Empirical transfer function determination by the use of Multilayer Perceptron

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Abstract

Neural Networks are relevant statistical methods to extract information from data when physical phenomena are very complicated and cannot be described in terms of theoretical analysis. Scatterometers are active microwave radar which accurately measure the power of the backscatter signal versus incident signal in order to calculate the normalized radar cross section (σ_0) of the ocean surface. We use Multilayer Perceptrons in order to determine the Geophysical Model Function and to estimate the variability of the signal of ERS-1, ERS-2 and NSCAT scatterometers.

1 INTRODUCTION

NSCAT is a dual swath, Ku-band, scatterometer which was designed by NASA and constructed under its supervision. The goal was to determine the wind vector over the ocean at global scale with an optimum space and time coverage. NSCAT uses 6 antennas, three for each swath which gave a very large and unique data set that allows us to determine the wind vector at the global scale. The two mid antennas operate in a dual polarized mode (vertical and horizontal mode) while the four others operate in a vertical polarized mode only. Most of the algorithms which have been proposed to compute the wind from scatterometer measurements are based on the inversion of the Geophysical Model Function (GMF). The GMF is the transfert function of the scatterometer, it gives the scatterometer signal (σ_0) as a function of the wind vector and the incidence angle (which is the angle between the radar beam and the vertical at the illuminated cell). The determination of an accurate GMF and of the error bars are then of a fundamental interest, this is done in the present paper by using Multilayer Perceptrons. This paper is articulated as follows. In section 2 we briefly introduce the geophysical problem and the data we use. Section 3 presents the NSCAT GMF and section 4 introduces the error bar estimation using Multilayer Perceptrons (MLPs).

2 THE GEOPHYSICAL PROBLEM

Scatterometers are active microwave radar which accurately measure the power of the backscatter signal versus incident signal in order to calculate the normalized radar cross section (σ_0) of the ocean surface. At first order the σ_0 depends on the sea roughness which is related to the wind speed v, the incidence angle θ (which is the angle between the radar beam and the vertical at the illuminated cell) and the azimuth angle χ (which is the horizontal angle between the wind and the antenna beam of the radar). The empirical approach widely used is to reproduce the statistical distribution of σ_0 measured by the scatterometer from the distribution of wind vectors. The methodology is based on collocations between NSCAT σ_0 and wind measurements. The accuracy of the GMF is then related to the number of such collocations and the quality of the collocated data set. Since the GMF is depending on many parameters such as the incidence angle, the wind speed and the wind azimuth, an accurate GMF estimation requires a large amount of data. Usually one uses winds obtained from numerical weather prediction models (NWP). Neural network (NN) GMFs have been derived for decoding the signals of ERS-1 and ERS-2 satellite which are European C-band scatterometers. Their performances have been compared with the usual GMFs used by the European Spatial Agency (ESA) [Stoffelen, A. and Anderson D. 97] and IFREMER, demonstrating the power of the approach [Mejia et al. 98]. As there are two different polarizations, two separate GMFs have been proposed: the NN-GMF-V and NN-GMF-H for NSCAT, the results are detailed in [Mejia et al. 98]. In the following we present the results for the vertical polarization. Both functions give similar results. The above models are made under the assumption that each observation σ_{0i} contains noise e_i such that:

$$\sigma_{0i} = \sigma_{0i}^{true} + e_i \tag{1}$$

where σ_{0i}^{true} is the expected value of the signal with respect to the wind vector and e_i is a noise whose variance depends on the wind vector and the incidence angle. This noise takes into account the global variability which includes the geophysical and the instrumental noise. If we use linear measurements, we can assume that e_i is Gaussian noise with zero mean. If we denote $Var\,(e_i \mid \vec{v_i}, \theta_i)$ the variance of e_i, where $\vec{v_i}$ is the wind vector, the problem is to estimate both

σ_{0i}^{true} and the variance of the noise.

3 THE NSCAT GEOPHYSICAL TRANSFER FUNCTIONS

Under Gaussian assumptions on the output distribution, MLPs can estimate empirical transfer functions by minimizing the log-likelihood cost function. In order to limit the strong nonlinearity due to the large dynamical range of the σ_0 values, we decided to code them in dB (logarithmic scale), which forbids the use of the Gaussian assumption. For these reasons we estimate σ_{0i}^{true} by using the classical quadratic error cost function. The quadratic error cost function computes the mean of the measured σ_0 given the wind vector and the incidence angle, the accuracy of the estimation depends on the size and the distribution of the learning data set. The overall data set used consists of 10 millions of collocations representing the four σ_0 and their related incidence angle. From this data set we randomly extracted 265000 collocated data where we tried to equally represent all speeds and directions at each incidence angle in order to get a statistically representative data set without bias. As the scatterometer response is a continuous function with respect to θ, χ and v, the computed NN-GMF can be modeled by a MLP [Bishop 95] with two hidden layers whose inputs are the above variables and its single output is a linear neuron giving the estimation of the required σ_0 measurement. In order to test the accuracy of the NN-GMF we apply statistical tests. For each incidence angle, the ECMWF wind vectors collocated with the observed σ_0 are partitioned in 37×7 bins of azimuth angle of 10^o and wind speed of $3\,ms^{-1}$ each. The wind speed ranges between 3 and $24\,ms^{-1}$. We obtain for each bin a sample of linear observed σ_0. According to (1) this sample is normally distributed. For each bin we compute the σ_0 corresponding to the wind vector at the center of the bin by using the NN-GMF. Let us denote by s this value with linear scale. We perform on each bin a Student's t-test and verify the hypothesis that s represents an estimate of the mean sample with a probability of 95%. The t-test shows that this hypothesis is rejected in a very limited number of bins. Owing to the results, we can conclude that the NN-GMFs estimate the mean value of the σ_0 with a probability of 95% in most cases.

4 DETERMINATION OF THE SIGNAL ERROR BARS

In section 3 we show that, for a given wind vector and incidence angle, NN-GMF gives a good estimation of the mean of the observed σ_0. The problem is now to estimate the variance of the observation. As this variance depends on the wind vector, the incidence angle and the σ_0 itself we use the NN-GMF network to estimate the σ_0 before the computation of the variance. We use now the likelihood formalism and estimate the required variance by using a second independent neural network (NN-VAR) (denoted $Var\left(e_i \mid \vec{v_i}, \theta_i\right)$ hereafter) We minimize the log-likelihood cost function

$$L = \frac{1}{2} \sum_i \left\{ \frac{\left(\sigma_{0i}^{true} - \sigma_{0i}\right)^2}{Var\left(e_i \mid \vec{v_i}, \theta_i\right)} + ln\left(Var\left(e_i \mid \vec{v_i}, \theta_i\right).2\pi\right) \right\} \quad (2)$$

As seen in the preceding paragraph $\sigma_{0i}^{true} \approx$NN-GMF$(\vec{v_i}, \theta_i)$ and we replace σ_{0i}^{true} by the output of the NN-GMF in formula (2). In this case, the minimization of equation (2) is taken with respect to $Var(e_i \mid \vec{v_i}, \theta_i,$NN-GMF$(\vec{v_i}, \theta_i))$ and NN-GMF$(\vec{v}, \theta)$ is kept fixed. NN-VAR is an MLP with 2 hidden layers, it uses the same inputs as NN-GMF and because the variance of the noise depends on the magnitude of the σ_0, we add an extra input which uses NN-GMF $(\vec{v}, \theta)$. Figure 1 shows the NN-GMF (white curve) with respect to the azimuth angle at two different wind speeds against the data for the incidence angle of 36^o. In the same figure we plot the interval which represents two computed NN-VAR standard deviation. Clearly the computed interval spreads the variability of the σ_0 signal. Figure 2 gives for one incidence angle the ratio between the computed NN-VAR standard deviation and the empirical standard deviation with respect to wind speed and azimuth angle, the value of this ratio indicates that the variance is well approximated.

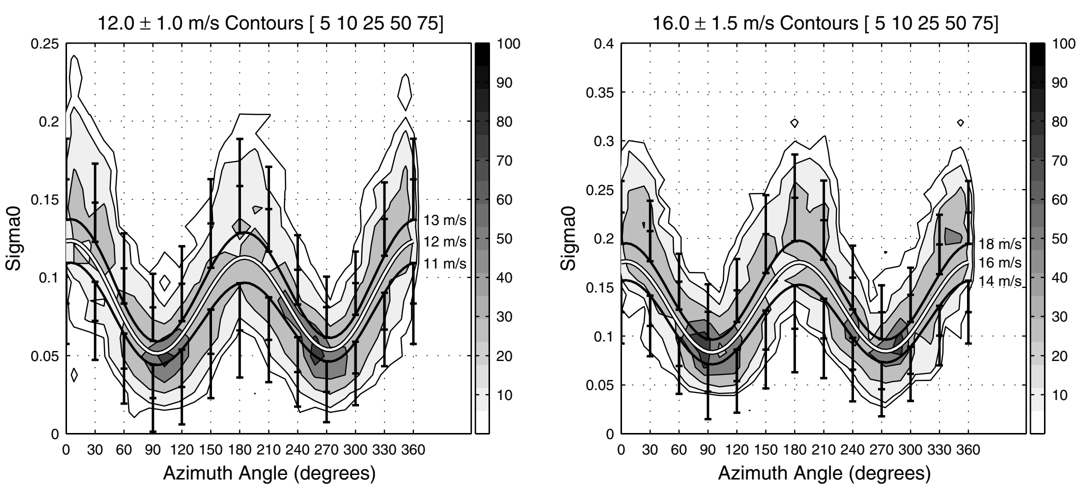

Fig. 1. *NN-GMF (white curve) with respect to the azimuth angle at two different wind speeds against the data for the incidence angle of* 36^o

The choice of two independent NN, to estimate the mean and the variance of the input noise, is motivated by the fact that the noise ϵ depends on the measure σ_0 itself. We have tried to estimate the σ_0^{true} and the variance of the noise by a unique NN with inputs $(\vec{v}, \theta)$ and two outputs cells. The two NN presented before give better results then the unique one.

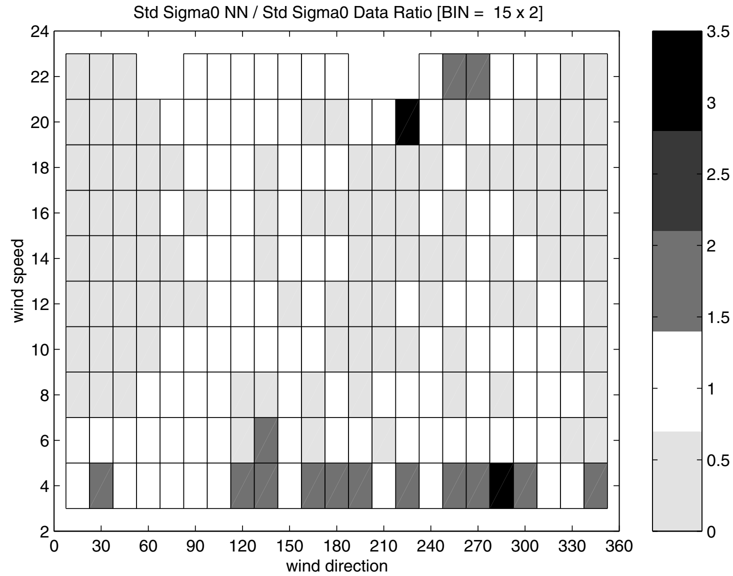

Fig. 2. *Ratio between the computed NN-VAR standard deviation and the empirical standard deviation with respect to wind speed and azimuth angle for the incidence angle of* 39.8^o

5 CONCLUSION

Neural Networks are relevant statistical methods for extracting information from data when physical phenomena are very complicated and cannot be described in terms of theoretical analysis. NNs provide empirical statistical models estimated from observations in the form of continuous functions. This paper shows the ability of MLP to model transfer function using the maximum likelihood formalism which allows us to estimate error bars.

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