SIX STATION LLWAS WIND SHEAR DETECTION ALGORITHM
PRELIMINARY REPORT

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I. INTRODUCTION

It is very difficult to reliably detect microburst wind shears with a network of anemometers whose spacing is comparable to that of the existing six-station LLWAS networks. By using a combination of the network mean (NMN) algorithm and divergence detection methods (TED) whose thresholds are variably set to reflect the geometric properties of each triangulation element (triangle or edge), we have been able to obtain fairly high microburst detection probability without incurring an unacceptable false alarm ratio. Our tests indicate that a detection probability of 80% with a false alarm ratio of 10% to 20% will be achieved by this system. Moreover, most false alarms occur during the time at the end of a microburst event when the strength has dropped just below the detection threshold level.

Tracking a gust front across a sparse network is also confusing. One problem is that with the NMN algorithm there is a tendency for inverse logic to cause alarms to occur on the far side of the network, long before the event arrives. A second problem is that there may be substantial gaps in the times of arrival of the shear region at the stations, which can cause alarms to flicker on and off across the network, rather than appearing as connected sequence of alarms associated with the passage of a single event. To deal with these problems, we have introduced the concept of adjusting the detection thresholds at each of the stations according to the level of the temporal shear (TS) at that station. Our test results indicate that this process has successfully dealt with both of these problems.

The NMN algorithm is the basis for the wind shear detection. We have enhanced it with the TED divergence estimations to improve microburst detection and by TS threshold adjustment to improve gust front tracking. One must wonder if these conditions might be detrimental to the opposite tasks. Our approach to answering this question is simulation testing. First, we studied the case where the simulated wind field contained only microbursts. This investigation allowed us to set the detection thresholds to be optimal for microburst detection (Table 1). We see that the TS does not adversely affect the microburst detection. Then we used these thresholds to try to detect gust fronts. The results of this study are in Table 2, where we observe that the addition of the divergence method is not detrimental to the gust front tracking. In this case, we see that the TS adjustment provides a significant increase in the ability to track a gust front. Then, using the same threshold level, we tested a simulated wind field that contained both microbursts and gust fronts, sometimes as simultaneous events. The results, in Table 3, show that the detection methods are not adversely affected by these new complications. Finally, we apply the methods to a file of recorded real data in which microburst events have been classified by meteorologists as to location and duration. In Table 4, we observe that for the real data the detection algorithms perform as we would expect, with a slightly diminished

Table 1. Microburst Test Results (Simulated Data)

METHOD	THR	POD	FAR	EPOD	EFAR	PSS	TSS	PTD
NMN	11.50	.84	.05	.84	.08	.89	.93	.37
NMN-TED	11.50	.88	.10	.87	.15	.86	.85	.40
NMN-TS (F=1.5)	8.00	.85	.05	.84	.10	.90	.83	.45
NMN-TS-TED (1.5) (Regular MB)	8.50	.88	.09	.86	.16	.87	.85	.46
NMN-TS-TED (1.5)* (Sharp MB)	8.50	.88	.01	.86	.06	.93	.87	
TED**	60%	.86	.09	.84	.14	.86	.83	

* The difference between the sharp MB and the regular MB is that the intensity of the regular MB decays gradually after the peak part of the event while the sharp MB decays very rapidly. The fact that the FAR drops so much for the sharp MB indicates that for the regular MB, most of the false alarms occur during the decay phase of the MB.

** TED alone has an FAR of .09. Therefore, the combined methods have an FAR $\geq$ .09. Therefore, we see that for both NMN and NMN–TS, combined systems issue false alarms at the same times, i.e., during the decay phase of the MB.

Table 2. Gust Front Test Results (simulated data)

METHOD	THR*	POD	FAR	EPOD	EFAR**	PSS	TSS
NMN	11.50	.78	.02	.50	.70	.92	.78
NMN-TED	11.50	.78	.02	.50	.70	.91	.77
NMN-TS (1.5)	8.00	.90	.09	.56	.79	.88	.87
NMN-TS-TED (1.5)	8.50	.90	.09	.56	.79	.88	.87

* Use the thresholds from the MB simulation test.

** In order to obtain a smooth transition of alarms during the passage of a gust front across the network we have extended the alarm duration. This causes the alarms to persist beyond the time that the shear is near the station (because of sparse network). Consequently, the EFAR is inflated.

III. RECURSIVE FILTER FOR DATA SMOOTHING

The purpose of data smoothing is to reduce short term random variations in the measured data. We achieve this by using a single pole recursive filter. One interpretation of this filter is that it reduces the noise level of the data by a multiplicative factor.

A. SPECIFY METHOD

The single pole filter used in our analyses is of the form

$$Y(t) = (1 - \alpha)X(t) + \alpha Y(t - 1)$$

where $t > 1$ and $0 < \alpha < 1$. The series $Y(t)$ is initialized by

$$Y(1) = X(1).$$

B. ALGORITHM SPECIFICATION

1) Parameters

α – recursive filter constant, $0 < \alpha < 1$

2) Input

A time series of data $X(t)$

3) Initialize
$Y(1) = X(1)$

4) Compute For $t > 1$

$$Y(t) = (1 - \alpha)X(t) + \alpha Y(t - 1)$$

5) Output

The time series of smoothed data $Y(t)$.

4) Compute for $t > 1$

[MODEL_SINGLE_STAT] [WF_TIME_SERIES]

$$U_\beta(t,i) = (1-\beta)u(t,i) + \beta U_\beta(t-1,i)$$

$$V_\beta(t,i) = (1-\beta)v(t,i) + \beta V_\beta(t-1,i)$$

$$U_\alpha(t,i) = (1-\alpha)u(t,i) + \alpha U_\alpha(t-1,i)$$

$$V_\alpha(t,i) = (1-\alpha)v(t,i) + \alpha V_\alpha(t-1,i)$$

[RESIDUAL]

$$R_{TS,u}(t,i) = U_\beta(t,i) - U_\alpha(t,i)$$

$$R_{TS,v}(t,i) = V_\beta(t,i) - V_\alpha(t,i)$$

[VARIANCE_UPDATE]

$$\sigma^2_{TS,u\gamma}(t,i) = (1-\gamma)R^2_{TS,u}(t,i) + \gamma\sigma^2_{TS,u\gamma}(t-1,i)$$

$$\sigma^2_{TS,v\gamma}(t,i) = (1-\gamma)R^2_{TS,v}(t,i) + \gamma\sigma^2_{TS,v\gamma}(t-1,i)$$

5) Output

$R_{TS,u}(t,i)$, $R_{TS,v}(t,i)$ the temporal shears at each station.
$\sigma^2_{TS,u\gamma}(t,i)$, $\sigma^2_{TS,v\gamma}(t,i)$ the TS variances.

V. NETWORK MEAN (WS DETECTION)

It has been shown that comparison of current LLWAS data with the mean wind field for the entire network is an effective method for the detection of dangerous wind shears, provided that

1. the network mean can be stably estimated,
2. data noise is correctly compensated,
3. detection thresholds are appropriately set.

The method that we shall describe uses a Chi-squared based, recursive trimming strategy to attain a stable estimate of the network mean wind field and its variance, data and model parameter filtering in conjunction with a Chi-squared based alarm test to compensate for data noise during testing for spatial wind shear, and detection thresholds that are varied in accordance with the level of TS to provide enhanced spatial wind shear detection.

B. ALARM THRESHOLD STRATEGY:

-If there is modest TS, then use the given threshold.
-If there is weak TS, then use a higher threshold.
-If there is strong TS, then use a lower threshold.

C. ALGORITHM SPECIFICATION

1) Parameters

α – recursive filter constant; 2 min. average (α=.8)
β – recursive filter constant; network mean (β=.8)
γ– recursive filter constant; network variance (γ=.995)
Trim_threshold = 10.0
σ^2 *min* = 4.0
Set_alarm_threshold = 13.0
F – threshold adjustment factor (F=1.5)
low_lim = 7.0
high_lim = 12.0

2) Input

u(t,i), v(t,i) the time series of wind field components at each of the *m* currently active stations i = 1,...,m

3) Initialization (for $t = 1, \ldots, 10$)

[START_UP_NMN]

i) Time-series averaging of the wind field data at each station with pole α, i.e., find $U_\alpha(t,i)$ and $V_\alpha(t,i)$ as follows:

[WF_TIME_SERIES]

for $t = 1$

$$U_\alpha(1,i) = u(1,i)$$
$$V_\alpha(1,i) = v(1,i)$$

for $t > 1$

$$U_\alpha(t,i) = \alpha U_\alpha(t-1,i) + (1-\alpha)u(t,i)$$
$$V_\alpha(t,i) = \alpha V_\alpha(t-1,i) + (1-\alpha)v(t,i)$$

f) Computations for $t > 10$

[MODEL_NMN]

i) Time-series averaging of the wind field data at each station **[WF_TIME SERIES]**

$$U_\alpha(t,i) = \alpha U_\alpha(t-1,i) + (1-\alpha)u(t,i), \quad V_\alpha(t,i) = \alpha V_\alpha(t-1,i) + (1-\alpha)v(t,i)$$

ii) Estimate of the network mean and variance

a) Estimate residuals of current data averages from model values for the previous time **[RESIDUAL]**

$$R_u^2(t,i) = [U_\alpha(t,i) - \bar{U}_{T\beta}(t-1)]^2, \quad R_v^2(t,i) = [V_\alpha(t,i) - \bar{V}_{T\beta}(t-1)]^2$$

b) Chi-squared test values for data trimming

[TRIM]

$$u\_denom = \max\{\sigma_{u\gamma}^2(t-1), \sigma_{min}^2\}, \quad v\_denom = \max\{\sigma_{v\gamma}^2(t-1), \sigma_{min}^2\}$$

$$\text{T\_test}(i) = \frac{R_u^2(t,i)}{u\_denom} + \frac{R_v^2(t,i)}{v\_denom}$$

c) Recall that m is number of currently active stations. Trim the data from up to $\lfloor \frac{m}{2} \rfloor$ stations whose test values which exceed the trim threshold or the $\lfloor \frac{m}{2} \rfloor$ which have the most extreme differences in case more than $\lfloor \frac{m}{2} \rfloor$ exceed the trim threshold; data from n stations remains ($n \geq m - \lfloor \frac{m}{2} \rfloor$)

d) Compute the network mean using data from the untrimmed stations, aka the trimmed data set j. **[REMODEL_NMN]**

$$\bar{U}_T(t) = (1/n)\sum_j U_\alpha(t,j), \quad \bar{V}_T(t) = (1/n)\sum_j V_\alpha(t,j)$$

e) Time-series average of the network mean

[TS_UPDATE]

$$\bar{U}_{T\beta}(t) = (1-\beta)\bar{U}_T(t) + \beta\bar{U}_{T\beta}(t-1), \quad \bar{V}_{T\beta}(t) = (1-\beta)\bar{V}_T(t) + \beta\bar{V}_{T\beta}(t-1)$$

f) Residuals for the trimmed data set j.

[RESIDUAL]

$$R_{Tu}^2(t,j) = [U_\alpha(t,j) - \bar{U}_{T\beta}(t)]^2, \quad R_{Tv}^2(t,j) = [V_\alpha(t,j) - \bar{V}_{T\beta}(t)]^2$$

g) Sample variance for the trimmed data

5. *Output*

The list of wind shear alarms at the stations for each polling time t

VI. DIVERGENCE BASED MICROBURST DETECTION

The physical characteristic of a microburst that makes it an aviation hazard is the presence of the low level divergent wind shear. When the event is inside of the LLWAS network and it is large enough to have a significant impact on more than one station, then it frequently is possible to measure significant wind field divergence by numerical differentiation of the wind field data. In this case, we can confirm that there is a microburst present, and issue a microburst warning.

A. THE METHOD

Two methods of divergence are used. Along a line between two stations, linear divergence is estimated. This quantity is a measure of the rate at which an aircraft would lose headwind if it flew along that path; its estimate of the strength of the hazard is most accurate when the center of the microburst lies near that path, and not too near to either of the endpoints. When the microburst center lies well interior to a triangle of stations, then the best estimate of the strength of the hazard is obtained by estimating the 2-dimensional wind field divergence. This quantity is numerically twice the magnitude of the theoretical linear divergence for symmetric microbursts.

The accuracy of the divergence estimates is dependent on the size of the edge or triangle in which the estimate is made, the proximity of the microburst center to the center of the geometric element, and the shape of the element, when it is a triangle. Therefore, the detection threshold must be set differently for each element of a triangulation of the LLWAS network. A table of these elements is computed separately, and is entered as part of the TED program. Roughly speaking, these thresholds are set so that a microburst will be detected when its center is located in the central portion of the element, for about alarm 60% of the area of that element. This rather low percentage is necessary to avoid false alarms, and will be higher for the advanced, denser LLWAS networks.

We note that for these sparse networks, the microburst identification probability is significantly lower than the wind shear detection capability. This is due to the fact that with the large distances between stations, it will rather frequently happen that a microburst will impact one station, but not two. In this case, we can expect to obtain a wind shear alarm at that station, but not a confirming microburst identification. On the other hand, even with the rather high thresholds, there are microbursts that are detected by wind field divergence before there are any station alarms.

B. ALGORITHM SPECIFICATION

d) For each triangle, compute the 2-dimensional divergence

$$x_1(m) = x(j) - x(i), \quad x_2(m) = x(k) - x(i)$$

$$y_1(m) = y(j) - y(i), \quad y_2(m) = y(k) - y(i)$$

$$u_1(m) = U_\alpha(t,j) - U_\alpha(t,i), \quad u_2(m) = U_\alpha(t,k) - U_\alpha(t,i)$$

$$v_1(m) = V_\alpha(t,j) - V_\alpha(t,i), \quad v_2(m) = V_\alpha(t,k) - V_\alpha(t,i)$$

$$u_x(m) = \frac{y_1(m)u_2(m) - y_2(m)u_1(m)}{2\,area(m)}$$

$$v_y(m) = \frac{v_1(m)x_2(m) - v_2(m)x_1(m)}{2\,area(m)}$$

$$\text{tri\_div}(m) = u_x(m) + v_y(m)$$

4. *Microburst alarms*

$$\begin{cases} \text{at edge } m & \text{if edge\_div}(m) > t_{\text{edge}}(m) \\ \text{at triangle } m & \text{if tri\_div}(m) > t_{\text{tri}}(m) \end{cases}$$

5. *Output*

List of microburst alarms at the triangles and edges for each polling time

Enhanced LLWAS Algorithm.

The enhanced LLWAS algorithm generates two different kinds of alarms: the network mean (NMN) and the microburst alarms. These alarms are combined into "sector" alarms. Sectors are areas of importance that contain one or more remote wind units.

The network mean (NMN) algorithm.

The NMN part of the enhanced LLWAS algorithm is a refinement of the original LLWAS algorithm. Again there is a reference wind vector and the wind speed at each position is compared against that reference.

Six remote wind units are used. All the wind units, including the centerfield, sample the wind speed once per second and calculate the 30 second running averages of the u and v wind components. The data of all stations are further smoothed by a numeric recursive filter. For the i^{th} station, the smoothed data will be u_i and v_i.

The reference is the network mean (NMN) which is defined the average of the smoothed wind data of all stations with the exception of those whose data differ more than a certain threshold. A chi-squared type of test is used to determine which data will be rejected:

$$\frac{[u_i(t) - U(t-1)]^2}{\sigma^2\ u(t-1)} + \frac{[v_i(t) - V(t-1)]^2}{\sigma^2\ v(t-1)} > \text{trim threshold}$$

where U(t-1) and V(t-1) are the U and V components of the previous NMN. σ_u(t-1) and σ_v(t-1) are the previous standard deviations for the network.

Up to three stations will be rejected from the NMN using the above criterion. If more than three stations fulfill the rejection test the three that differ the most will be excluded. Using the trimmed data, the new network mean U and V components and the corresponding standard deviations will be computed.

Using the network mean as a reference, the smoothed data from all stations (including the centerfield) are compared in order to generate the alarms. A chi-squared type of test is employed:

$$\frac{[u_i(t) - U(t)]^2}{\sigma^2_u(t)} + \frac{[(v_i(t)-V(t)]^2}{\sigma^2_v(t)} > \text{alarm threshold}$$

The 30 second running averages are used to calculate a measure of the temporal shear at each location. The temporal shear adjusts the alarm threshold for the location, making the alarm generation more sensitive at high temporal shear values.

Microburst Detection.

The six remote wind units are used in the microburst detection algorithm. The 30 second running averages of the wind data are further smoothed by a numeric recursive filter.

To detect a microburst, the divergence of the wind field is calculated. Two methods of divergence calculation is employed: a one dimensional calculation along the line that connects two stations (edge), and a two dimensional calculation over a triangle defined by three stations.

The condition for an edge alarm between station I and station J is:

$$(v_i - v_j) \cdot r/l > \text{edge threshold}$$

where v_i and v_j are the wind vectors measured at locations i and j; r is the unit vector along the direction (i,j) and l is the length of the edge ij.

The condition for an alarm in a triangle formed by the i, j and k stations is:

$$\frac{y_1 \cdot u_2 - y_2 \cdot u_1 + v_1 \cdot x_2 - v_2 \cdot x_1}{2 \cdot \text{area}} > \text{triangle threshold}$$

where:

$$x_1 = x_j - x_i, \quad x_2 = x_k - x_i$$
$$y_1 = y_j - y_i, \quad y_2 = y_k - y_i$$
$$u_1 = u_j - u_i, \quad u_2 = u_k - u_i$$
$$v_1 = v_j - v_i, \quad v_2 = v_k - v_i$$