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Atmospheric Measurement Techniques
Discussions

Interactive comment on "Mobile sensor network noise reduction and re-calibration using Bayesian network" *by* Y. Xiang et al.

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Thank you very much for your comments. Indeed they are very relevant and can help improve the quality of the paper substantially. I am currently working on the improved contents of the paper. However, I think some of the general remarks can be answered before the revision is done.

1, It is mentioned that the M-Pods measure relative humidity, but these measurements are not used in the analysis of the results. To my knowledge, many low-cost sensors show a non-linear response to changes in RH. Did the researchers experience problems with this, and if yes, can the proposed method be used to compensate for it?

Yes, the relative humidity is measured. However, during our test, we found that for

the sensors we used, the correlation of RH to the sensor readings is not as significant as temperature. There are many possible reasons for that. It could be that because the sensors we are using usually operates at very high temperature, which makes the temperature fluctuation more dominant. But the detailed reason is still unknown to us.

2, After noise removal, the M-Pod data stream is binned in one-minute intervals (Section 7.1.2). How does this time period relate to the response time of the different gas sensors to ambient concentrations? If the response time is longer than one minute, the time series will be strongly auto-correlated. Although this auto-correlation might be negligible for slowly varying signals (for instance during the side-by-side calibration period), it might become important for rapidly varying signals, for instance when the sensors are used in mobile applications. Does the proposed recalibration method suffer from auto-correlated signals?

This is a very interesting point. The metal-oxide sensors we are using are actually quite sensitive to the pollutants. They respond typically within seconds. Therefore, during our experiment, we do not suffer the auto-correlation problem. However, I agree that for rapid changing signals and slow responding sensors, this could well be a problem. I think we can use a more flexible averaging interval to solve this problem. The details of such techniques is out of the scope of this work and can be explored in the future work.

3, The Bayesian network derives the conditional probability densities from a training period. How does the network react for new air pollution events (e.g. extreme winter or summer smog episodes) which were not included in the training set?

The Bayesian network must be pre-trained to be working. Therefore, it cannot handle the unmet air pollution events. However, since the requirement for the training set is that it should be the normal data without errors, it is possible to train the Bayesian network on the fly if we can pre-calibrate the sensors before the new event.

4, Throughout the paper it is mentioned that the error of the measurements increases when the sensor drifts. This is true of course, but these error are strongly biased. It would be better to make a clearer distinction between the error contribution due to bias and due to a random component.

The Bayesian network just gives an estimation of ground truth value and cannot distinguish between bias and random noise. They can be distinguished during post processing. For example, if the mean of the error during a long enough time period is constantly positive or negative, we can consider this as drift. We are not making this distinction in the paper because 1), the sensor readings are pre-processed and most of the random noises are filtered out and 2), the drift is the relatively dominant noise in our experiment.

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