Interpolating Satellite derived Wind Field Data using Ordinary Kriging, with application to the Nadir Gap

Michael R. Inggs and Richard T. Lord
Radar Remote Sensing Group, Dept of Electrical Engineering, University of Cape Town
Private Bag, Rondebosch 7700, South Africa
Tel: +27 21 650 3756 Fax: +27 21 650 3465
Email: rlord@eleceng.uct.ac.za

Abstract—Satellite wind sensors are unable to obtain measurements directly below the satellite, creating a "nadir gap" centred on the sub-satellite track. This is true of active sensors such as scatterometers, as well as for microwave radiometers, newly used for this purpose. In addition, sensor coverage in equatorial regions is incomplete. Using processed ERS-1 wind field data, it is shown in this paper that Ordinary Kriging is an appropriate technique to interpolate this "nadir gap". Furthermore, wind field data can also be extrapolated away from the swath using this method, thereby effectively yielding better ocean coverage[1].

INTRODUCTION

This work was inspired by a desire to try and improve the spatial coverage of wind sensors in equatorial regions, where polar orbiting sensors in sun-synchronous orbits display significant gaps in the daily coverage. It then became apparent that the technique could also be used to fill the "nadir gap", defined below.

Due to the inability of satellite scatterometers to obtain wind field measurements for incidence angles below 20°, the NASA Scatterometer (NSCAT) wind field swaths have a gap (called the "nadir gap") centred on the sub-satellite track where no wind measurements are available. Fig. 1 illustrates the NSCAT antenna illumination pattern on the ocean surface. The swaths on either side of the sub-satellite track are 600 km wide, separated by a 329 km wide gap.

Recent work by Wentz [8] has shown that it is possible to use spaceborne radiometer data to measure the wind speed and velocity over the ocean surface. Satellite radiometers have the advantage over scatterometers of being less bulky and hence more reliable and cost effective. However, as for the active sensors, radiometers cannot measure wind vectors for incidence angles between zero and twenty degrees, resulting in a similar "nadir gap" centred on the sub-satellite track.

The following interpolation and smoothing techniques for spatial data were investigated and compared [3]:

1. Trend Surface Analysis
2. Splines
3. Kernel Smoothing
4. Kriging

[1]A more detailed version of this paper has been submitted for publication to the IEEE Transactions on Geoscience and Remote Sensing.

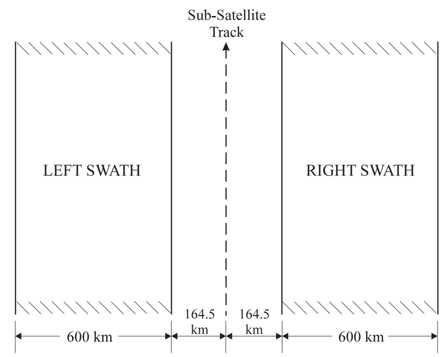

Figure 1: NSCAT antenna illumination pattern

Both kriging [5] and spline based methods [5] seemed to be appropriate techniques to interpolate wind field vectors. Ordinary Kriging seemed most appropriate since it was specifically developed for interpolation in the case of random variables that exhibit spatial autocorrelation. Wind field data was expected to exhibit a high degree of autocorrelation. Furthermore, Ordinary Kriging has been successfully applied in a number of areas, such as soil mapping, mining, rainfall modelling and hydrology [5].

The paper goes on to review Kriging briefly. To test the validity of the technique, artificial as well as ERS-1 wind field data was used. The nadir gap was simulated by removing a strip from the centre of the ERS-1 wind data. Good results were obtained and are reported here.

KRIGING WIND VECTORS

Wind field data consists of *vector* variables rather than scalars. According to Young [9], the kriging technique can be extended to the spatial analysis of vector variables by defining the estimation variance and vector semi-variogram in terms of the magnitude of difference vectors. However the vectors have to be stationary, spatially correlated random variables.

As for scalar variables, the vector semi-variogram can be estimated using

$$\gamma(\mathbf{h}) = \frac{1}{2n(\mathbf{h})} \sum |\mathbf{v}_{z_i} - \mathbf{v}_{z_j}|^2 \tag{1}$$

where the summation is over all $n(\mathbf{h})$ pairs which are a vector distance $\mathbf{h}$ apart.

This definition of the vector semi-variogram is consistent with the definition of the semi-variogram for scalar variables. For the remainder of this article, the word "semi-variogram" will refer to the *vector* semi-variogram, unless stated otherwise.

Young [9] defines the estimation variance as the vector difference:

$$\text{var}\left[\mathbf{v}_0 - \hat{\mathbf{v}}_0\right] = E\left[\left(\mathbf{v}_0 - \hat{\mathbf{v}}_0\right)^2\right] \quad (2)$$

This definition for the estimation variance is consistent with the vector semi-variogram, and can be minimised to yield the kriging equations just as for the scalar case.

IMPLEMENTATION ON ERS-1 DATA

Before this method was implemented on real ERS-1 wind field data, it was tested using synthetic data sets. The "perfect" structure of synthetic data sets enabled immediate evaluation of the obtained results, which looked very promising [3]. This paper goes on to describe only the results obtained for real ERS-1 data.

Description of Implementation Procedure

The kriging algorithm was implemented on seven data sets, which were all 19 wind vectors wide and 38 wind vectors long. These data sets were sections of longer ERS-1 wind field swaths. For each data set, 7 columns of vectors were removed from the middle of the swath. This gap was then interpolated, and the results were compared with the original strip. Furthermore, for each swath, 6 columns of vectors were extrapolated from each side of the swath.

Once the gap had been interpolated, the results were compared with the original values by calculating the root-mean-square (r.m.s.) value of the differences in the speed and angle values, and also the r.m.s. value of the magnitude of the difference vectors. The error in the speed component was also calculated as a percentage, by calculating the ratio between the speed r.m.s. value and the average speed in the *original* data strip.

Interpreting Wind Field Semi-Variograms

All the results shown and discussed in this paper have been obtained by fitting a spherical semi-variogram model to the calculated semi-variograms. The spherical model is probably the most commonly used semi-variogram model, and is defined by the equation

$$\gamma(h) = \begin{cases} s\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] & \text{if} \quad 0 \leq h \leq a \\ s & \text{if} \quad h > a \end{cases} \quad (3)$$

where s is the sill and a is the range. It has a linear behaviour at small separation distances near the origin, but flattens out at larger distances, and reaches the sill at a.

Table 1: RMS errors for real data

Swath	*Speed* [m/s]	*Angle* [Deg]	*Vector* [m/s]	*Avg Speed* [m/s]	*Speed* [%]
1	0.795	6.098	1.457	11.718	6.783
2	0.603	5.783	1.096	9.404	6.410
3	0.573	13.140	1.361	5.780	9.917
4	0.414	4.805	0.758	7.685	5.384
5	0.866	8.691	1.279	6.492	13.342
6	0.650	74.407	1.341	7.940	8.191
7	0.287	8.143	0.727	4.858	5.912
Avg	0.598	17.295	1.146	7.697	7.991

It has been found that the wind field data displays a mixture of geometric and zonal anisotropy. When modelling anisotropy, one usually starts by determining the anisotropy axes by experimentally determining the directions corresponding to the minimum and maximum range or sill. For this paper it has been assumed that the anisotropy axes correspond to the directions parallel to the swath and perpendicular to the swath.

The range of influence of most semi-variograms extended virtually over the whole width of the swath. The 6 extrapolated columns of vectors and the 7 interpolated columns of vectors fall well within the range of most wind field semi-variograms.

A weighted non-linear least squares method was used to fit semi-variogram models to the calculated graphs. The points closer to the origin were given higher weights than points further away, because they are inherently more accurate, as they are calculated using more data pairs. A comparison between the results obtained using the spherical model, and the results obtained using the exponential model, showed that the spherical model yielded better results on average. However the poorer results from the exponential model were obtained because the model-fitting algorithm sometimes produced extremely large range and sill values for the semi-variogram models. Semi-variograms that did not reach a well-defined sill produced extremely large range and sill values. When the semi-variogram parameters were estimated by "eye", with emphasis on fitting the bottom region of the graph reasonably well, both models yielded good results.

Interpolation and Extrapolation Results

Table 1 summarises the r.m.s. errors obtained from interpolating the middle strip of the data sets. The average speed r.m.s. error obtained for the seven real data sets that were examined is of the order of 0.6 m/s or 8 %, which is acceptable, especially when one considers that the NSCAT system is required to measure wind speeds with an accuracy better than 2 m/s or 10 %, whichever is greater [7]. However the average angle r.m.s. error is 17.3°, which seems unacceptably high. The reason for this high average is the very large angle r.m.s. error of data set 6. This result is surprising, since when one looks

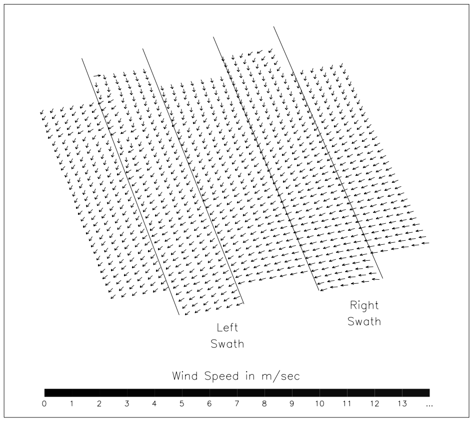

Figure 2: Interpolation and Extrapolation Results

at the interpolated vectors shown in Fig. 2, one cannot imagine that there is such a big difference between the original vector angles and the interpolated vector angles. However the original data set might have contained a few ambiguity errors, which gave rise to this high angle r.m.s. error. The NSCAT system is required to measure wind direction with an accuracy better than 20° [7]. The average angle r.m.s. error obtained here is therefore still in the range required for the NSCAT system.

Results obtained for Swaths of Data

When the same procedure was applied to whole swaths of data, the average speed r.m.s. error obtained was 10.1 %, which is slightly higher than the average of 8.0 % obtained for the real data sets. The average angle r.m.s. error was 49.0°, which is significantly higher than that obtained from the above data sets, which was 17.3°. This increase in the r.m.s. errors is probably due to underlying trend. The average speed and direction of wind vectors at the bottom of the swath is significantly different to that at the top of the swath. To minimise this effect, the kriging algorithm should be applied to successive smaller sections of a swath, each section being about 38 vectors long.

CONCLUSIONS

The results obtained from interpolating and extrapolating ERS-1 data sets have shown that it is feasible to use Ordinary Kriging to interpolate and extrapolate wind field vectors.

Both the spherical and exponential semi-variogram models were used to obtain results, however the spherical model yielded better results on average. It has been shown that fitting exponential models by "eye", with emphasis on fitting the bottom region of the graph very well, also yielded good results. Thus, the quality of the fitted semi-variogram model, especially near the lower region of the graph, plays a very important role in the accuracy of the results obtained.

The extent to which data can be extrapolated, and the limits of the size of the gap that can be interpolated, has not been rigorously investigated. The large range of influence of the semi-variograms does seem to suggest, however, that vectors estimated half a swath width away from the boundary of the swath are still reasonably accurate, given that enough samples have been used in the kriging equations. It follows that the size of the gap that can be interpolated between two swaths should be less or equal to one swath width. A more conservative estimate would require the gap to be less or equal to two thirds of a swath width. The "nadir gap" of the NSCAT scatterometer, and possibly of future radiometer systems, which is less than a third of the swath widths on either side wide, can therefore be interpolated quite easily.

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