Weather Sensor Fault Detection with Time-Dependent Recursive Thresholds

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Abstract

This paper describes a methodology for self-tuning fault detection of meteorological measurements. The idea is to utilize recursive least squares – Kalman filter combination to filter the measurements and use the residual to detect the possible erroneous measurements. The alarm thresholds for suspicious are designed to be recursive and adaptive.

1. Introduction

For everyday safety and life, people, and several types of businesses require information on the short-term development of local weather. The typical phenomena include thunderstorms, fog, temperature inversions and sea breeze. In very short term, these phenomena are forecasted with nowcasting techniques. Nowcasting is usually considered in 0-6 hour timeframe and in few kilometers spatial domain.

Observations are necessary prerequisites for weather forecast models. The recent development of advanced and inexpensive equipment has made possible to measure meteorological phenomena densely in large weather station networks with short measurement interval, thus offering new possibilities in weather analysis and nowcasting.

New types of measurement networks and temporally and spatially increased amount of data bring up also challenges. The incoming flow of in-situ surface observations can easily be in different order of magnitude than before. The final data quality control of all differing measurements has traditionally been left to human experts, meteorologists [4].

The requirement for human process supervision is essential also in the future, but the number of human quality controlled measurement points should be kept at minimum with new automated algorithms and applications. In automated quality control, traditionally the simplest and widely used single station methods have included various limit checks and parameter cross-comparisons.

The request for meteorological metadata is steadily increasing. The measurement values alone are incomplete. Indicators of the measurement quality and uncertainty must accompany the actual measurement values. This type of metadata can be deduced from various quality assurance methods.

Meteorological observation networks are likely to develop towards autonomous dynamic data processes. For instance, there is need for adaptive data collection strategies depending on the weather patterns but also a requirement to incorporate automatic fault detection methods deeper into maintenance processes. It is also not uncommon instruments to be broken by, *e.g.*, a lightning or a bird. Some devices are sensitive to icing or radio frequency disturbances. Error sources are numerous all the incidents cause errors in the meteorological data.

Sudden fault maintenance actions in a surface weather station network are costly, which is further emphasized in hard to reach and harsh environments like communication masts or lighthouses at the sea. Timely detection and analysis of problems and corresponding selection of the most efficient maintenance decisions make a significant difference in daily operations and economically.

The weather measurements utilized in this paper are from the Helsinki Testbed -mesoscale measurement network in the coastal part of southern Finland [1], which is led by Finnish Meteorological Institute and Vaisala measurements company. In 2005, the existing Finnish weather observation network was supplemented with nearly 60 stations equipped with Vaisala WXT510 weather transmitters. Of these stations, 42 consist of cellphone base station masts, converted to meteorological towers by installing weather transmitters on them at least at two levels per mast. The results of this study directly serve the idea behind a testbed in refining quality assurance techniques.

This paper is organized as following. The overview of the proposed fault detection system is taken in Section 2. Mathematical details of residual generation

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and recursive alarm thresholds are presented in Sections 3 and 4, respectively. Examples are given in Section 5 and conclusions are drawn in Section 6.

2. Fault detection overview

In contrast to control engineering applications, the weather sensor fault detection has a few special features. Namely, the phenomenon itself, weather, can be non-linear and time-varying. The local fault detection model for the weather measurement can change drastically and disturbances can be very large. Therefore the changes in measured weather parameters cannot be predicted accurately based on a single measurement. This brings up main the problem – how to separate measurement errors out of natural weather phenomena.

The outline of the proposed fault detection is drawn in Figure 1. The preprocessing stage takes care of the most obvious faults, based on step and consistency checks similar to the ones applied in operational use in Finnish Meteorological Institute [4] and Oklahoma Mesonet [10]. As a weather station network, the latter one has many characteristics similar to the Helsinki Testbed.

After the preprocessing, our approach [5] is to use recursive least squares (RLS) method [2] to update an autoregressive model for the measurement in interest. This model is applied as the corresponding state-space representation in Kalman filter (KF) [3].

This approach has a few advantageous characteristics. Firstly, the RLS update takes the time-varying nature of the phenomenon into account. Secondly, the Kalman filter supplies the optimal linear estimation. However, since KF has strict conditions for *e.g.* noise, some data preprocessing must be done in order to remove the most obvious outliers.

After the filtering has generated the residual, this residual can be compared to alarm thresholds. Our idea is to use standard quality monitoring 3σ-limit, where σ refers to the standard deviation of the residual. If the residual is too large, the measurement can be flagged as erroneous or suspicious.

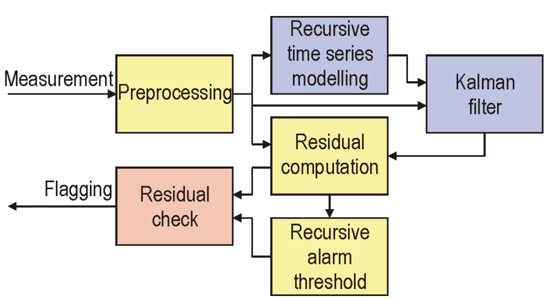

Figure 1: Outline of the measurement flagging.

3. Residual generation

As mentioned in the above, the residual formation starts with RLS modelling of the measurement. The RLS method is chosen in order to guarantee the adaptation to the sometimes rapidly changing weather. After that KF is used to make filtered estimate on the measurement, and the corresponding filtering residual is used as a fault detection residual. Extensive reviews of residual generation techniques can be found in [6] and [7].

The RLS model is based on estimation of autoregressive model

$$\mathbf{x}(k+1) = \mathbf{A}(k)\mathbf{X}(k)\,, \tag{1}$$

where $\mathbf{A}(k)$ = [$\mathbf{A}_0(k)$ … $\mathbf{A}_m(k)$] is the RLS-updated coefficients and $\mathbf{X}(k)$ = [$\mathbf{x}^T(k)$ … $\mathbf{x}^T(k\text{-}m)$]^T are the corresponding m – 1 latest measurements. $\mathbf{x}(k)$ is the measurement vector at time k of size n x 1. $\mathbf{A}(k)$ matrix is updated according to RLS equations

$$\gamma(k) = \frac{\mathbf{C}(k)\mathbf{X}(k)}{\mathbf{X}^T(k)\mathbf{C}(k)\mathbf{X}(k)+\beta}\,,$$
$$\mathbf{A}(k+1) = \mathbf{A}(k) + \gamma(k)\big(\mathbf{x}(k+1) - \mathbf{A}(k)\mathbf{X}(k)\big)\,,$$
$$\mathbf{C}(k+1) = \big(\mathbf{I} - \gamma(k)\mathbf{X}(k)\big)\mathbf{C}(k)\big/\beta\,,$$

where $\gamma(k)$ is the update gain, $\mathbf{C}(k)$ is the inverse of the covariance matrix of the variables in $\mathbf{X}(k)$, β is the forgetting factor, and $\mathbf{I}$ is a unit matrix. The forgetting factor β is chosen from the range (0, 1], usually close to one.

The Kalman filter can be applied to the model (1), when the model taken into state-space representation. Let's define matrices $\mathbf{\Phi}$ and $\mathbf{H}$ by

$$\mathbf{\Phi}(k) = \begin{bmatrix} \mathbf{A}(k) \\ \mathbf{0}_{nmxn} \quad \mathbf{I}_{nm} \end{bmatrix} \text{ and } \mathbf{H} = \begin{bmatrix} \mathbf{I}_n & \mathbf{0}_{nxmn} \end{bmatrix},$$

where $\mathbf{0}_{nxm}$ is a n x m zero matrix, and $\mathbf{I}_n$ is an n x n unit matrix. Now the RLS model (1) can be written in a state space representation

$$\begin{cases} \mathbf{X}(k+1) = \mathbf{\Phi}(k)\mathbf{X}(k) + \mathbf{w}(k) \\ \quad \mathbf{x}(k) = \mathbf{H}\mathbf{X}(k) + \mathbf{v}(k) \end{cases} \tag{2}$$

where $\mathbf{w}$ and $\mathbf{v}$ are independent unknown process and measurement noises with $\mathbf{w}(k) \sim N(0,\mathbf{Q}(k))$, $\mathbf{v}(k) \sim N(0,\mathbf{R}(k))$, $\mathbf{\Phi}(k)$ and $\mathbf{H}$ are the state transition matrix between time steps k and k + 1, and the observation matrix.

The Kalman filter equations are

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$$\hat{\mathbf{X}}(k+1\,|\,k)=\mathbf{\Phi}(k)\hat{\mathbf{X}}(k\,|\,k)\,,$$
$$\mathbf{P}(k+1|k)=\mathbf{\Phi}(k)\mathbf{P}(k|k)\mathbf{\Phi}(k)^{T}+\mathbf{Q}(k)\,,$$
$$\mathbf{K}(k+1)=\mathbf{P}(k+1\,|\,k)\mathbf{H}^{T}\left(\mathbf{H}\mathbf{P}(k+1\,|\,k)\mathbf{H}^{T}+\mathbf{R}(k)\right)^{-1},$$
$$\mathbf{P}(k+1\,|\,k+1)=\left(\mathbf{I}-\mathbf{K}(k+1)\mathbf{H}\right)\mathbf{P}(k+1\,|\,k)\,,$$
$$\hat{\mathbf{X}}(k+1\,|\,k+1)=\hat{\mathbf{X}}(k+1\,|\,k)+\mathbf{K}(k+1)\left(\mathbf{x}(k+1)-\mathbf{H}\hat{\mathbf{X}}(k+1\,|\,k)\right).$$

The noise covariance matrices **Q** and **R** are estimated recursively. The filtered measurement $\hat{\mathbf{x}}(k|k)$ corresponding to the measurement $\mathbf{x}(k)$ can solved by $\hat{\mathbf{x}}(k|k)=\mathbf{H}\hat{\mathbf{X}}(k|k)$. More details of this use of RLS-KF combination can be found in [5].

3.1 Data preprocessing

Some measurement errors may be so large that the KF assumptions of white process and measurement noises in (2) become violated. Therefore some data preprocessing must be done. Additionally, the most obvious errors are detected without need for further computations. The two applied of preprocessing tests are step and consistency checks.

The step checks monitor that the changes between successive measurements are within predefined limits. Unphysically large steps refer to an erroneous measurement. The consistency checks monitor whether the measurements are physically possible or not. Example constraints for temperature, barometric pressure, relative humidity and wind measurements are shown in Table 1.

Note that the presented constraints are not fine-tuned for Helsinki Testbed observations; they are for research stage only. In the operating system, the geography, historical extremes, season changes, measurement interval and meteorological dependencies must be taken more carefully into account. The corresponding Oklahoma Mesonet constraints can be found in [10].

Table 1: Examples of preprocessing check thresholds.

Measurement	Type	Constraint
Temperature	Step	$\|T(k) – T(k-1)\| > 3°C$
	Consistency	$T > 50°C, T < –50°C$
Barometric pressure	Step	$\|p(k) – p(k-1)\| > 2hPa$
	Consistency	p > 1200 hPa, p < 700 hPa
Relative humidity	Step	$\|RH(k) – RH(k-1)\| > 12\%$
	Consistency	RH < 10 %, RH > 110 %
Wind speed	Step	$\|WS(k) – WS(k-1)\| > 30$ m/s
	Consistency	WS > 40 m/s, WS < 0.1 m/s
Wind direction	Step	$\|WD(k) – WD(k-1)\| > 50°$, while $WS(k) > 5$ m/s

4. Recursive alarm thresholds

Since the noise in KF is assumed to be white, the residual should also be normal distributed. Hence, for example, 99.5% of points of a process variable should be within 2.81σ of expected value, where σ is the standard deviation. With this reasoning, 3σ-thresholds for residual are suitable in fault detection [8].

In here, deviations of several meteorological variables are dependent on the diurnal solar heating, as well as passing frontal patterns. Therefore the alarm threshold must also be time of day -dependent. In our case, sampling interval of 5 minutes corresponds to an alarm threshold vector with 288 entries. Similar diurnal variation is observed also in temperature in Oklahoma mesonet, and it reduces the reliability of temperature step checks significantly [10].

Since the magnitudes and variances of different weather measurements are very different, the recursive updates must include a few initialization stages. Firstly the magnitude of the variance must be determined. In the second stage, the subsequent are used for initialization of time-dependency of the variance. After that, the each entry of variance vector can be updated.

Mathematically, the initialization stage of residual variance estimate $\hat{\sigma}$ is

$$\hat{\sigma}^{2}(k)=\lambda_{i}\hat{\sigma}^{2}(k)+\left(1-\lambda_{i}\right)\left(x(k)-\hat{x}(k)\right)^{2}, \qquad (3)$$

where λ_i is a forgetting factor. The initialization stage of time-of-day-dependency is done by using zero-order-hold in a few measurement periods for a day after the initialization (3) has converged.

After the initialization stages, the normal function is to update the variance as in (3). Moreover, in order to guarantee not having too much unnecessary alarms, the variance update is not done symmetrically, but

$$\hat{\sigma}^{2}(k)=\begin{cases}\lambda_{u}\hat{\sigma}^{2}(k-288)+\left(1-\lambda_{u}\right)\left(x(k)-\hat{x}(k)\right)^{2}, \\ \qquad \text{if } \left|x(k)-\hat{x}(k)\right|>\hat{\sigma}(k-288), \\ \lambda_{d}\hat{\sigma}^{2}(k-288)+\left(1-\lambda_{d}\right)\left(x(k)-\hat{x}(k)\right)^{2}, \\ \qquad \text{if } \left|x(k)-\hat{x}(k)\right|\le\hat{\sigma}(k-288),\end{cases} \qquad (4)$$

where λ_u and λ_d are forgetting factors chosen as $\lambda_u < \lambda_d$. Note that (4) requires keeping the previous 288 variance values in memory.

It must also be taken into account that the variance update (4) is sensitive to randomly occurring large residual values. Hence a temporal smoothing should be done. Our suggestion for temporal smoothing in step k is

$$\hat{\sigma}_s^2(k-2)=\lambda_2\hat{\sigma}^2(k-2)+(1-\lambda_2)\hat{\sigma}^2(k),$$
$$\hat{\sigma}_s^2(k-1)=\lambda_1\hat{\sigma}^2(k-1)+(1-\lambda_1)\hat{\sigma}^2(k),$$
$$\hat{\sigma}_s^2(k)=\lambda_0\hat{\sigma}^2(k)+\lambda_{10}\hat{\sigma}^2(k-1)+(1-\lambda_0-\lambda_{10})\hat{\sigma}^2(k-2),$$

where $\hat{\sigma}_s^2$ refers to a smoothed variance estimate, and λ_2, λ_1, λ_0 and λ_{10} are forgetting factors. After the smoothing, the original variance estimates are replaced by the smoothed ones.

In our examples, we have used the initialization stage of 4 hours, and the time-of-day-initialization stage of three days. The variance estimation forgetting factors λ_i, λ_u and λ_d are chosen as 0.9, 0.95 and 0.975, respectively. The temporal smoothing forgetting factors λ_2, λ_1, λ_0 and λ_{10} are chosen to be 0.99, 0.9, 0.89 and 0.1, respectively. An example 3σ-threshold initialization and adaptation is shown in Figure 2.

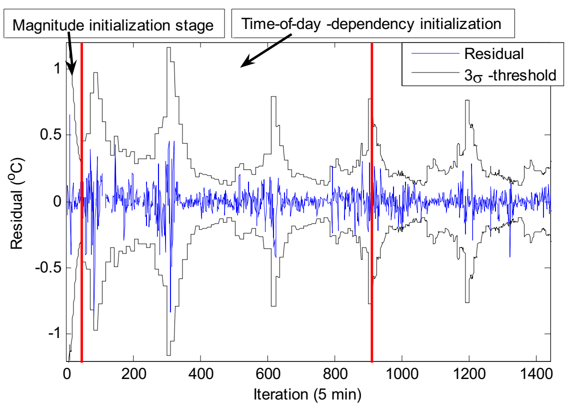

Figure 2: An example of recursive alarm threshold initialization for temperature.

5. Examples

This section includes examples of the proposed residual and alarm threshold forming solution. Relative humidity, barometric pressure and temperature examples are drawn in Figures 3, 4 and 5, respectively. In each figure, upper part includes the measurement in black and filtered result in red. The lower parts have the residual in red and 3σ-threshold in black.

Detection of errors in relative humidity can be very tedious. In the Figure 3, the normal daily variations cause threshold crossing residuals, but also residuals of a few noisy measurements are over the threshold. Interestingly, magnitude of 3σ-threshold is clearly tighter when compared to sensor accuracy specification (±3% below 90% RH and ±5% in range 90-100% RH) [9].

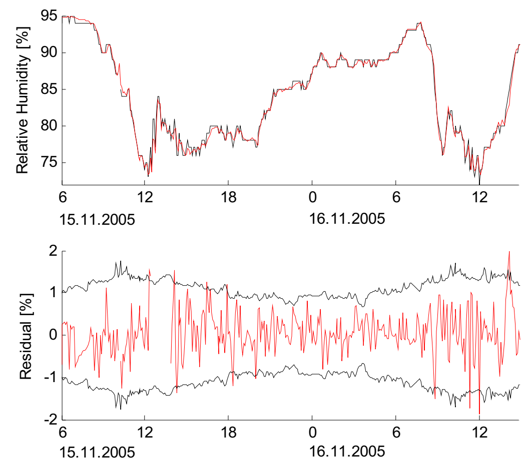

Figure 3: An example on relative humidity.

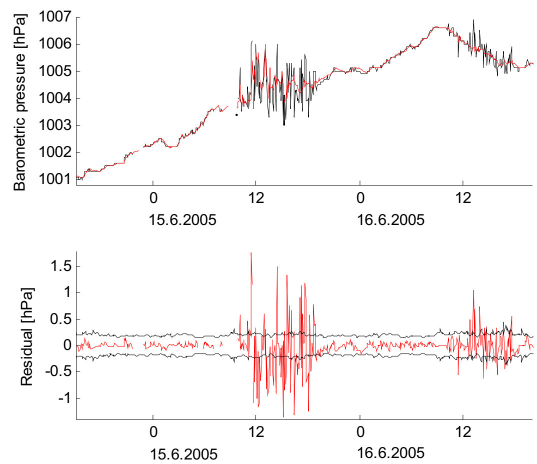

Figure 4: An example on barometric pressure.

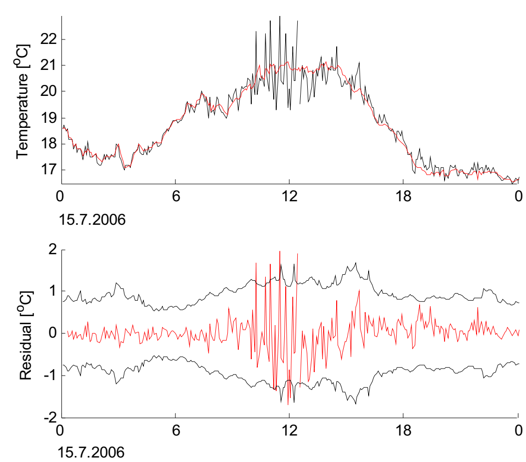

Figure 5: An example on temperature.

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While realizing threshold test does not reveal absolute sensor accuracy, this example suggests chosen threshold may be unnecessarily strict for sensor type in question. To reduce false alarms, supplemental rules for consecutive data points or 4σ-threshold may be applied.

The barometric pressure and temperature examples in Figures 4 and 5 are taken from a station suffering from occasional water inside the radiation shield. In both cases, water causes distinct noise in observations, which is detected by recursive thresholds.

Residual threshold for pressure is again tighter than sensor accuracy specification (±0.5 hPa at 0-30 ºC [9]). Residual spikes, however, now often exceed both the threshold and given accuracy. Contrasting the previous two parameters, temperature sensor accuracy (±0.3 ºC at 20 ºC [9]) is consistently better than 3σ-threshold. There are basically two reasons for this. Firstly, the water leakage problem has increased recursively adapted thresholds. Secondly, the temperature as a phenomenon has larger temporal variations than barometric pressure.

Interestingly, the increase of the thresholds due to a fault is a blessing in a disguise for a fault detection. Even though an increased threshold causes fewer alarms, an increase in residual variance and the corresponding threshold is valuable information itself. If one station has much larger and unexplainable residual variation than the others, it is likely that this station is suffering from a fault.

It should be noted that the proposed technique detects well only spike errors and noise. For example, detection of bias and drift must be done with additional techniques taking advantage of the spatial and temporal density of mesoscale measurement network. Possible solution is application of spatio-temporal techniques (*e.g.* Barnes weighting [11]) to estimate permanent and significant difference to neighbor stations.

6. Conclusions

All in all, the proposed recursive threshold technique works well for different meteorological measurements. The technique detects spikes and noise effectively in the measurements, which are being passed by preprocessing. However, all measurements causing residuals over the threshold can not be flagged erroneous or even suspicious.

Additionally, the thresholds give a valuable insight on excessive noise in the measurements, which is important knowledge while determining the maintenance needs of weather stations. In addition to the fault detection, the research is aiming to life-cycle and reliability estimation of the weather stations.

7. References

[1] W. Dabberdt, J. Koistinen, J. Poutiainen, E. Saltikoff, H. Turtiainen, "The Helsinki Mesoscale Testbed - An Invitation to Use a New 3-D Observation Network", *Bulletin of the American Meteorological Society*, Vol. 86, no. 7, pp. 906-907, 2005.

[2] J. Holst, *Adaptive Prediction and Recursive Estimation*, Department of Automatic Control, Lund Institute of Technology, Sweden, 1977.

[3] G.C. Goodwin, K.S. Sin, *Adaptive Filtering Prediction and Control*, Prentice-Hall, NJ, USA, 1984.

[4] F. Vejen (ed.), C. Jacobsson, U. Fredriksson, M. Moe, L. Andersen, E. Hellsten, P. Rissanen, Þ. Pálsdóttir, Þ. Arason, *Quality Control of Meteorological Observations*, Nordklim report, 2002, http://www.smhi.se/hfa_coord/nordklim/task1/quality_control.pdf.

[5] V. Hasu, J. Poutiainen, H. Koivo, "Self-Tuning Recursive Modelling And Estimation Of Weather Measurements", *Proc. MATHMOD 2006*, Vienna, Austria, 2006.

[6] V. Venkatasubramanian, R. Rengaswamy, K. Yin, S.N. Kavuri, "A review of process fault detection and diagnosis – Part I: Quantitative model-based methods", *Computers and Chemical Engineering*, vol. 27, pp. 293-311, 2003.

[7] P.M. Frank, "Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy- A survey and Some New Results", *Automatica*, vol. 26, no. 3, pp. 459-474, 1990.

[8] L.H. Chiang, E.L. Russell, R.D. Braatz, *Fault Detection and Diagnosis in Industrial Systems*, Springer-Verlag, London, 2001.

[9] Vaisala, 2005, "Weather Transmitter WXT510 User's guide.M210470EN-B", Helsinki, Finland, 2005.

[10] C.A. Fiebrich, K.C. Crawford, "The Impact of Unique Meteorological Phenomena Detected by Oklahoma Mesonet and ARS Micronet on Automated Quality Control", *Bull. Am. Meteor. Soc.*, vol. 82, no. 10, pp. 2173-2187, 2001.

[11] S.L. Barnes, "Applications of the Barnes objective analysis scheme. Part I: Effects of undersampling, wave position, and station randomness", *J. Atmos. Oceanic Technol.*, vol. 11, pp. 1433-1448, 1994.

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