Neural Network Wind Retrieval From ERS-1 Scatterometer Data

P. Richaume[1,*], F. Badran[2], M. Crepon[1], C. Mejia[1], H. Roquet[3], S. Thiria[1]

[1] *Laboratoire d'Océanographie Dynamique et Climatologie, Université Paris VI, Paris, France*
[2] *Chaire de Recherche Opérationnelle, CNAM, Paris, France*
[3] *Météo-France SCEM/CMS, Lannion, France*

Abstract

This paper presents a neural network methodology to retrieve wind vectors from ERS1 scatterometer data. First a neural network (NN-INVERSE) computes the most probable wind vectors. Probabilities for the estimated direction are given. At least 75 % of the most probable wind directions are consistent with ECMWF winds (at ± 20°). Then the remaining ambiguities are solved by an adapted PRESCAT method, which uses the probabilities provided by NN-INVERSE. Several statistical tests are presented to evaluate the skill of the method. Its good performance is mainly due to the use of a spatial context and to the probabilistic approach for estimating the direction. Comparisons with other methods are also presented. The good performance of the neural method suggests that self-consistent wind retrieval is possible.

Keywords: Inverse model; Ambiguity modelling; Remote sensing;

1. Introduction

We present a Neural Network method for retrieving wind fields from ERS-1 scatterometer measurements, called σ_0 (sigma naught). A scatterometer is an active microwave radar that measures the ocean roughness for different geometry of observation, incidence angle θ and azimuth χ. Because this roughness is mainly due to the wind stress on the ocean surface, the σ_0 space contains the wind information: speed and direction (see [15] for a full description). The wind retrieval consists in determining the wind parameters given swath of σ_0 cells. This is a difficult inverse problem since the processes are highly non-linear and non-injective. Thus, it is first necessary to model the multiple wind solutions that may occur for the same measurement and then to decide which solution correspond to the truth. The former refers to the inversion of the process, whereas the latter refers to the removal of ambiguities.

We use a neural network methodology based on the study of Thiria *et al* [17]. It consists in two separate phases: a first one inverts the ERS-1 measurements with neural networks and provides ambiguous wind vectors (NN-INVERSE), and a second one removes the wind direction ambiguities with an adapted version of an existing algorithm.

[*] Corresponding author. E-mail: philippe.richaume@cesbio.cnes.fr; prich@lodyc.jussieu.fr

The major difference with the usual methods is that NN-INVERSE is a transfer function mapping the wind vector from the σ_0 that models directly the inverse process. Whereas the existing methods use a GMF (Geophysical Model Function) [8,14] that model the forward process (e.g. estimates σ_0 given the wind parameters). Thus, they require minimisation between observed and estimated σ_0 at each measurement in order to retrieve the set of possible wind parameters [3,10,13,15,16]. In opposite, NN-INVERSE is an explicit model represented by an algebraic function that does not require such minimisation. The NN-INVERSE model estimates directly the set of possible wind parameters given the σ_0.

2. The NN-INVERSE model

We use similar architectures as described in [17]. Since the σ_0 measurements strongly depend on the incidence angle θ, the n tracks of the swath are inverted separately. The NN-INVERSE MODEL is made of n modules M_i, ($i = 1 \ldots n$) which extract the wind vector from σ_0. On each track i, the inverse problem is split into two sub-problems leading to the determination of two distinct transfer functions: a transfer function denoted $S\text{-}NN_i$ estimates the wind speed and a second transfer function denoted $A\text{-}NN_i$ estimates azimuth probabilities given the σ_0 triplets and the estimated wind speed. We approximate these $2{*}n$ transfer functions by using multilayer perceptrons (MLP) [2] since these models are universal approximator [4][5].

To take advantage of the information embedded in the spatial consistency of the wind field at the scatterometer scale [17], the inputs of the neural networks *S-NN* and *A-NN* consist in a set of σ_0 cells centred on the analysed one (Fig. 2a) [6]; we denote $G(s_0)$ this input data set. The size and the shape of the neighbourhood we deal with, represent an adequate trade-off between the performances and the number of parameters to be estimated during the modelling phase (the so-called learning phase).

Intrinsic errors in the most probable wind directions can remain due to the characteristics of the problem. In most cases they appear as inverted directions at ±180°. These ambiguities are removed by a third level, which uses the probability of the different aliases provided by *A-NN*. The full wind retriever is shown on Fig. 1.

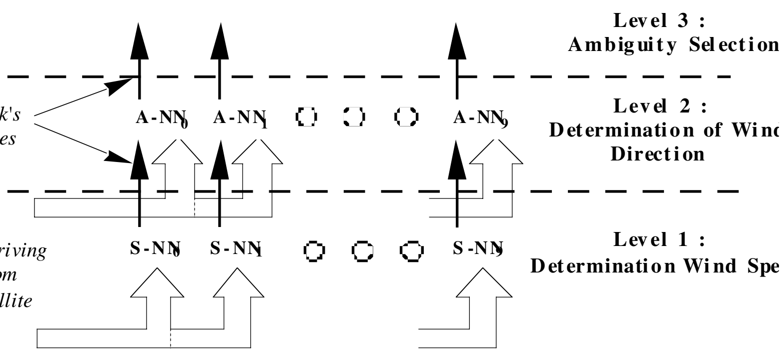

Fig. 1: Architecture of the full NN-INVERSE model showing the connection between $S\text{-}NN_i$ and $A\text{-}NN_i$.

2.1 Wind speed determination (S-NN)

S-NN$_i$ estimates the wind speed at each cell of the i^{th} track using $G(s_0)$ at the corresponding point. It is a full connected 4 layered MLP (Fig. 2b). The input layer is composed of 13*3 neurons which represent the 13 different triplets of the spatial window $G(s_0)$. The output layer has a unique linear neuron that estimates the wind speed. The two hidden layers have 26 neurons each with sigmoidal transfer function. Near the edges of the swath adapted non-symmetric spatial windows $G(s_0)$ are defined.

2.2 Wind direction determination (A-NN)

A-NN$_i$ is a full connected 4 layered MLP (Fig. 2b) which determines the wind direction using $G(s_0)$ and the wind speed $\hat{v}$ estimated by *S-NN$_i$*. It possesses an input layer of 13*3+1 neurons ($G(s_0)$ and $\hat{v}$) and two hidden layers of 25 neurons each. According to [17], the *A-NN$_i$* has 36 outputs each one providing the posterior probabilities of the associated interval of azimuth, $p\left(\chi \lfloor I_i \middle| G(\sigma_0), \hat{v}\right)$. These probabilities are used in order to determine the four most probable azimuths (aliases) with their associated posterior probabilities. Each alias is determined with an accuracy of ±15° by computing the expected value of 3 adjacent intervals and combining them.

The *S-NN$_i$* and *A-NN$_i$* have 1405 and 2616 parameters are respectively estimated from a learning set. These parameters are determined by minimising a quadratic cost function:

$$C(W) = \sum_k \left| S_k - Y_k \right|^2$$

where S_k represents the output computed by the MLP and Y_k the reference output provided by the corresponding data set, the summation being taken on the dedicated learning set. This cost function is simple and sufficient to obtain directly an approximation to the wanted probabilities [12].

This modelling phase is done once and for all and for each MLP. When using NN-INVERSE, wind parameters are directly computed by applying the associated MLP functions to observations.

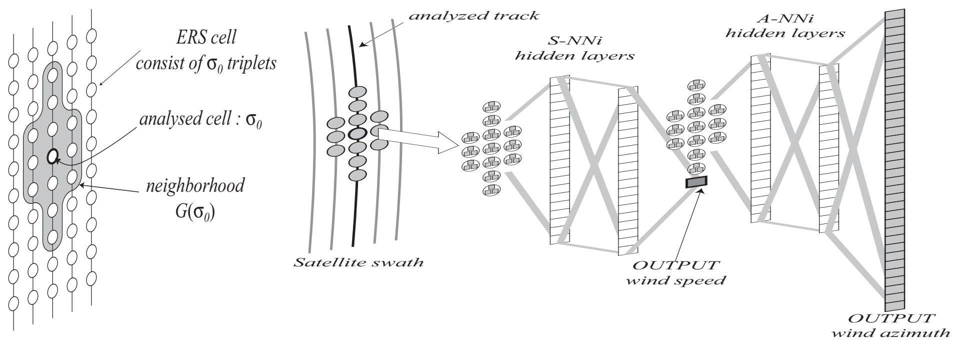

Fig. 1: a) Spatial context used for the determination of the wind speed and the wind direction; b) the two stage neural network inversion.

3. The data set

The parameters of the different MLP were computed from ERS-1 scatterometer σ_0 collocated with ECMWF wind vectors interpolated by CERSAT/IFREMER (I-ECMWF hereafter). The data period extents from July 94 to April 96 onto the North Atlantic Ocean, on an area of (100W, 5W) of longitude and of (60N, 20 N) of latitude. The overall used data set consists of approximately 390000 collocated pairs $(G(\sigma_0), (v,\chi))$ for each track; (v,χ) represents the speed and the azimuth of wind at the centre of $G(\sigma_0)$. For each MLP, the learning set (LEARN) is made of about 24000 pairs. The distribution we use is Quasi Uniform for wind vectors in the domain [0°, 360°] x [3.5 m/s, 25 m/s]. In order to test the performances of NN-inverse we built the QU-TEST test set with the remaining data and having the same statistical characteristics. For full wind fields test, we use another set made of 322 contiguous swaths of collocated ERS1 σ_0 and I-ECMWF wind fields observed in May 1996. This test set is denoted S-TEST and does not contain any observations used for learning. The following figure Fig. 3 shows an example of such retrieved full wind field of S-TEST.

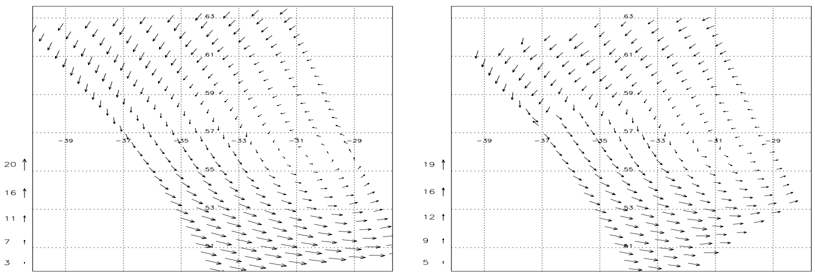

Fig. 3: a) Meteorological wind field; b) NN-INVERSE wind field after the removal of ambiguities.

4 Performances of NN-INVERSE before disambiguation

We present now statisa)cal tests to evaluate the accuracy of b)e NN-INVERSE model against I-ECMWF winds before removing the ambiguities. These tests are independent of errors due to a bad selection of aliases in the ambiguity removal procedure.

track	0	2	4	6	8	9
bias (m/s)	-0.2	-0.1	-0.1	-0.1	0.0	0.0
RMS (m/s)	1.6	1.5	1.6	1.6	1.6	1.7

Table 1: Performances of NN-INVERSE (S-NN) when approximating the wind speed: the first row gives the error bias with respect to the track and the second gives the RMS error with respect to I-ECMWF speeds.

The results of Table 2 show the good quality of the first rank solution; the first alias (the wind direction having the highest probability and presented in row 1 of Table 2) given by the NN-inverse matches the I-ECMWF direction at ±20° in 75% of the collocations; for the first plus the second alias (presented in row 2 of Table 2) in 87% of the collocations. The skill of usual methods is about 60% [13]. These good performances are mainly due to the spatial context used in the input of the *S-NN* and *A-NN* and due to the overall neural network ability to model non-linear phenomena.

Table 1 shows that the error bias and the RMS error on the wind speed, are very low and not dependent of the track, which proves the good quality and the homogeneity of NN-inverse methodology since each track is inverted by using a specific NN model.

Track	0	2	4	6	8	9
1 (%)	78.4	79.3	78.1	73.7	71.4	66.3
1+2 (%)	85.1	86.9	87.5	87.6	88.2	86.9
1+2+3 (%)	86.1	87.6	88.4	88.4	88.8	87.6
1+2+3+4 (%)	86.5	88.0	88.7	88.7	89.1	87.9

Table 2: Agreement of the wind direction retrieval with I-ECMWF. Each row displays the performances reached by A-NN_i, for each track *i* and for the most probable solution (first alias denoted 1), the first plus the second alias (denoted 1+2), and so on. A given direction is considered correct if the computed direction matches I-ECMWF direction by less than ±20°.

5. Ambiguity removal

The ambiguity removal is done by using an adapted version of PRESCAT [16] denoted PRESCAT-NN hereafter. In PRESCAT-NN, we select the different solutions using a trade-off between the closest NN-INVERSE aliases to the direction of NWP first guess and their probabilities. If the probability of the first alias given by NN-INVERSE is high, then priority is given to it.

6. Performances after Disambiguation and Comparisons with other Methods

We check the performances of the NN-Inverse model after the disambiguation phase and compared them to these of ESA and CERSAT/IFREMER wind products on the S-TEST data set. ESA wind retrieval is based on the CMOD4 GMF [16,14] and CERSAT/IFREMER is based on the CMOD-IFR2 GMF [9,10]. In these comparisons we use exactly the same data for the three methods. When one of the methods does not provide a solution for a given signal the associated wind vectors of the two others are also removed from the test.

We also checked the accuracy of the different inversion methods independently of ambiguity removal errors. For this purpose, as suggested by Stoffelen and Anderson [14], we use a subset of S-TEST, denoted S90-TEST. S90-TEST contains only data where the wind direction of the three products are pointing in the same half plane as defined by the I-ECMWF wind. When one product selects an ambiguous direction, the corresponding three products will be thrown out from S90-TEST. We thus reject data with possible ambiguous direction at 180° from S90-TEST.

Table 3 (Table 4) gives the error bias and standard deviation for the wind speed, the wind direction, the wind vector and the percentage of agreement with I-ECMWF wind direction at ±20° (denoted Perf at @ 20° in the tables) for S-TEST (S90-TEST). The three first columns show the performances computed on the true distribution of S-TEST (S90-TEST). In the three last ones performances are computed as follow: we first consider five bins of wind speed and compute separately the performances in each bin, later we average these performances in order to give the same weight to each wind speed interval.

Data Set 71436 data	S-TEST True Distribution			S-TEST Mean Bin Average		
inverse model	**NN_INV**	CERSAT	ESA	**NN_INV**	CERSAT	ESA
Speed Bias in m/s	0.2	**-0.1**	-0.7	**-0.2**	-0.9	-1.7
Speed Stdv in m/s	**1.4**	**1.4**	1.5	1.6	**1.5**	**1.5**
Dir Bias in degree	-0.2	**-0.1**	-0.5	**-0.1**	-0.6	0.7
Dir Stdv in degree	**19.9**	28.6	46.5	**19.6**	25.4	48.8
Vector Bias in m/s	**0.2**	0.3	0.4	**0.7**	1.2	1.7
Vector Stdv in m/s	**2.8**	3.4	4.9	**3.4**	3.8	6.7
Perf @ 20° in %	**88.9**	82.0	77.4	**87.8**	82.8	77.4

Table 3: Performances of the different inversion methods on S-TEST; in **bold** the best performances.

Data Set 69133 data	S90-TEST True Distribution			S90-TEST Mean Bin Average		
inverse model	**NN_INV**	CERSAT	ESA	**NN_INV**	CERSAT	ESA
Speed Bias in m/s	0.2	**-0.1**	-0.7	**-0.3**	-1.0	-1.7
Speed Stdv in m/s	**1.3**	1.4	1.4	**1.4**	1.5	**1.4**
Dir Bias in degree	-0.8	-0.9	**-0.6**	**-0.5**	-1.1	0.6
Dir Stdv in degree	**14.2**	16.3	43.4	**14.2**	15.6	46.7
Vector Bias in m/s	**0.2**	0.3	0.4	**0.8**	1.1	1.7
Vector Stdv in m/s	**2.3**	2.5	4.6	**2.9**	3.0	6.4
Perf @ 20° in %	**89.2**	84.4	78.9	**88.3**	84.8	78.5

Table 4: Performances of the different inversion methods on S90-TEST; in **bold** the best performances.

In Table 3, the performances are computed after the ambiguity removal and averaged on the 10 tracks. We took the wind vectors given by PRESCAT-NN and the dealiased wind vectors distributed by CERSAT and by ESA. Table 3 displays results in term of wind vector error statistic estimation (bias and standard deviation) for the three methods and shows that NN-inverse compares nicely with the others methods. We also remark that the standard deviation for the wind speed and wind direction agree with the specifications of ESA, which are ±2m/s and ±20°. NN-inverse is the only method that fulfils these specifications for the wind direction. Moreover, one remarks that the mean bin average performances of NN-inverse are less deteriorated than others, stressing the importance of the quasi-uniform distribution used when learning. We also notice, in this case, that the standard deviation of wind direction and Perf@20° improve showing that at high wind speed the stability of wind direction is strengthen and is measured better by scatterometer.

Comparison between results of Table 3 and Table 4 shows that global performances of NN-INVERSE do not increase very much, but they still appears better than the two others. This is due to the high quality and accuracy of the first rank solution of NN-INVERSE that gives a considerable help to the ambiguity removal. For CERSAT product, the increase of performances is very clear and the good overall score suggests that CMOD-IFR2 is a quite accurate GMF but that the ambiguity removal scheme is weak.

Nevertheless, this could also be explained by the advantage of using spatial context rather that a one cell inversion. Whatever the accuracy of inversion and the skill of the ambiguity removal are, it will not be able to retrieve a good wind field if there is not sufficient well oriented winds (first rank alias).

Conclusion

This paper presents a Neural Networks methodology to retrieve the wind vector from ERS1 scatterometer data. The inversion of scatterometer data leads to complex transfer function that may give several values for the direction. The performances of the Neural Network methodology are very good specially for the wind direction since the NN-INVERSE model has a better skill (75%) for the most probable wind direction (rank 1 solution) than the other methods whose skills are about 60% [13]. This clearly shows the improvement of NN-INVERSE with respect to other methods. After disambiguation the correct direction is retrieved with a score of 89%.

Comparison with other methods has been processed. It appears that the NN have a very good skill. The advantages of the neural network method are linked to:

- their ability to model non-linear phenomena without strong assumptions about the forms of the functions and noises involved in the physical processes,
- the possibility to directly estimate the probability of the different wind aliases by using neural networks working in classifier mode which is of importance for the ambiguity removal phase,
- the possible use, in a simple way, of a spatial context embedding geophysical features which are learned and which improves greatly the performances of the first alias solution and thus the skill of any ambiguity removal algorithm.

In the present study we adapted a version of the PRESCAT algorithm to remove the ambiguities, which uses a meteorological wind field provided by a NWP model as a first guess. The probability estimation of the neural network wind direction is explicitly used as a constraint in this version. Due to the accuracy on the first alias provided by **NN-INVERSE** method we can envisage a self-consistent Neural Network ambiguity removal method similar to this proposed in [1].

Scatterometer winds are of major interest in geophysics and meteorology [11,16,]. The neural network approach proved to be efficient, accurate, general and re-usable, as for new scatterometers like NSCAT [7] with at most the same performances.

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