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1. INTRODUCTION

To derive geophysical parameters from satellite borne sensor measurements, a new multi-parameter empirical retrieval approach is introduced. It is shown that multi-parameter retrieval algorithms are more robust and accurate than single-parameter retrieval algorithms. NNs are well suited for developing such multi-parameter retrieval algorithms. A new NN empirical algorithm (OMBNN3) which simultaneously retrieves four geophysical parameters: surface wind speed (W), columnar water vapor (V), columnar liquid water (L), and sea surface temperature (SST) T_s from five SSM/I (Special Sensor Microwave Imager) brightness temperatures (BTs) (T19V, T19H, T22V, T37V, and T37H) is presented and compared with several single-parameter algorithms to illustrate advantages of the multi-parameter approach.

2. DERIVING GEOPHYSICAL PARAMETERS FROM SATELLITE MEASUREMENTS

Satellite remote sensing data are routinely used by weather prediction centers, forecast offices, fisheries, Coast Guard, oil industry, Navy and others. Most users commonly work with geophysical parameters such as pressure, temperature, wind speed and direction, water vapor, etc. Satellite sensors generate measurements in terms of radiances, backscatter coefficients, BTs, etc. Satellite retrieval algorithms which transform satellite measurements into geophysical parameters play the role of mediator between satellite measurements and users.

Conventional methods for using satellite data involve solving an inverse (or retrieval) problem and deriving a transfer function (TF), f , which relates a single geophysical parameter of interest, g , (e.g., surface wind speed over the ocean), to a vector of satellite measurement, s (e.g., SSM/I BTs),

$$g_i = f(s) \quad (1)$$

The TF, f , may be derived explicitly or assumed implicitly. A single-parameter retrieval algorithm is a particular representation of the transfer function (1).

Usually satellite measurements, s , contain information on several related geophysical parameters. Therefore, in principle, under favorable conditions, these

parameters can be retrieved simultaneously from the vector s ,

$$G = F(s) \quad (2)$$

where $G = \{G_i\}_{i=0,1,\dots}$ is a vector of multiple geophysically related parameters. A multi-parameter retrieval algorithm is a particular representation of the transfer function (2).

Single-parameter retrieval algorithms (1) produce retrievals (e.g., g_k) which do not correspond to any particular atmospheric state or ocean surface state. These retrievals correspond to some unknown "mean" atmospheric and surface states which can not be specified without additional information. Thus, single-parameter retrieval algorithms effectively average over an ensemble of atmospheric and surface states for all of the related geophysical parameters except for the one which is retrieved. This averaging gives rise to additional errors in this single retrieved parameter which do not arise in the multi-parameter approach. If g_k is a geophysical parameter retrieved by a single-parameter algorithm (1) and G_k is the same parameter retrieved by the corresponding multi-parameter algorithm (2), then this additional systematic error (bias) can be estimated as,

$$\overline{(G_k - g_k)} = \sum_i \alpha_i b_i + \sum_i \beta_i \sigma_i^2 + \sum_{i,j} \gamma_{ij} c_{ij} + \dots \quad (3)$$

The horizontal bar above the symbols on the left-hand side implies averaging over G_i ($i \neq k$) which are not known for single-parameter algorithms. b_i and σ_i^2 are the biases and variances of these geophysical parameters, and the c_{ij} are correlation coefficients between these parameters; α_i , β_i and γ_{ij} are coefficients which are described in (Krasnopolsky et al. 1999). Similar estimates can be obtained for additional variances (random errors). It is clear from (3) that the multi-parameter retrievals, G_k , compared with single-parameter retrievals, g_k , do not contain additional systematic (bias) or random errors. Avoiding these additional errors is an important advantage of the multi-parameter approach.

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3. NNs FOR MULTI-PARAMETER RETRIEVALS

The above considerations show that both single- (1) and multi-parameter (2) retrieval algorithms can be considered as continuous mappings which map a vector of sensor measurements, $\mathbf{s} \in \mathcal{R}^n$, to a vector of geophysical parameters, $\mathbf{G} \in \mathcal{R}^m$. In the case of empirical algorithms, these mappings are constructed, using discrete sets of collocated vectors \mathbf{s} and \mathbf{G} (matchup data sets $\{\mathbf{s}_i, \mathbf{G}_i\}$). Single-parameter algorithms (1) may be considered as degenerate mappings where a vector is mapped onto a scalar (or a vector space onto a line).

Linear and nonlinear regressions are standard tools that can be used to develop single-parameter retrieval algorithms (to model TF). If TF is nonlinear, the linear regression can give only a local approximation, or, if it is applied globally, this approximation usually has poor accuracy. Nonlinear regression is usually better suited for modeling TFs. However, in this case, we need to introduce a particular kind of nonlinearity in advance, which we use to approximate the TF under consideration. This may not always be possible, because we may not know in advance what kind of nonlinear behavior a particular TF demonstrates, or this nonlinear behavior may be different in different regions of the TF's domain. If an incorrect nonlinear regression is chosen (by chance), it may represent a nonlinear TF with less accuracy than a linear regression. Regressions can also be used for multi-parameter retrievals; however, from a computational point of view, this problem is nonstandard.

In the situation described above, where we do know that the TF is nonlinear but do not know what type of nonlinearity to expect, and where multi-parameter retrievals are desirable, we need a flexible, self-adjustable approach that can accommodate various types of nonlinear behavior, represent a broad class of nonlinear mappings, and one that can be easily used for both single- and multi-parameter retrievals. Neural networks (NNs) are well suited for a very broad class of nonlinear approximations and mappings. It has been shown (Funahashi 1989, Chen and Chen 1995) that a NN with one hidden layer can approximate any continuous mapping defined on compact sets in \mathcal{R}^n . Thus, any retrieval problem which can be mathematically reduced to a nonlinear mapping like (1) or (2) can be solved using a NN with one hidden layer.

4. A SSM/I EMPIRICAL MULTI-PARAMETER RETRIEVAL ALGORITHM: OMBNN3

As an example of the approach described above, here we introduce a multi-parameter empirical algorithm (2) which has been developed (Krasnopolsky et al. 1996) to retrieve a vector of geophysical parameters $\mathbf{G} = \{W, V, L, T_s\}$ from five SSM/I BTs (T19V, T19H, T22V, T37V, and T37H). These parameters are surface wind speed (W), columnar water vapor (V), columnar liquid water (L), and sea surface temperature (SST) T_s . Fig. 1 shows the architecture of a simple feed forward NN with one hidden

layer which implements the OMBNN3 algorithm. This NN has $n = 5$ inputs, $m = 4$ outputs, and one hidden layer with $k = 12$ neurons. This NN can also be written explicitly as,

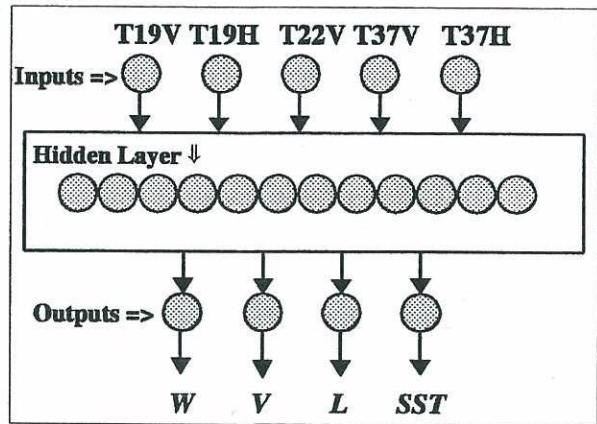


Fig. 1. OMBNN3 architecture.

$$G_q = b_q + a_q \tanh \left\{ \sum_{j=1}^k \omega_{qj} \left[\tanh \left(\sum_{i=1}^n \Omega_{ji} T_i + B_j \right) \right] + \beta_q \right\}, \quad q = 1, \dots, m \quad (4)$$

where the matrix Ω_{ji} and the vector B_j represent weights and biases in the neurons of the hidden layer; $\omega_{qj} \in \mathcal{R}^{k \times m}$ and the $\beta_q \in \mathcal{R}^m$ represent weights and biases in the neurons of the output layer; and a_q and b_q are scaling parameters.

For wind speed, high quality ground truth observations, including buoy and ocean weather station wind speed measurements, are available to create matchups with the SSM/I BTs. Evaluating the different algorithms was performed by comparing them with independent ground truth observations. Table 1 shows the summary wind speed statistics for clear and clear + cloudy conditions.

Table 1. Biases and RMS errors (m/s) for different SSM/I wind speed algorithms, for clear and clear+cloudy (in parentheses) conditions.

Algorithm	Bias	RMS Errors
Linear Regression (Goodberlet et al. 1989)	-0.2(-0.5)	1.8 (2.1)
Nonlinear Regression (Petty, 1993)	-0.1(-0.3)	1.7 (1.9)
Physically-Based (Wentz, 1997)	0.1(-0.1)	1.7 (2.1)
OMBNN3 (Krasnopolsky et al. 1996)	-0.1(-0.2)	1.5 (1.7)