

P4.5 AN ANEMOMETER DATA QUALITY CONTROL METHOD DESIGNED FOR A TURBULENCE AND WIND SHEAR PREDICTION ALGORITHM

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1. INTRODUCTION

The Research Applications Program (RAP) at the National Center For Atmospheric Research (NCAR) was funded by the FAA to develop a prototype wind hazard warning system for the International airport in Juneau Alaska reported by Barron et. al. (2004). The prototype operational system uses regressions to predict hazards such as turbulence and wind shear from a network of meteorological sensors, specifically radar profilers and anemometers are employed reported by Morse et. al. (2004). This network of sensors are located in the Juneau region including the nearby mountains. As one can imagine, the weather in southeast Alaska can be severe at times, particularly in the winter when most of the hazardous winds occur. Because of these challenging conditions and the critical nature of the warning system, i.e., aircraft safety, both the anemometer and profiler data must be quality controlled.

For the anemometers, a quality assurance methodology was developed to report a 1 minute value for wind speed and direction for the anemometers. The methodology includes a "temporal test" to calculate a confidence for the high rate data by a linear least squares best fit algorithm, an algorithm to calculate confidence weighted statistics e.g. a confidence weighted mean and variance and a "combiner" algorithm to report a single "site" value for wind speed and direction for the locations where there are two co-located anemometer "stations" (i.e. the mountain top anemometers).

There is a need to verify this quality assurance methodology. For this reason an independent verification algorithm has been developed. This algorithm is based on ideas found in IODA reported by Weekley et. al. (2003). IODA is a quality assurance algorithm based on fuzzy image processing and classification techniques. Several years of anemometer data were analyzed and it will be shown that the current quality assurance techniques mitigate outlier problems found in these anemometers.

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2. JUNEAU QUALITY ASSURANCE

The Juneau quality assurance algorithms assumes: the time series data from the anemometers are stationary over the quality control window (i.e. N previous data points); most of the data in the quality control window is a "good" measurement; for sites with two anemometers it is unlikely for both anemometers to fail simultaneously and it is unlikely for an anemometer to fail and report a "larger" value. The quality assurance algorithm is designed to mitigate three types of outliers: infrequent random excursions, outliers from instrument failures (or failure modes), and time series data from two co-located stations that appear nominal to a human expert but do not agree with each other. As mentioned earlier there are three parts to the Juneau quality assurance methodology, the temporal test, the statistics test, and the combiner algorithm for both the wind speed and wind direction. For simplicity the discussion will be restricted to wind speed only.

The temporal test uses a least square second order polynomial fit over a "window" (i.e. 30 points or so) of high rate (one second) time series data. An expected value for the next point in the time series is estimated using the polynomial. When the next value is reported, in real time, the difference between the actual value and the expected value is calculated and normalized by the variance in the data over the window i.e.:

$$(1.1) \quad z = \left(\frac{y - \hat{y}}{\sigma} \right)$$

A confidence is calculated from this z-statistic that varies between 0 and 1 using:

$$(1.2) \quad C(z) = e^{\left(\frac{(a-z)^n}{b} \right)}$$

where a, b, n are constants. The high rate confidence simply reflects how close a measured value is to the expected value estimated from the fit of the last N points. A confidence near 1 means the measured value is close to the fit and a confidence near 0 is far from the fit (normalized by the variance in the data). The temporal test is similar in methodology to standard methods such as discounted least squares and autoregressive of order k (AR(k)). There is one added wrinkle to the temporal test, initially the fit over the window is applied with all points equally weighted. However, once the algorithm has initialized, a confidence weighted fit is performed. The more recent points

are given greater consideration than earlier data. Where the time weighting function is of the form:

$$(1.3) \quad \Psi(t) = e^{\left[-d \left(\frac{e-t}{i} \right)^j \right]}$$

where d, e, i, j are constants. The temporal test is skillful in assigning a low confidence to infrequent random excursions. Once a confidence has been assigned to the high rate data a "low rate" one minute value is calculate by the averaging algorithm.

The averaging algorithm returns confidence weighted statistics (mean, variance, min, max) and their associated confidences over the averaging interval (1 minute). The primary function of the averaging algorithm is to reduce the data rate of the anemometer data and to restart the temporal test if the mean confidence drops below a threshold for the averaging interval.

The combiner algorithm is applied to the one minute confidence weighted values reported by the one minute averaging algorithm for the two "stations" and returns a single value for the "site". The combiner algorithm is a set of rules for the following cases: i.e. both stations have zero-confidence, one station has zero confidence and the other has non-zero confidence, both stations have non-zero confidence and "agree", both stations have non-zero confidences and "disagree". For the trivial case when both stations have zero confidence the site value is given zero confidence and a missing value is reported. For the case where one station has zero confidence and the other non-zero confidence the values for the high confidence station are reported. For the cases where both stations have non-zero confidence the instruments are said to agree if the wind speed for both anemometers is below a threshold or the difference between the two anemometers is below a threshold. The instruments are said to disagree if the low rate wind speed for either anemometer is above a threshold and the difference between the anemometers is larger than a threshold value. The motivation for the threshold for wind speed is the activation energy for the instrument, i.e. the wind speed measurements are uncertain for speeds less than about 5 ms^{-1} . If the wind speeds agree, then the confidence weighted average of the data reported by the stations is combined into the "site" value. If the wind speeds disagree, the station with the higher wind speed is reported as the "site" value. A similar set of rules can be constructed for the wind direction. The primary function of the combiner algorithm is to mitigate errors introduced by failure modes i.e. errors that the temporal test is not designed to detect.

3. FAILURE MODE MITIGATION

To give an independent test of the ability of the Juneau quality control methodology to mitigate failure modes, a fuzzy logic image processing algorithm to classify the data from the pair of co-located anemometers was developed. The algorithm is similar in methodology to a prototype algorithm developed to quality control time series data from a single instrument (IODA). In this application a scatter plot for an hour of data is created from the high rate data taken from the two instruments located near the summit of Sheep Mountain. An "image map" is calculated from the scatter plot and clusters of data are found. A set of "best" clusters are selected and statistics for the clusters are calculated. A score for the "best" clusters using fuzzy methods can be calculated from the statistics of the "best". Where the fuzzy methods give scores for: Nominal data, spurious clusters, clusters from a failure, clusters from low wind speeds, suspect cluster from a low wind speeds, spurious clusters from a low wind with a poor fit (i.e. a poor linear fit of the data in the scatter plot), spurious clusters from a low wind with a good fit, clusters from a high wind with a good fit but with a large number of outliers, clusters from a high wind with a poor fit, and frozen clusters. Where frozen clusters occur when the anemometers are either not reporting or effected by ice. A cluster is then classified according the highest scoring rule. For instance an hour of data is "nominal" if the score for the nominal fuzzy rule is greater than any of the scores calculated from the other fuzzy rules.

Figures 1 and 2 are examples of nominal data, and clusters from a high wind with a poor fit. These two cases are compliments of each other i.e. the only difference between the fuzzy rules for these cases are the statistics that relate to the quality of the fit. Both figures show the time series data for two different 1 hour intervals. In the nominal case (Figure 1), notice both the time series agree as can be seen in the scatter plot shown directly below the time series plots. Notice in the

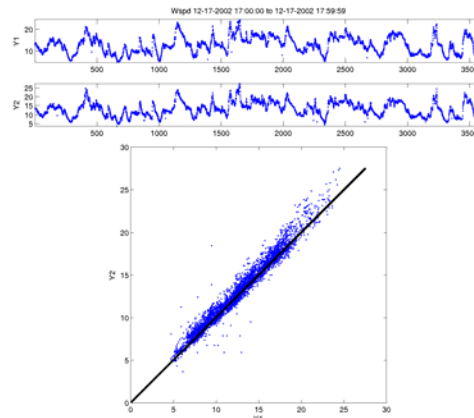


Figure 1: Nominal data time series for Sheep Mountain 1 and 2 with scatter plot.

nominal case all the data are well correlated since there is a single, dense, cluster of points near the line $Y1=Y2$ (solid black line). Also notice there is a slight bias between the two anemometers i.e. $Y2$ tends to be larger than $Y1$ and most of the ordered pairs of points are slightly shifted above the line $Y1=Y2$. The data shown in Figure 2 is for the "drop-out" case. Notice the second time series has suspicious "drop-outs" which do not appear in the first time series. In this case a nut loosened on the second anemometer wind speed head allowing the anemometer to drift upwards off the spindle and report false low values. In this case the data is less correlated as can be seen from the scatter plot below the two time series. Notice there are disperse points which do not belong to the cluster of points centered on $\sim 13 \text{ ms}^{-1}$ i.e. where the values from $Y2$ is small and $Y1$ is large (in all the plots the data for $Y2$ is from Sheep Mountain 2).

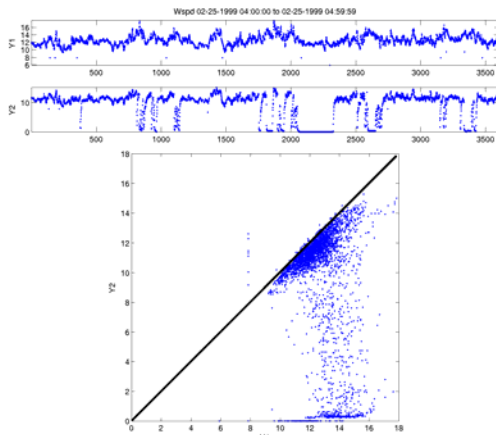


Figure 2: Drop-out time series data for Sheep Mountain 1 and 2 with a scatter plot

The fuzzy logic image processing algorithm was run on years of one second data collected from the anemometers in Juneau Alaska. The hours of "suspect" data (i.e. where clusters from a high wind with a poor fit) were found and the distribution of "suspect" scores was determined. Four hundred hours with a suspect score greater than 0.8 were identified and the one minute "station" values were collected along with the one minute "site" values. A similar set of data was collected for "nominal" data.

Figure 3 is a scatter plot of the one minute "station" values reported by Sheep Mountain anemometer 2 versus the values reported by Sheep Mountain 1. For the suspect data notice that the scatter plot in Figure 3 of one minute station values is similar to the scatter plot of one second values shown in Figure 2. The color of the data in Figure 3 indicates the confidence assigned to the data by the combination algorithm, where a cool color indicates a high confidence and a warm color

indicates a low confidence. The color scale has been compressed

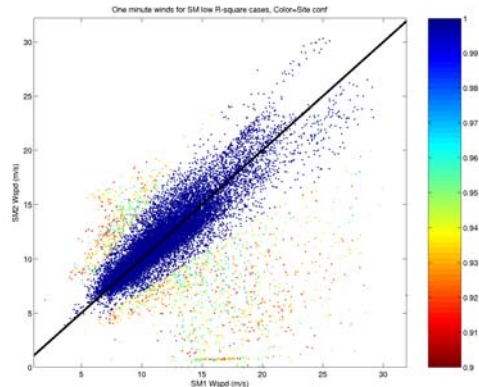


Figure 3: Scatter plot of Sheep Mountain 1 and 2 for multiple "suspect" hours.

to the interval $[0.9 \ 1]$ to make the difference in confidences more visible. Notice that there is a "clump" of higher confidence data near the center of the plot and the disperse points outside have a lower confidence. Figure 4 is a scatter plot of the one minute "site" wind speeds reported by the "combination" algorithm versus the "station" wind speeds reported by Sheep Mountain 2 for the same times in Figure 3. In general the site wind speed i.e.

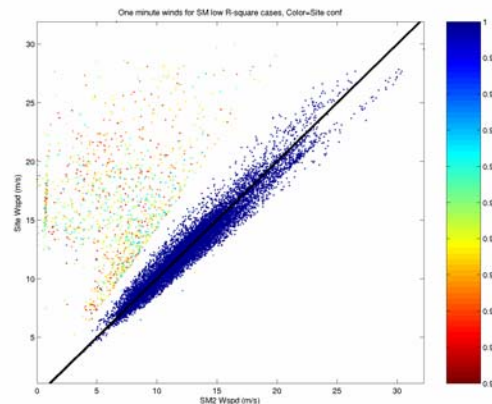


Figure 4: Scatter plot of Sheep Mountain site data vs. Sheep Mountain 2 station data for 400 hours of "suspect" 1 hour time intervals.

either the winds from Sheep Mountain 1 agree and are averaged for the site value; or the value reported by Sheep Mountain 2 is selected as the "site" value. Notice there is a second cluster of points in figure 4 separated from the primary cluster of points by a small gap. In this case the values reported from Sheep Mountain 2 are smaller than the site values. These points are the cases where Sheep Mountain 2 disagrees with Sheep Mountain 1, and Sheep Mountain 1 is reporting a higher wind speed and is selected rather than Sheep Mountain

2. The fact there is a gap between these points and the points where the Sheep Mountain 1 agrees with the site values is a consequence of the thresholds used in the combiner algorithm and the averaging of the two sites when the anemometers agree.

Figure 5 is a scatter plot of Sheep Mountain 2 versus Sheep Mountain 1 for 400 hours of "Nominal" data. Notice that in general the data from both anemometers are in good agreement i.e. within a ms^{-1} or so.

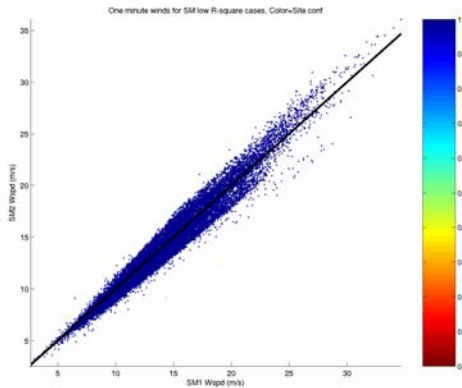


Figure 5: Scatter plot of Sheep Mountain 1 versus Sheep Mountain 2 for multiple "nominal hours".

Figure 6 are histograms of the "nominal" and the "suspect" one minute wind speed data for the 400 hours studied. The mean "site" value over the 400

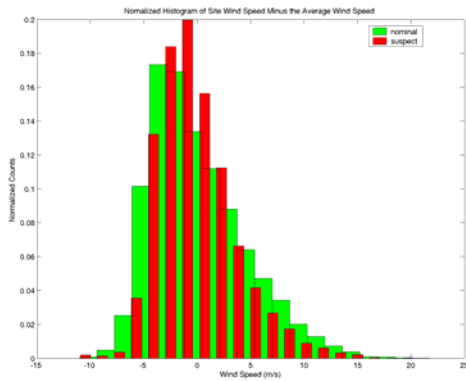


Figure 6: Normalized histograms of one minute wind speed data for both "nominal" and "suspect" data.

hours for the "nominal" data was subtracted from the "nominal" one minute winds. Likewise, the mean over the 400 hours of "suspect" data was subtracted from the one minute "suspect" wind speeds. Both histograms were normalized by the total number samples in the 400 hours. Notice that the "nominal" histogram shown in green is a slightly different distribution than the histogram for the "suspect" cases shown in red. Figure 7 is a similar

plot for the histograms of the one minute site variance of the 400 hours. These variances are used to find isolated outliers, and they are also used as regressors in the Juneau system to estimate turbulence. Any errors introduced by a failure mode are mitigated in the combiner, consequently biases in the data can be introduced into the data by the averaging algorithm. Notice again the distributions are different. Such differences are not unexpected since the temporal test is designed to remove isolated random excursions. However, in the case of numerous outliers the temporal test may fail. Figure 7 also shows there are slightly greater number of large variance cases for nominal data. This would indicate that when suspect data is present the system under estimates the variance. The smaller variances could result in and underestimate of turbulence.

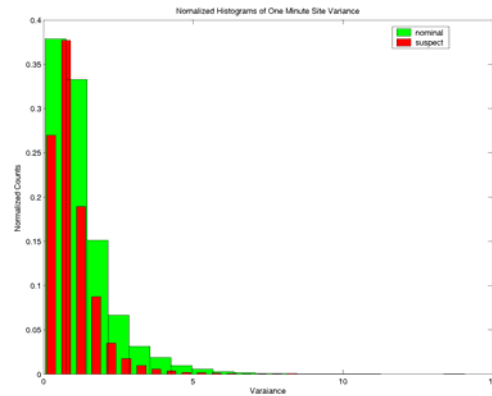


Figure 7: Normalized histograms of one minute wind speed variance for both "nominal" and "suspect" data.

4. CONCLUSION

From Figure 3 it is clear there are numerous cases where the one minute wind speed reported from Sheep Mountain 1 disagrees with the one minute wind speed reported from Sheep Mountain 2. There are some deficiencies in the Juneau Quality Assurance Methodology. For instance reporting the max value of the two anemometers when the anemometers "disagree" may over-estimate the wind, and the temporal test assigns a high confidence to failure mode data. However, the temporal test is primarily designed to remove isolated random excursions and certain failure modes violate the assumptions of the temporal test. Consequently, one would not expect the algorithm to perform well in failure mode cases. On the other hand, the "combiner" algorithm is skilled in reporting a "reasonable" value even though one of the instruments may be failing. Despite these deficiencies the methodology removes most of the outliers. Additional work should include a similar study for the wind direction

data and other anemometer pairs to verify the quality assurance methodology is valid for these additional cases.

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REFERENCES

- Barron, R. and V. Yates, 2004: Overview of the Juneau terrain-induced turbulence and wind shear project. Proceedings, 11th AMS Conf. on Aviation, Range and Aerospace Meteorology, Hyannis, 4-8 Oct. (on cd)
- Morse, C.S., S.G. Carson, D. Albo, S. Mueller, S. Gerding and R.K. Goodrich, 2004: Generation of turbulence and wind shear alerts: Anatomy of a warning system. Proceedings, 11th AMS Conf. on Aviation, Range and Aerospace Meteorology, Hyannis, 4-8 Oct. (on cd)
- Weekley, R. A., Goodrich, R.K., Cornman, L.B, 2003: Fuzzy Image Processing Applied to Time Series Analysis, CD-ROM, *3rd. Conf. Artificial Intelligence Applications to the Environmental Sci.*, AMS, paper 4.3