Global Optimization Algorithms for Field-Wise Scatterometer Wind Estimation

Charles G. Brown and David G. Long
Brigham Young University, MERS Laboratory
459 CB, Provo, UT 84602
801-378-4884, FAX: 801-378-6586 browncg@salt.ee.byu.edu

Abstract—Field-wise scatterometer wind estimation determines the vector wind at many resolution elements simultaneously by estimating the parameters of a wind field model. According to simulations, it results in more accurate estimates than traditional point-wise estimation, which estimates the vector wind one resolution element at a time. Further, field-wise estimation produces fewer ambiguities than point-wise estimation.

Field-wise estimation necessitates locating the local minima of a high-dimensional, non-linear objective function. Conventional optimization techniques can be employed if initial search points within the capture regions of the local minima can be found. We develop and evaluate two novel approaches for determining initial search points for field-wise estimation. The accuracy of each algorithm is evaluated using simulated NASA Scatterometer (NSCAT) data.

INTRODUCTION

Field-wise scatterometer wind estimation involves indentifying the local minima of the high-dimensional and non-linear field-wise objective function. The local minima correspond to the optimized model-based estimates of the true wind field, and the goal of field-wise estimation is to locate the local minimum closest to the true wind.

Conventional optimization techniques may be used for field-wise estimation if initial values close to the true wind can be found. Previous approaches have used point-wise retrieved wind fields as initial values for gradient-search algorithms. When the retrieved field has few ambiguity removal errors, local optimization using its model fit as the initial value converges to the closest local minimum to the true wind. However, if the retrieved field has excessive errors, then it might yield a minimum far from the true wind. Consequently, we investigate global optimization algorithms that do not rely on pre-processing by point-wise ambiguity removal schemes in their search for initial values.

We develop algorithms to locate all of the local minima of the field-wise objective function, or at least a subset of the local minima that contains the closest to the true wind. Due to the computational expense of evaluating the objective function, traditional global optimization schemes prove intractable. In this paper we present two problem-specific algorithms that seek to identify initial values close to the true wind. First, a brief definition of field-wise wind estimation is provided, and descriptions of the pseudo-objective function and cluster-based algorithms follow. The performance of the two algorithms is evaluated using simulated NSCAT data.

FIELD-WISE WIND ESTIMATION

Field-wise wind estimation is the process of estimating wind field model parameters, denoted by the column vector $\hat{\mathbf{X}}$, from scatterometer backscatter measurements. The model-based wind field is the matrix product $\hat{\mathbf{W}} = F\hat{\mathbf{X}}$, where $\hat{\mathbf{W}}$ is a column vector containing the rectangular components of the wind vector cells. The matrix F is the wind field model, and the model fit to the wind field $\mathbf{W}$ is $\hat{\mathbf{X}} = F^{\dagger}\mathbf{W}$, where $F^{\dagger}$ is the pseudo-inverse of F [3].

Estimates of the model parameters are all the local minima of the field-wise objective function

$$J(\hat{\mathbf{W}} = F\hat{\mathbf{X}}) = -\sum_{n=1}^{N^2}\sum_{k=1}^{L_n} \ln p(z_n(k) \mid \hat{\mathbf{X}})$$

with

$$p(z_n(k) \mid \hat{\mathbf{X}}) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{Var\left[z_n(k)\right]}} \cdot \exp\left\{-\frac{1}{2}\left[z_n(k) - \sigma_n^0(k)\right]^2 / Var\left[z_n(k)\right]\right\},$$

and

$$\sigma_n^0(k) = \mathcal{M}\left\{(u_n, v_n), k\right\}.$$

N is the number of cells on each side of the square region, and n is the wind vector cell index [3]. L_n is the number of measurements in cell n. The k^{th} measurement in cell n is denoted $z_n(k)$, and $p(z_n(k) \mid \hat{\mathbf{X}})$ is the likelihood of observing $z_n(k)$ given that $\hat{\mathbf{W}} = F\hat{\mathbf{X}}$ is the parameter vector of the model fit to the true wind. $\mathcal{M}$ represents the geophysical model function that relates (u_n, v_n), the vector wind in cell n, to the true value of $\sigma_n^0(k)$, which is the noiseless measurement that would be observed for the vector wind (u_n, v_n). Note that J may be expressed either as a function of $\hat{\mathbf{W}}$ or $\hat{\mathbf{X}}$.

In the following sections, we present two algorithms for globally optimizing the field-wise objective function. They are designed to locate a subset of the local minima of $J(\hat{\mathbf{X}})$ that contains the minimum closest to the true wind.

0-7803-3836-7/97/$10.00

PSEUDO-OBJECTIVE FUNCTION ALGORITHM

The pseudo-objective function (POF) algorithm locates the local minima of a simplified objective function, called the pseudo-objective function, and the local minima of the POF are then used as initial values in local optimizations of the full objective function J.

The model used in the POF describes the wind direction field by the polynomial model $p(c_1, c_2, c_3) = c_1 + c_2 x + c_3 y$, where x and y are the rectangular coordinates of the wind vector cell, and the origin of the coordinate system is such that c_1 is the mean direction of the wind field. The POF value of the model parameter set (c_1, c_2, c_3) is found by combining the direction field described by $p(c_1, c_2, c_3)$ with point-wise speed estimates, which are taken from the true simulated wind in this paper. Then, the resulting vector wind field is converted into the rectangular form $\hat{\mathbf{W}}$, and $J(\hat{\mathbf{W}})$ is the POF value of the parameter set (c_1, c_2, c_3).

The POF algorithm searches the reduced parameter space (c_1, c_2, c_3) for all local minima. The wind fields $\hat{\mathbf{W}}$ corresponding to local minima are constructed according to the POF model, and their wind field model parameter vectors $\hat{\mathbf{X}}$ are calculated from $\hat{\mathbf{X}} = F^{\dagger}\hat{\mathbf{W}}$, with F defined by the KL model [1]. The model vectors $\hat{\mathbf{X}}$ then are used as initial values in local optimizations of the full objective function J with a higher-order model. For simplicity the 6 parameter KL model is used in this paper.

CLUSTER-BASED ALGORITHM

The cluster-based (CB) algorithm (refer to Fig. 1) identifies initial values for local optimization by examining combinations of point-wise ambiguities. Before the CB algorithm is executed on a region, spurious ambiguities are removed according to [4] with a threshold of $\alpha = 10^{-4}$.

Examination of all possible ambiguity combinations for a given region is computationally intractable, even after removing improbable ambiguities, so the CB algorithm limits the search to typical wind fields. For each region a random set of 20 000 typical wind fields, represented by 6 parameter KL model parameter vectors, is generated. The model parameter vector for each typical wind field is drawn from a multi-variate normal population. Parameter means are assumed to be zero and variances are dictated by the eigenvalues of the autocorrelation matrix used to generate the KL model [1], [2].

In the next stage of the algorithm, the typical wind fields are used to select combinations of point-wise ambiguities. For each typical wind field, each of its vectors is compared with the point-wise ambiguity set in the same wind vector cell, and the closest ambiguity is selected. The field of point-wise ambiguities closest to the vectors of a typical wind field is its closest ambiguity field. The direction rms error between the 20 000 typical wind fields and their closest ambiguity fields is used to rank the typical winds in ascending order of error, and the model parameter vectors $\hat{\mathbf{X}}$ corresponding to the 500 highest ranked typical winds are clustered.

Finally, each cluster center is optimized to minimize direction rms error between the cluster center and its closest ambiguity field (the closest ambiguity field changes as the cluster center parameters are optimized). Note that this optimization step reduces direction rms error only. A more accurate speed field can be obtained by taking speeds from the closest point-wise ambiguities. The optimized cluster centers are the CB estimates of the wind field.

TEST RESULTS

The POF and CB algorithms were tested on simulated NSCAT data generated from wind fields obtained from the European Center for Medium-Range Weather Forecasting (ECMWF). From the simulated wind set, 80 NSCAT half-revolutions were simulated, and ambiguous point-wise estimates were made for each of the half-revolutions [3].

In order to evaluate the performance of the POF and CW algorithms, we define the skill of a field-wise estimation algorithm as its ability to model the direction of each individual vector of the true wind. For each region, the POF and CB algorithms produce a set of estimates of the true wind field. The estimate closest to the true wind, in a direction rms sense, is compared with the true wind. If a vector in the closest to true field is more than 20° off the corresponding vector in the true field, then it is counted as a single error, otherwise it is a success. The error and success rates are calculated by summing the numbers of single errors and successes per region and dividing by the total number of vectors in all of the regions combined.

The POF algorithm was run on 13 simulated NSCAT half-revolutions. Each half-revolution was divided into square regions, 12 NSCAT 50 km wind vector cells to a side. The regions overlapped by 50%. Regions missing data were rejected. The total number of regions in the test set was 566. The POF algorithm generated a set of estimates for each region, and the closest to the true wind was selected. The success and error rates for the closest to true estimates are recorded in Table 1. One possible source of error in the POF algorithm is the 6 parameter KL model used in the final optimization stage. Table 2 displays the mean direction rms error, relative to the true wind, of the 6 parameter KL model fit and the closest to true estimate. Since the KL model error is close to that of the closest estimate, the POF algorithm introduces only a little more average error than the model fit.

The CB algorithm was tested on 19 simulated NSCAT revolutions. The revolutions were divided into regions in the same manner as for the POF test. Regions missing data were rejected. The total number of regions in the test set was 911. For each region the CB algorithm generated a set of wind field estimates, and out of this set the closest

Skill Statistics

Algorithm	Success Rate	Error Rate
POF	88%	12%
CB	93%	7%

Table 1: *The skill of the pseudo-objective function (POF) and cluster-based (CB) algorithms is evaluated by comparing the closest to true estimate with the true wind. The success rate represents the probability that any given vector of the closest estimate will be within* 20° *of its corresponding vector in the true wind field.*

Mean Direction RMS Error Statistics

Algorithm	Mean DRMS Error of Closest Estimate	Mean DRMS Error of KL Model Fit
POF	15.5°	9.9°
CB	13.1°	10.5°

Table 2: *This table compares the mean direction rms (DRMS) error of the pseudo-objective function (POF) and cluster-based (CB) algorithms to that of the 6 parameter KL model fit to the true wind. The closest to true estimate of the POF and CB algorithms introduces only a little more average error than the 6 parameter KL model fit alone.*

estimate to the true wind was selected. The success and error rates for the closest to true estimates are recorded in Table 1. Since the CB algorithm also uses the 6 parameter KL model, one possible reason for inaccuracy in the estimates is modeling error due to the simplistic wind field model. Table 2 displays the mean direction rms error, relative to the true wind, of the 6 parameter KL model fit and the closest to true estimate. The average error for the closest estimate is not much different than that of the KL model fit, so the closest estimate of the CB performs almost as well, on average, as the KL model fit to the true wind.

CONCLUSION

The POF and CB algorithms locate a set of local minima of the field-wise objective function without relying on pre-processing by point-wise ambiguity removal algorithms. Both algorithms identify local minima that are close to the true wind a high percentage of the time, and some of the errors in the closest to true estimates can be attributed to modeling error in the 6 parameter KL model. Subsequent local optimizations using higher-order models can be expected to make the estimates more accurate. Further improvements in accuracy might be obtained by using POF and CB estimates as initial values for median filter processing.

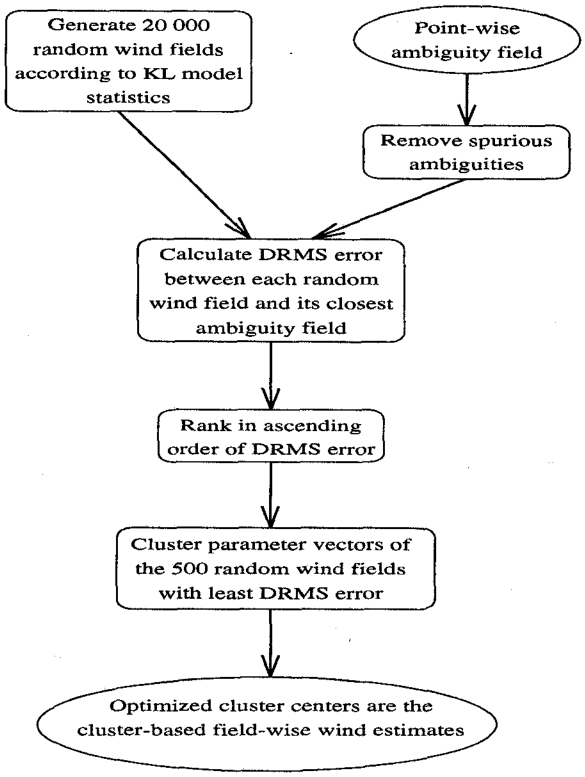

Figure 1: Cluster-Based Algorithm

References

[1] C. G. Brown *et al.*, "Wind Field Models and Model Order Selection for Wind Estimation," IGARSS, August 1997.

[2] A. E. Gonzalez and D. G. Long, "A Quality Assurance Algorithm for NASA Scatterometer Ambiguity Removal," IGARSS, August 1997.

[3] D. G. Long and J. M. Mendel, "Model-Based Estimation of Wind Fields Over the Ocean From Wind Scatterometer Measurements, Part II: Model Parameter Estimation," IEEE Trans. Geosci. Remote Sensing, vol. 28, no. 3, pp. 361-373, May 1990.

[4] T. E. Oliphant and D. G. Long, "Development of a Statistical Methods for Eliminating Improbable Wind Aliases in Scatterometer Wind Retrieval," IGARSS, pp. 1715-1717, May 1996.