Hurricane Wind Field Estimation from SeaWinds at Ultra High Resolution

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Abstract—**Although SeaWinds was not originally designed to observe tropical cyclones, new higher resolution products resolve much of the horizontal structure of these storms. However, these higher resolution products (reported at 2.5km) are inherently noisier than the standard 25km products and the high rain rates often associated with hurricanes corrupt the wind estimates. Fortunately, these storms have structure which can be exploited using a model.**

This paper develops a new procedure for hurricane wind field estimation from the SeaWinds instrument at ultra high resolution. We develop a simplified hurricane model to provide prior information to be used in maximum aposteriori probability (MAP) wind estimation. Using the hurricane model ameliorates the effects of rain and noise on the scatterometer measurements and directly provides useful hurricane parameters such as the eye center location and intensity.

I. Introduction

In the extreme conditions of hurricanes, direct measurements of wind and rain are difficult to obtain. Direct measurements also lack the spacial coverage necessary to observe an entire tropical cyclone. The SeaWinds scatterometer remotely observes ocean winds over a large region; however, the relatively course resolution (25km) of the standard wind product limits its use in resolving small scale features. Tropical cyclones are apparent in the 25km product, but important storm parameters such as the eye center may not be well resolved.

Fortunately, the SeaWinds scatterometer densely samples the ocean, which makes it possible for the resolution to be enhanced and reported on a 2.5km grid [1]. At this resolution the storm structure is more obvious. However, the 2.5km products are inherently noisier than their 25km counterparts and heavy rain rates associated with tropical cyclones contaminate the wind estimates.

This paper describes a new method for ultra high resolution wind field estimation of tropical cyclones from SeaWinds. The new approach utilizes maximum aposteriori probability (MAP) wind estimation. Prior information is provided via a low-order hurricane wind field model. The hurricane model ameliorates the effects of rain and noise as well as providing estimates of hurricane parameters such as the eye location. The eye center estimates of the new method are analyzed and compared to the hurricane eye locations provided by the National Hurricane Center (NHC). The quality of the new wind field estimates are analyzed using simulation.

II. Background

SeaWinds measures the radar backscatter, denoted σ^0, from the Earth's surface. Over the ocean σ^0 is related to the wind speed and direction through the geophysical model function (GMF). Measurements from multiple azimuth angles are necessary to estimate the wind direction. SeaWinds makes four different types of measurements (vertical and horizontal polarization beams, each with a fore and aft look) which provide several samples from different azimuth angles for each resolution cell [2].

Conventionally, the wind is estimated in two steps. First, maximum likelihood estimation (MLE) is performed for each resolution cell. Since the MLE objective function is multimodal, ML estimation results in multiple wind vector solutions called ambiguities. The second step requires choosing the appropriate ambiguity. For the standard 25km product (L2B) the ambiguities closest to numerical weather prediction (NWP) winds are selected and then a spatial median filter is used to select the final ambiguities [3].

High resolution σ^0 products can be obtained by applying image reconstruction to each of the four flavors of σ^0 measurements. This provides four separate σ^0 fields with regularly spaced samples. Wind retrieval is then performed for each high resolution cell, producing high resolution wind ambiguities. High resolution ambiguity selection is problematic because the NWP winds used in ambiguity selection poorly represent small scale features. This is further complicated by rain contamination in tropical cyclones.

The method presented in this report takes a different approach. A low-order 'snap-shot' model of the horizontal structure of hurricanes appropriate for scatterometery is developed. The hurricane model is used to provide the mean of a field-wise prior distribution of the wind. This prior is used to augment the ML objective function, producing a field-wise MAP estimate of the hurricane wind field.

III. Method

This section delineates the theory behind the new method for hurricane wind field estimation from SeaWinds data. The development is based on MAP estimation. The prior probabilities needed for this type of estimation are found using a low-order hurricane model whose parameters are simultaneously estimated along with the wind vector field. For each resolution element the prior distributions of the wind speed and direction are assumed to be Gaussian with means given by the hurricane model and arbitrary variances (the Gaussian approximation

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is verified empirically in Section IV and nominal values for the variances are obtained). For a particular hurricane model instantiation, the prior distribution for the entire field is given by the model. The best prior is found by using the hurricane model parameters that maximize the field-wise MAP value.

Point-wise MAP estimation maximizes the probability of the wind given the σ^0 measurements ($P(S,D|\sigma^0)$). This probability distribution can be found using Bayes' rule $P(S,D|\sigma^0) = P(\sigma^0|S,D)P(S,D)/P(\sigma^0)$ where $P(\sigma^0|S,D)$ is the conventional MLE objective function and $P(S,D)$ is the prior distribution of the wind (the term $P(\sigma^0)$ is constant for all wind vectors and can be neglected). The MAP objective function, $P(S,D|\sigma^0)$, is essentially a weighted version of the ML objective function, $P(\sigma^0|S,D)$. The point-wise ML objective function represents a joint distribution of independent Gaussian random variables and has the form [4] $P(\sigma^0|S,D) = \prod_i \frac{1}{\sqrt{2\pi}\xi_i} e^{-\frac{(\sigma_i^0 - \mathcal{M}_i(S,D,...))^2}{2\xi_i^2}}$ where σ_i^0 represents the i^{th} σ^0 measurement, $\mathcal{M}_i(S,D,...)$ represents the σ^0 value resulting from projecting the given wind vector through the GMF with the same measurement geometry as the i^{th} measurement, and ξ_i is a variance term that is a function of the measurement noise and the modeling uncertainty of the GMF. Therefore, if the point-wise prior distribution is known, the point-wise MAP estimate can be found by scaling the ML objective function by $P(S,D)$ and searching for the maxima.

The field-wise prior distribution, $P(\bar{S},\bar{D})$, is found as follows. For each resolution cell, the speed and direction are assumed to be independent Gaussian random variables with means given by the field-wise hurricane model and some variance. Using this construction the prior distribution at a particular location has the form

$$P(S,D) = \frac{1}{\sqrt{2\pi}\xi_S} e^{-\frac{(S-\mathcal{S})^2}{2\xi_S^2}} \frac{1}{\sqrt{2\pi}\xi_D} e^{-\frac{(D-\mathcal{D})^2}{2\xi_D^2}},$$

where $\mathcal{S}$ and $\mathcal{D}$ are the speed and direction of the hurricane model winds for the point of interest. This construction provides prior distributions for each resolution cell. Each resolution cell is also assumed to be independent from each other. The notion of correlation between adjacent cells is captured by the similarity of the means of the prior distributions rather than imposing correlation between the distributions. This allows for small scale variability and preservation of high frequency information. Independence between resolution cells causes the field-wise prior ($P(\bar{S},\bar{D})$) to be equal to the product of the point-wise priors ($\prod_{m,n} P(S,D)$). Assuming that the resolution cells are independent from each other also enables the field-wise ML objective function to be written as the product of the point-wise objective functions. Thus, the field-wise MAP objective function has the form

$$P(\bar{\sigma}^0|\bar{S},\bar{D}) = \frac{1}{P(\bar{\sigma}^0)} \prod_{m,n} \left\{ \frac{1}{2\pi\xi_S\xi_D} e^{\frac{-(S-\mathcal{S}(\bar{\alpha}))^2}{2\xi_S^2}} e^{\frac{-(D-\mathcal{D}(\bar{\alpha}))^2}{2\xi_D^2}} \prod_i \frac{1}{\sqrt{2\pi}\xi_i} e^{-\frac{(\sigma_i^0 - \mathcal{M}_i(S,D,...))^2}{2\xi_i^2}} \right\} \quad (1)$$

where $\bar{\sigma}^0$, $\bar{S}$, and $\bar{D}$ represent the σ^0 fields, the wind speed field, and the wind direction field of the study region, respectively. σ_i^0, S, and D represent the i^{th} σ^0 measurement, the wind speed, and the wind direction for a particular resolution cell at index (m,n) of the fields. $\mathcal{S}(\bar{\alpha})$ and $\mathcal{D}(\bar{\alpha})$ represent the hurricane model speed and direction for a cell at index (m,n) where $\bar{\alpha}$ is the vector of hurricane model parameters.

Note that the field-wise MAP objective function in Equation 1 is a scaled product of the point-wise objective functions of each cell in the field-wise grid. Likewise, it can be shown that with this construction the field-wise MAP value is a scaled product of the point-wise MAP values for a particular model instance, $MAP_{fw} = \frac{1}{P(\bar{\sigma}^0)} \prod_{m,n} MAP_{pw}$. The best model instance is the one that maximizes the field-wise MAP value. Thus, the field-wise MAP value becomes the hurricane model objective function $l = \max_{\bar{\alpha}}\{MAP_{fw}(\bar{\alpha})\}$, where $\bar{\alpha}$ represents the hurricane model parameters.

The field-wise MAP estimation approach can be viewed as point-wise MAP estimation with priors given by a field-wise model. Note that as the variance terms ξ_S and ξ_D approach ∞, the field-wise MAP objective function converges to the point-wise MLE objective function. Furthermore, as ξ_S and ξ_D approach zero, only solutions that are in the space spanned by the hurricane model produce a non-zero MAP value and the field-wise MAP problem statement essentially becomes equivalent to model-based MLE. Thus the variance terms control how much the hurricane model is imposed. The relative values between ξ_S, ξ_D and ξ_i are a measure of the importance of the model speed error, the model direction error, and the actual measured σ_0 error respectively.

The new approach diverges from conventional model-based methods. Conventional model-based methods force the wind estimate to be in the space spanned by the model. For a practical low-order model, forcing the wind field estimate to be in the space spanned by the model restricts the wind field estimates to low resolution and to contain only information captured by the model. The new construction allows for the preservation of the information obtainable by a non-model-based approach (point-wise MLE), but weights winds that are consistent with the model more heavily.

Imposing a prior on the wind has positive consequences, and shortcomings. The new method ameliorates the cross-track pinning of the winds caused by rain and simplifies, or even eliminates, the issue of ambiguity removal. However, the priors modify the MLE objective function so that the resulting estimates are no longer 'pure' measurements. Nevertheless, the MAP estimation method for imposing the hurricane model is less severe in this respect than true model-based estimation.

IV. IMPLEMENTATION

This section describes an implementation of field-wise MAP estimation of hurricane wind fields. First we develop a low-order hurricane model. Then we describe a simplification of the method by using field-wise MAP ambiguity selection.

The hurricane model is derived based on real SeaWinds data. We align a large number of conventional high resolution wind fields of northern hemisphere hurricanes so that their centers are in the same location and then generate empirical probability density functions (pdfs) for the wind speed and direction as a function of distance from the eye center. The resulting pdfs are approximately Gaussian. We thus formulate a simplified model for the means and use nominal values for the variances.

The hurricane model is very simplistic. We assume that a hurricane is composed of a symmetric cyclonic wind field with a superimposed mean wind flow. The simplistic model has three parameters: the eye center location, the size (maximum wind speed), and the mean flow. A simple curve is fit to the means of the wind speed pdfs as a function of distance from the eye. We assume that the wind speed ramps up linearly from about half of the maximum speed to the maximum speed, and then falls off exponentially to 7 m/s (which is the mean wind speed over the ocean). Fitting this curve to the mean of the empirical distributions provides nominal values for the radius of the eye, and the decay rate (time constant) of the exponential portion. The mean direction relative to the eye center is constant as a function of distance from the eye.

Since the estimation procedure must search a non-linear objective function of several variables in order to obtain a wind field estimate, it is computationally taxing. This can be a deterrent for using such a method in near real time processing. We consider a simplification of the new approach by constraining the solution space to that spanned by the point-wise ambiguities. This reduces the search space considerably, as well as producing an estimate of the wind that is not biased by the model.

This new field-wise MAP ambiguity selection procedure begins with conventional high resolution point-wise estimation. The ambiguities are then chosen to maximize the log of the field-wise MAP objective function. This field-wise MAP ambiguity selection procedure produces estimates of the hurricane model parameters as well as choosing appropriate ambiguities. However, because the hurricane model is simplistic, the estimate of the eye center may differ from the true eye center location. Therefore, it is more accurate to first estimate the eye center location and then apply field-wise MAP ambiguity removal to estimate the remaining parameters. An automated method for finding the eye center based on the circular Hough transform (CHT) is developed.

The CHT is used to find circles in a binary image (an image composed of ones and zeros). The CHT is calculated by drawing a circle of radius R from each pixel that has a value of 1 in the binary image and accumulating the number of these circles that hit each pixel. Thus, if there is a circle in the image with radius R the maximum value of the CHT will be at the same index as the center point of the circle. For finding the hurricane eye we convert the speed field to a binary image and compute the CHT for a radius similar to that of an average hurricane. Then we weight the CHT by the inverse of the speed field. This suppresses circle centers in high wind speed regions and emphasizes those centered in low wind speed regions (like the eye center). Then we search for the maximum of the weighted CHT and report the index as the hurricane eye center. We note that there may be several local maxima in the weighted CHT which could produce eye center 'ambiguities'. For simplicity we choose only the absolute maxima.

Field-wise MAP ambiguity removal is not equivalent to field-wise MAP estimation. Mere ambiguity selection cannot provide the same immunity to rain and noise that is possible with MAP wind retrieval because the MLE ambiguities may be rain contaminated. Nevertheless, MAP ambiguity selection is useful in two ways. First, it can provide an estimate of the wind that is not biased by the model. Second, performing field-wise MAP ambiguity selection provides estimates of the hurricane model parameters which can be used in MAP wind retrieval. Performing MAP estimation with these hurricane model parameters is more computationally efficient than simultaneously estimating the wind and the hurricane model parameters. Thus, field-wise MAP estimation (or wind retrieval) can also be done in near real time and the field-wise MAP ambiguity selection is produced as a side product.

V. Analysis

It is difficult to validate the results of the new method because truth data is limited. The best track hurricane eye locations provided by the NHC are used as ground truth for hurricane eye locations for real data while simulation is used to test the quality and integrity of the estimated winds.

The eye center location from the new method is compared to the best track locations provided by the NHC. A number of SeaWinds observations (213) of named tropical storms from the North Atlantic basin from 1999 to 2005 are processed with the new method. Figure 1 shows the histogram of the distance from the best track eye center for the new method. The mean and standard deviation are also reported. Most of the cases are in the low distance bins suggesting that the new method finds the eye close to the best track location with high probability.

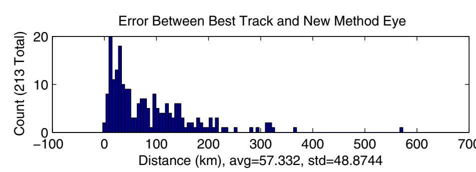

Fig. 1. Histogram of distance from best track location for circular Hough transform eye finding method.

Simulation is used to analyze the effectiveness of the new approach. H*WINDS [5] are used as a truth data set of wind fields that represent true storms. Synthetic σ^0 values are generated by projecting H*WINDS and synthetic rain rates through the simultaneous wind and rain model described by Draper [6] and adding noise. Conventional ultra high resolution wind retrieval and the new method are applied and the results are compared.

We simulate σ_0 fields for various rain rates and calculate the error of the resulting wind fields. Ideal ambiguity selection (the conventional high resolution ambiguity closest to the

H*WINDS), MAP ambiguity selection and MAP estimation are compared. For simulation the MAP ambiguity selection and MAP estimation eye center is fixed to the true eye center. Figure 2 shows the RMS error versus rain rate averaged over several H*WIND fields. On average the MAP estimation procedure reduces the RMS error lower than even ideal ambiguity selection (and thus does much better than the conventional ambiguity selection). Also, MAP ambiguity selection approaches ideal ambiguity selection in the RMS error sense.

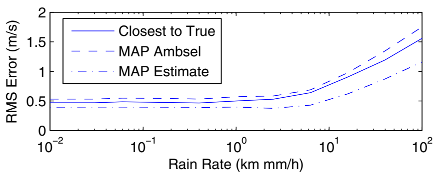

Fig. 2. RMS error versus rain rate for ideal ambiguity selection, MAP ambiguity selection, and MAP estimation.

Figure 3 shows an example of a real storm. Conventional wind retrieval, field-wise MAP ambiguity selection, and field-wise MAP wind retrieval are all depicted. The new approach finds the eye center better than the conventional method (conventional eye is based on the curl of the vector field) and improves the ambiguity selection in rain contaminated regions (such as in the lower left quadrant of the storm). The field-wise MAP wind retrieval method produces a more smooth and less squared off storm than even the field-wise MAP ambiguity selection.

VI. Conclusion

The new wind retrieval method can be used to augment scatterometer hurricane analysis. It provides an automated method to find the eye center location as well as improves wind direction estimates–especially in the rain contaminated portions of the storm. Furthermore, the method can be adapted for near real time analysis.

In simulation, MAP estimation of hurricane winds produces a lower RMS error than even ideal ambiguity selection of conventional high resolution winds. Also, MAP ambiguity selection produces a result similar to ideal ambiguity selection. This suggests that where an eye center can be found in the data, the MAP estimation and MAP ambiguity selection approaches are superior to the conventional high resolution approach.

MAP estimation using a hurricane model may also ameliorate some of the issues with simultaneous wind and rain retrieval in hurricanes. Future work will consider a wind and rain model for simultaneous wind and rain MAP estimation.

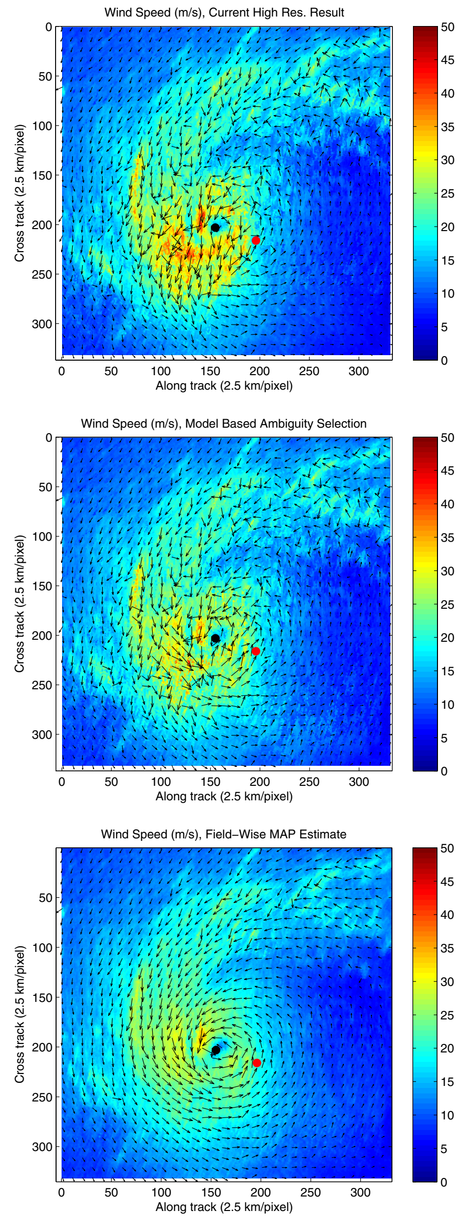

Fig. 3. Hurricane Floyd (1999) example. The top image represents the conventional high resolution wind field. The middle image is the result of the model-based MAP ambiguity selection. The bottom image represents the field-wise MAP estimate of the wind field. The wind vector fields are down sampled by 10 for plotting. The black dots represent the eye center reported by the new method and the red dots represent the conventional high resolution eye center based on the curl of the vector field.

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