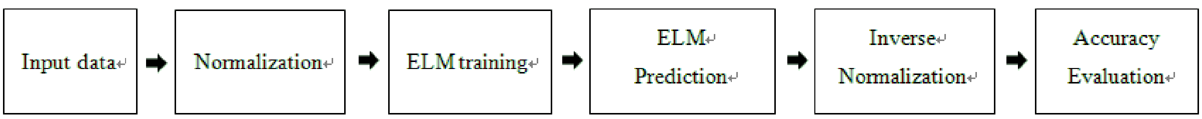

Figure 1: ELM modeling structure

Experiment

Fig. 2 shows a comparison of σ^0 between the ELM model output value and the samples. The training accuracy of ELM is rather high which for both data sets the correlation coefficients exceed 99%. The training accuracy of ASCAT samples is lower than the simulated data, which is reasonable since most of the samples of ASCAT observation are distributed at the low wind while the simulated data is fairly well-distributed.

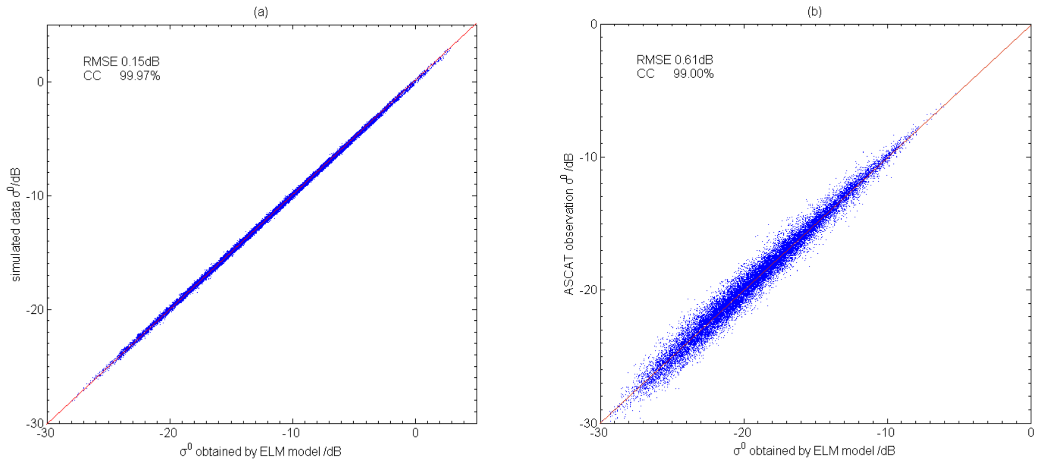

Figure 2: Comparison of σ^0 between the ELM model output and the samples: (a) simulated data experiment; (b) ASCAT observation experiment.

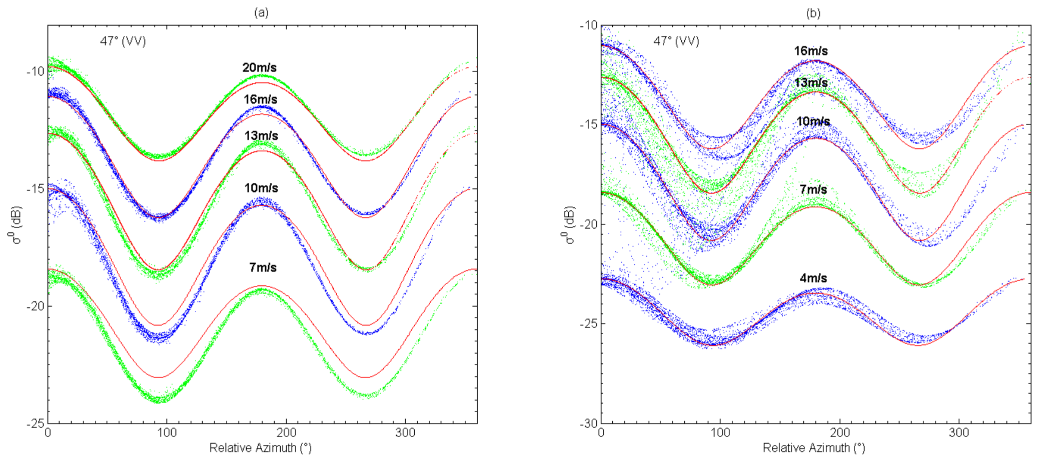

Figure 3: Comparison of σ^0 between ELM model output and CMOD5.N for various wind speeds at an incidence angle of 47°: (a) simulated data experiment; (b) ASCAT observation experiment. Red curve denotes σ^0 of CMOD5.N. Blue and green scattering dots represent σ^0 of ELM model at different wind speeds.

Compare the two experimental results, we can find that the ELM model using the simulation data is in line with the CMOD5.N with a higher degree than scatterometer observation. While the result of the ASCAT observation is a little divergent which is due to the uneven distribution of observations. As we can see from Fig. 2(b), low wind less than 10m/s accounted for about 60%, therefore, the predicted values fit well with the CMOD5.N curve at 4m/s, 7m/s wind speed in Fig. 3(b) while it is divergent at high speed wind due to a lack of training data. Fig. 3(a) shows that the ELM method has a good feasibility for the modeling of GMF even in the case of sparse samples. The training effect has a great deal with the distribution of the sample data as can be seen from Fig. 3(b). However, it has a strong generalization ability, which is conductive for the extraction of an overall model. It can greatly reduce the time of modeling compares to the traditional method of statistical modeling and neural networks, and therefore, it is useful for the upgrade of the new geophysical model function.

Conclusion

In this paper, we introduce a new method called ELM to establish the geophysical model function. Simulation result shows that the σ^0 computed from the ELM model suits well with the one derived from the CMOD5.N, indicating that using ELM for the modeling of GMF is feasible. However, the output of the ELM model is displayed in a scattered way rather than a strict smooth curve due to the uneven distribution and sparse sampling of the training data. But the result extracted the overall law of the GMF and reflected the true state of the objective world. Since the uneven distribution of ASCAT observation in parametric space, the result demonstrated in Fig. 3(b) may not effectively reflect the local law of the ELM model. Next, we will use more typical observations to verify the validation of ELM model.

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