BINARY CLASSIFICATION OF WIND FIELDS THROUGH HYPOTHESIS TESTING ON SCATTEROMETER MEASUREMENTS

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ABSTRACT

Scatterometers are radars specially designed to near-surface wind over the ocean from space. Traditional scatterometer wind estimation inverts the model function relationship between the wind and backscatter at each resolution element, yielding a set of ambiguities due to the many-to-one mapping of the model function. Field-wise wind estimation dramatically reduces the number of ambiguities by estimating the wind at many resolution elements, simultaneously, using a wind model that constrains the spatial variability of the wind. However, the appropriate choice of the model order needed for a particular wind field is not known a priori. *The approximate model order is valuable because of the implicit trade-off between the computational complexity of high-order models and the imprecise model fit of low-order models. In this paper, a simple binary classification of wind fields is proposed which identifies whether or not a region will be well modeled by a low-order wind model. The raw scatterometer measurements provide data about the wind that can be exploited through hypothesis testing to identify the appropriate model order to use in field-wise wind estimation. Improved processing algorithms lead to better use of the data.*

INTRODUCTION

Naval radar operators during World War II observed considerably more noise in their radar returns during stormy weather; with this simple beginning, scatterometry was born [Ulaby et al., 1981]. Scatterometers are high frequency radars designed to infer the physical state of a system based on measuring the backscatter from that system. In particular, the last 20 years have seen the use of several space borne scatterometers to estimate near-surface ocean winds with considerable success [Naderi et al., 1991]. The estimation procedure is not unique; that is, several wind vectors (as many as six) are typically found that could have produced the measurements.

For example, Fig. 1 displays all of the possible wind vectors based on point-wise wind estimation, throughout a region; correctly identifying a unique wind field from the many possible combinations is not a well defined process, involving considerable computational resources and often prone to error. To ameliorate the problem of selecting unique wind vectors, field-wise estimation has been introduced in which an assumed model for the spatial correlation of wind vectors constrains the possible estimates [Long, 1989, Oliphant, 1996]. Flexible models which span a wide range of wind fields require many parameters—searching a high-dimensional space for wind field estimation is computationally prohibitive [Gunther and Long, 1994]. On the other hand, models with only a few param-

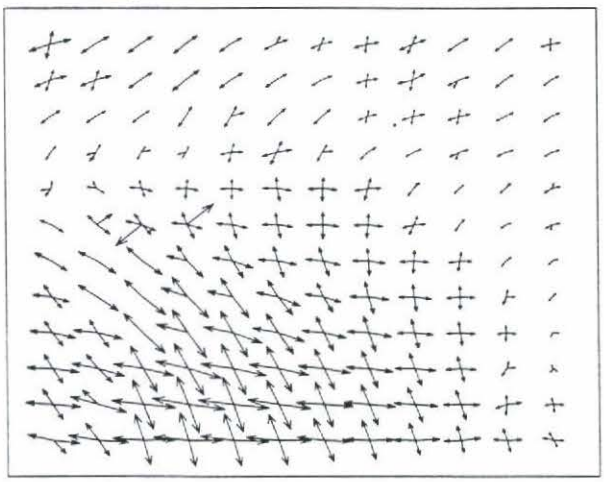

Figure 1: *Constructing a unique wind field from the multiple point-wise estimates is a daunting task. Each resolution element can have as many as six point-wise estimates. Determining the optimal field for a 12 by 12 region would require comparing as many as* 6^{144} *fields.*

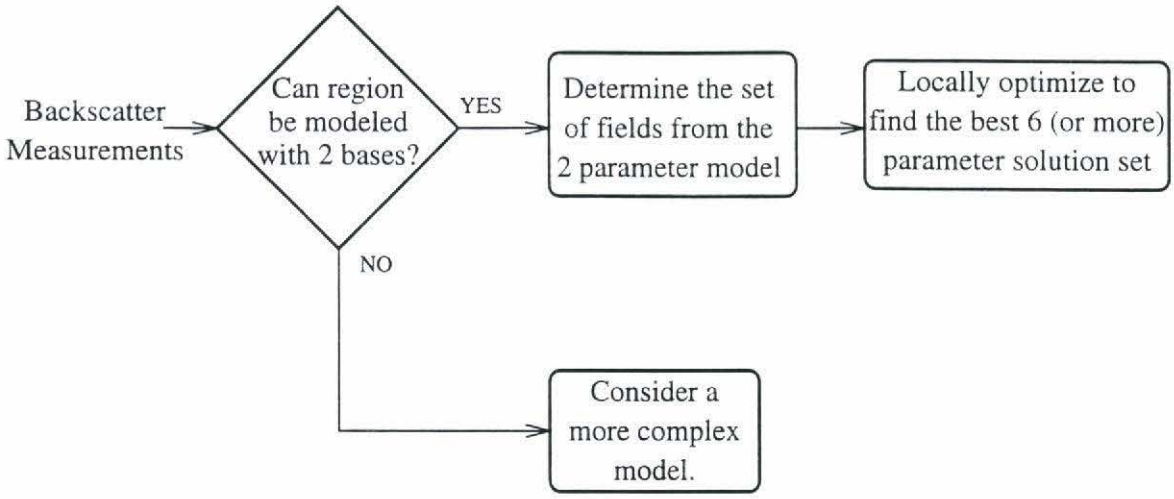

Figure 2: *Flow diagram for hypothesis testing. A statistic of the backscatter measurements for a region is computed, and a hypothesis test performed on this statistic. If the region is identified by the test as likely to be well modeled by a mean wind field, a set of fields is determined by globally optimizing that two-dimensional space; these solutions serve as initial values in a local optimization in a higher-dimensional space to more accurately estimate the wind field. If the hypothesis test reveals that the field will not be (probably) adequately fit by two bases, more work will need to be done. Experience suggests that a slight majority of wind fields are adequately fit by a mean wind field; those that are not can be used to develop models specifically designed for more difficult wind fields. Such models could include low wind speed models and non-linear models for fronts and cyclones. Additional hypothesis tests could be cascaded after this one: if the region is not fit by two bases, is it a low wind speed region or a front or a cyclone?*

eters are easily searched, but represent a limited range of wind fields [Long and Mendel, 1990]. In this paper a simple algorithm is examined to identify, directly from the backscatter measurements, whether or not a particular region can be well modeled by a simple, low-order model. This approach decreases the average number of model parameters without significantly increasing the average modeling error.

Due to the nature of the wind estimation objective function, simple gradient search techniques can not guarantee convergence to the global optimum; the wind model vector space must be searched exhaustively. While exhaustively searching even a 6 dimensional vector space is prohibitive, a two dimensional search is fairly straightforward. An exhaustive search involves selecting a two dimensional (i.e., mean) wind field and computing the probability of measuring the actual scatterometer measurements given that wind field and identifying the wind field (or set of fields) that maximizes that probability. Figure 2 indicates a simple block structure of a hypothesis test to identify from the measurements whether or not a field is well modeled by a mean wind field. If a field is well modeled, there is no need to waste additional resources trying to estimates higher order parameters; a mean wind field can be estimated, and if a better estimate is required, a local optimization in a higher dimensional space can be performed. If the field is not well modeled by a mean wind field, then substantially more work needs to be done with this field—perhaps a six parameter model, or a low-order non-linear model tuned to specific wind phenomena would work. The methodology presented here could easily be extended to additional hypotheses to continue reducing the set of difficult wind fields.

In the next section a statistic on the measurement is identified which has a strong correlation to the error of the model fit; it is this statistic that can be used in a hypothesis test. Hypothesis testing is then briefly described and specifically applied to wind field classes and the backscatter statistic. Finally, some conclusions are presented to put this work in perspective.

STATISTICS ON THE MEASUREMENTS

Initial examination of the backscatter field over a region reveals little relationship to the underlying wind field. Figure 3 shows a gray scale image of

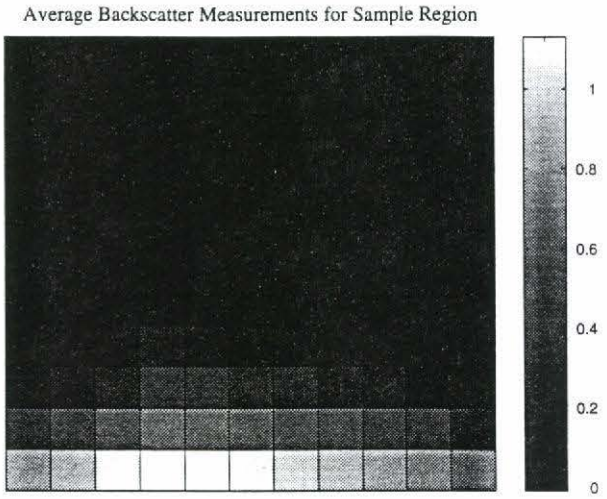

Figure 3: *The average backscatter measurements for the wind field region displayed in Fig. 1. While there is some relationship between the backscatter and the wind speed and complexity, the relationship becomes unclear for cells along the top because the backscatter is dramatically reduced with the increased incidence angle.*

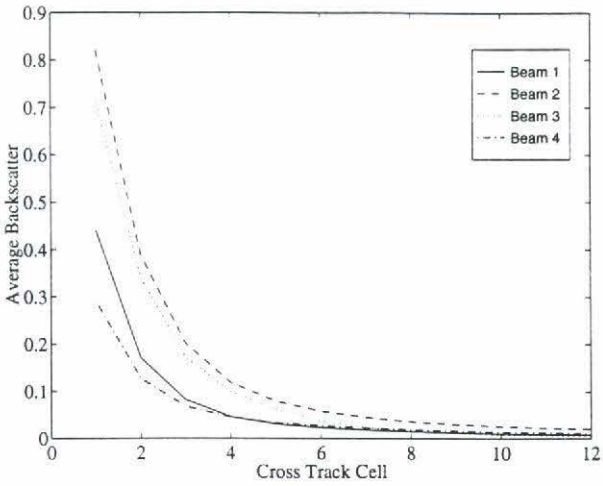

Figure 4: *The average backscatter for very smooth wind fields, i.e., those which a two parameter model fits the JPL nudged wind with less than 0.1 NRMS error.*

the average backscatter measurements for the region displayed in Fig. 1. While there is some correspondence between the magnitude of the backscatter and the wind speed, the cells at the top of the image (which have much larger incidence angles) have negligible backscatter values, because of the strong incidence angle dependence of the measurements [Wentz, 1984]. In order to observe the variability of the backscatter caused by wind variations, the incidence angle dependence must be removed. I selected over 2000 regions from NSCAT (NASA Scatterometer) data in which a two parameter model (the mean wind field) fit the field selected by Jet Propulsion Laboratories (JPL) very well, according to the normalized-vector RMS error. Each of these regions had fairly constant along track backscatter values and a strong cross-track dependence for the backscatter. Averaging over all the regions, and over the along-track cells to yield the cross-track dependence of the backscatter for each beam (the beams have different relative azimuths and possibly different calibration errors) provides the average backscatter for each beam as a function of the cross track cell. The results are shown in Fig. 4 where the curves show the cross-track dependence of the backscatter for each beam. Now we can examine the normalized backscatter of a region, where we normalize by dividing each backscatter measurement by the averages described by Fig. 4. Any patterns or variations in the normalized backscatter should then be due to the underlying wind pattern.

The statistics of the normalized backscatter seem to have some relationship with the quality of fit of the wind model to the wind field. Examining more than 5000 regions, the RMS of the standard deviation of the normalized backscatter from each beam is highly correlated with the VRMS (Vector RMS) error between the mean wind field estimate and the JPL estimate of the wind; this standard deviation is selected as the statistic for use in the hypothesis test. Figure 5 shows the relationship between the statistic and the VRMS error for the 5000 wind fields. By setting a VRMS error criterion, the field can be classified as *good* or *bad* based on whether the field exceeds the criterion for quality.

HYPOTHESIS TESTING

Wind field classification algorithms can be used to select models with a minimal number of parameters while keeping the error within an acceptable range. The result increases the computational efficiency of field-wise estimation without significantly increasing the modeling error. In this section a simple classification algorithm is described which tests the hypothesis that a field is poorly modeled by a low-order model—specifically, by a mean wind field. Referring to Fig. 2, a VRMS error threshold is selected to identify fields with error greater than the threshold

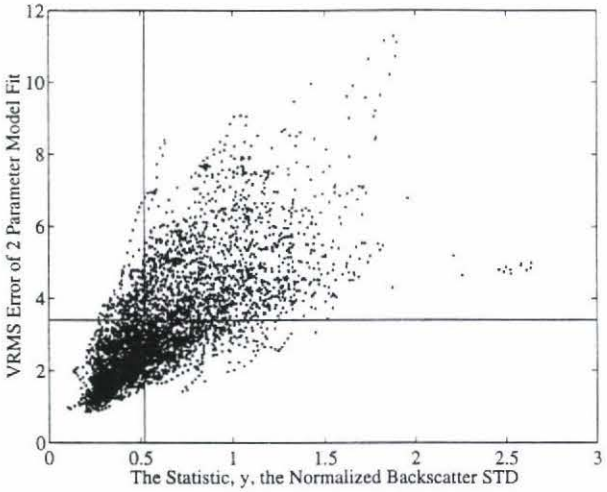

Figure 5: *In general, the fields that are poorly fit by a mean wind field (these have a high VRMS error) have a large value of the measurement statistic (the std of the normalized backscatter).*

as a *bad* field (since it is poorly fit with two bases) and fields with less error as *good*. Either the region is adequately modeled by a low-order model (designated good, θ_0), or it is poorly modeled by the low-order model (bad, θ_1). Comparing the statistic, y, to a threshold, ν, provides the basis for the binary hypothesis test [Scharf, 1991]:

$$\text{Wind Class Declaration} = \begin{cases} \theta_1 & \text{if} \quad y > \nu \\ \theta_0 & \text{if} \quad y \leq \nu. \end{cases}$$

The statistic, y, is defined as the standard deviation of the σ^0 values of all the beams normalized by the average backscatter values to remove the cross track dependence.

The choice of a threshold for the VRMS error of model fit identifies a field as being either well (θ_0) or poorly (θ_1) modeled by a mean wind field. The definition of "well" modeled, and the choice of the threshold, depends on the particular application. The horizontal line in Fig. 5 illustrates, for a given application, the separation of the wind fields into two classes—θ_0 if the VRMS error is below the line and θ_1 if the error is above the line. Having identified the fields as θ_0 or θ_1, the empirical probability density functions of good and bad wind fields can be computed as functions of the statistic. Figure 6 plots these densities for a few values of the VRMS error threshold.

The density functions of good and bad wind fields displayed in Fig. 6 provide the probabilistic measures necessary for a hypothesis test. By setting a threshold on the measurement statistic, we can test the hypothesis that a wind field will be bad. If our measurement is less than the threshold, the field is declared good, θ_0; if the measurement is above the threshold, the field is declared bad, θ_1. The vertical line in Fig. 5 illustrates this point by identifying a threshold on the statistic; the two classes of wind fields (separated by the horizontal line) and the two classes of declared wind fields (distinguished by the vertical line) define four distinct regions in the figure, which can be characterized through two numbers: the probability of false alarm and the probability of detection.

The probability of false alarm is the probability that we incorrectly identify a good field as bad; this probability is computed as the area under the pdf of good fields above the threshold. The probability of detection is the probability that we correctly identify a bad field as bad; this is computed as the area under the pdf of bad fields above the threshold. Optimally we want a low probability of false alarm and a high probability of detection; adjustment of the hypothesis threshold requires a trade-off between these quality measures.

In this case, the probability of detection is critical. If we miss detection of a bad wind field, we will try to use the two-parameter model on a field that contains more features than a simple mean flow. On the other hand, the probability of false alarm is not so important. If we classify a good wind field as bad, we will look at it more closely and use a more involved model—this more complicated model will work just fine and the wind will be estimated with a little more trouble. Of course if we set our threshold too low, we classify everything as bad and don't gain any savings in computation from the classification. Figure 7 displays characteristic curves for our four VRMS thresholds that identify the quality of the fit by displaying the probability of detection against the probability of false alarm as the statistic threshold is adjusted.

If, for example, the wind field class θ_0 is defined as wind fields that have a 2 parameter model fit VRMS error less than 3.4 m/s (below the horizontal line of Fig. 5), and with the choice of $\nu = 0.52$ (selected to declare half the wind fields in θ_0 and half in θ_1), the probability of correctly classifying a θ_1 wind field (probability of detection) is 86% and the probability of incorrectly classifying a θ_0 wind field (probability of false alarm) is 32%. With these thresholds (rather arbitrarily chosen) 50% of the wind fields are declared to be well modeled by just 2 parameters—in fact, the average VRMS error of these fits is 2.2 m/s. For comparison, if two parameters had been used for

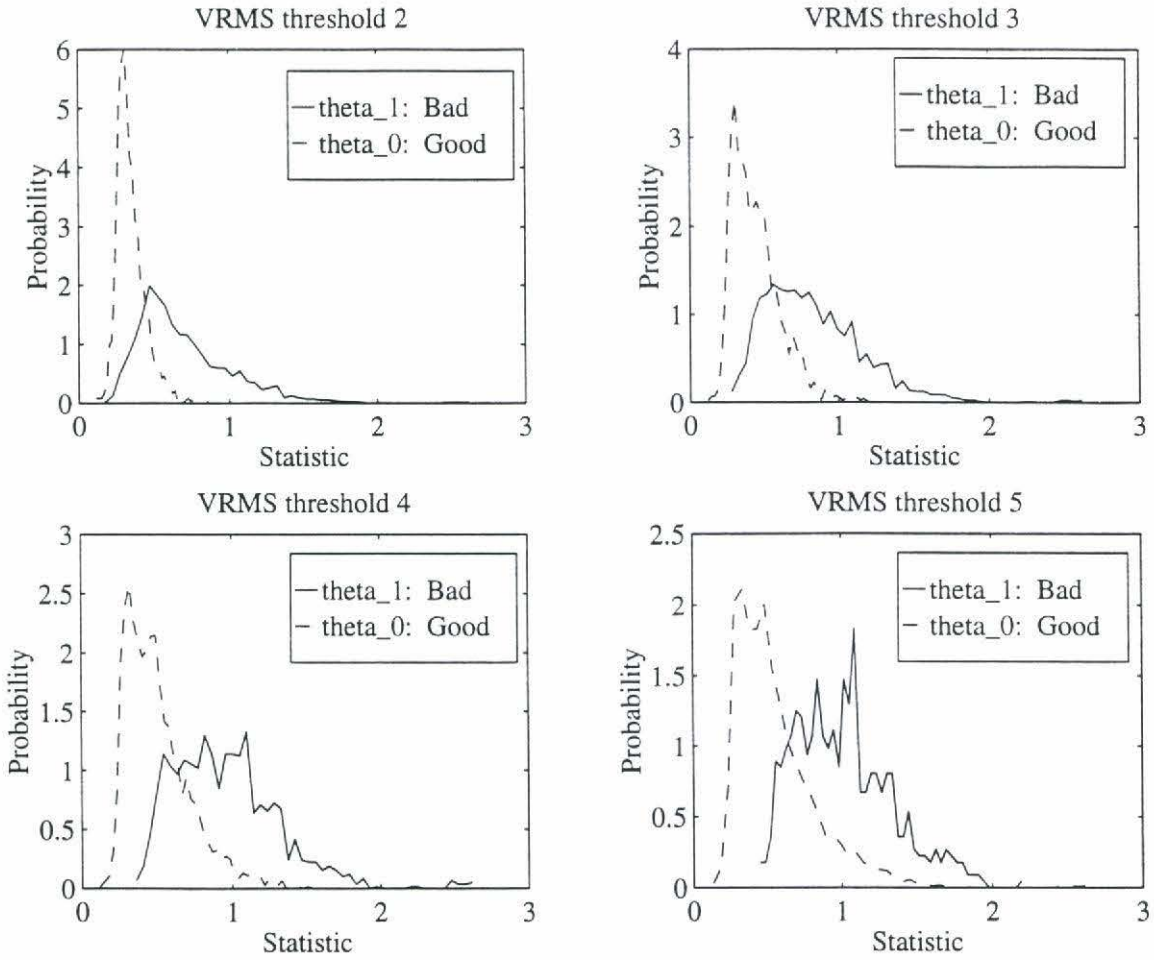

Figure 6: *Empirically derived probability density functions of good and bad wind fields as functions of the statistic of the scatterometer measurements. As the VRMS error threshold is increased, the empirical density function becomes more erratic because there is a much smaller data set with which to estimate the density.*

all the regions, the average VRMS error would have been 3.2 m/s, and if 40 parameters had been used, the average VRMS error would have been 1.2 m/s. Thus for a moderate increase in modeling error, the number of required parameters was reduced from 40 to two in half the regions—with a significant computational saving.

CONCLUSIONS

Field-wise wind estimation profoundly reduces the number of ambiguities and reduces the computational load of scatterometer wind estimation. Increasing the number of model parameters increases modeling accuracy; however, it also increases computational expense. Classification algorithms, such as that presented here, can be used to decrease the average number of model parameters without significantly increasing the average modeling error. Identifying, *a priori*, fields that will be well modeled by a low-order model conserves computing resources for more difficult fields. Further, fields that are classified as poorly modeled by a mean wind field can be used to develop improved models specific to certain features like fronts and cyclones. Low-order models can be developed for these cases without the need of using the generic model which would require many parameters to model unusual fields.

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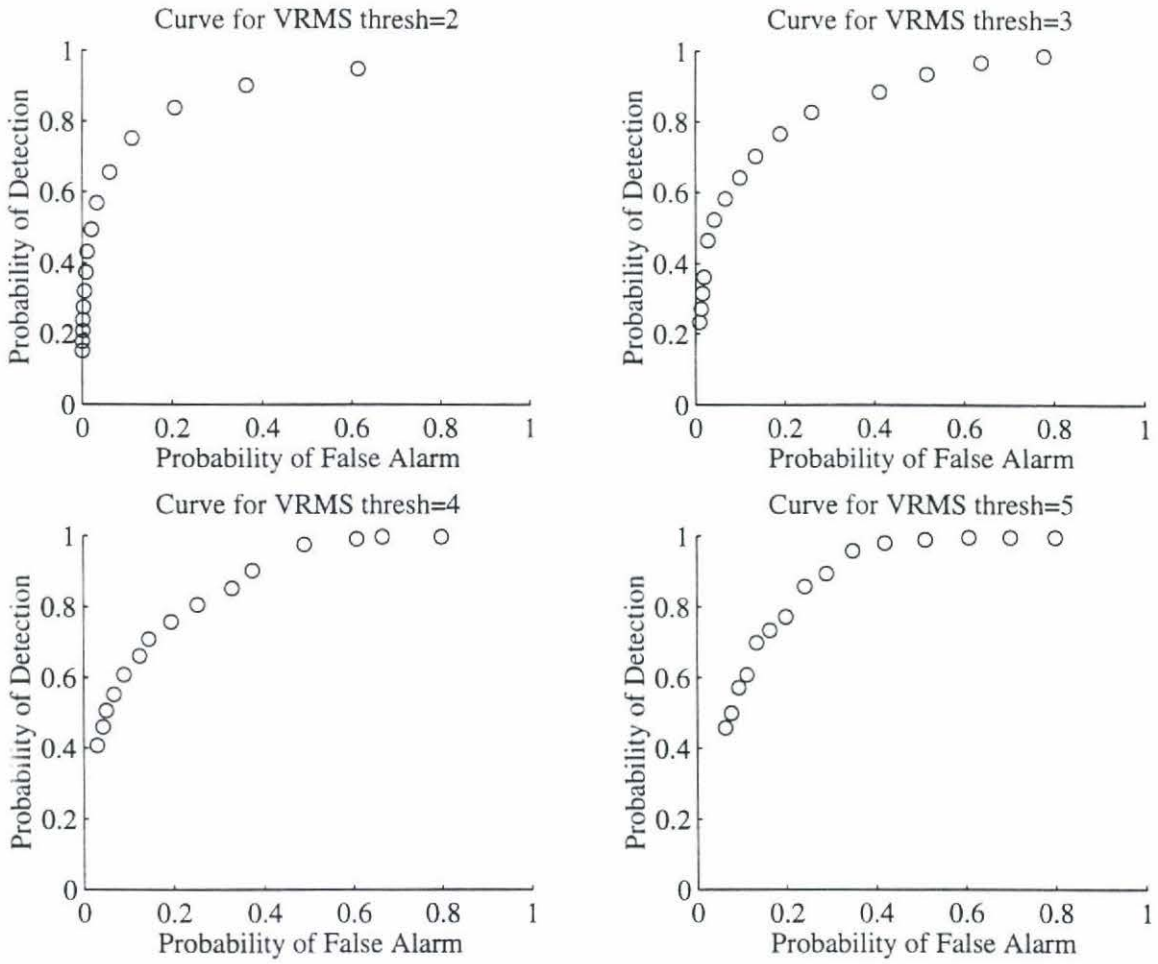

Figure 7: *Characteristic curves based on adjusting the threshold on the measurement statistic (for each of four VRMS error thresholds identifying the quality of the fit). The goal is to choose a threshold on the statistic to yield a low probability of false alarm while maintaining a high probability of detection.*

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