Dynamic Gas Sensor Network for Air Pollution Monitoring and Its Auto-Calibration

Wataru Tsujita
Department of Physical Electronics
Tokyo Institute of Technology
Tokyo, JAPAN
wtsujita@mn.ee.titech.ac.jp

Hiroshi Ishida
Dept. of Mechanical Systems Engineering
Tokyo Univ. of Agriculture and Technology
Tokyo, JAPAN
h_ishida@cc.tuat.ac.jp

Toyosaka Moriizumi
Department of Physical Electronics
Tokyo Institute of Technology
Tokyo, JAPAN
mori@mn.ee.titech.ac.jp

Abstract

The use of a dynamic gas sensor network is proposed for air pollution monitoring, and its auto-calibration is discussed to achieve the maintenance-free operation. Although the gas sensor outputs generally show drift over time, frequent recalibration of a number of sensors in the network is a laborious task. To solve this problem, instead of the static network proposed in the related works, we propose to realize a dynamic gas sensor network by, e.g., placing sensors on vehicles running on the streets or placing some of them at fixed points and the others on vehicles. Since each sensor in the dynamic network often meets other sensors, calibration of that specific sensor can be performed by comparing the sensor outputs in such occasions. The sensors in the whole network can thus be calibrated eventually. The simulation results are presented to show that adjusting the sensor outputs to the average values of the sensors sharing the same site improves the measurement accuracy of the sensor network.

Keywords

gas sensor, sensor network, auto-calibration, environmental monitoring

1. INTRODUCTION

Air pollutions are serious problems in the world. The present environmental monitoring instruments are expensive and bulky. The cost and size of them limit the number of monitoring sites so that the details of the formation and transport of pollutant clouds cannot be monitored. To reduce the cost and the size of the instruments, many researchers in the world have been developing gas sensors and sensor systems for air pollution monitoring [1]–[3].

Once such a gas sensor system is realized, a dense environmental monitoring network can be easily built by putting a number of gas sensor systems. However, the lack of long-term stability of the gas sensor outputs is an inevitable problem, which causes the deterioration of the measurement accuracy over time. The frequent recalibration of a number of individual sensors in the network is a time-consuming and laborious task. Calibration of physical sensor networks have already been proposed, which take advantage of duplicated measurements among the sensors [4], [5]. The errors contained in the outputs of physical sensors are generally well characterized, and reliable models for signal transport, e.g., propagation of light, are often provided. Therefore, sensors placed at different sites can be calibrated by considering the signal transport between them and comparing their outputs. On the other hand, the gas sensor output is influenced by various factors including variations in the weather condition, interference gases, and aging. Even if several gas sensors are exposed to the same gas concentration, the different sensor outputs might be measured. However, characterization of all such factors is difficult to attain. In a static gas sensor network, since the transport model of the gas concentration, i.e., the atmospheric diffusion, is not established, sensor outputs measured at different sites can not be directly compared for purpose of the calibration of the sensors.

Here we propose to use a dynamic gas sensor network for air pollution monitoring, and its auto-calibration is discussed to achieve the maintenance-free operation. The dynamic gas sensor network consists of a number of gas sensors including different types (e.g., metal oxide sensors, QCM sensors, and an electrochemical sensors) for monitoring a single target gas. The recent advances in the MEMS technology will enable the development of miniaturized sensor nodes for the dynamic network. Intensive research is being done to develop wireless sensor network by using the MEMS technologies [6], [7].

If gas sensors are placed on vehicles running on the streets, the gas sensors can be moved nearly at random. At some frequency, each gas sensor encounters other gas sensors and they share a single location. Since several types of gas sensors are used in the network, the characteristics of the measurement error are different. Some of the sensor outputs are lower than real gas concentration and the others are higher than real concentration, although they are exposed to the same gas concentration at the same site. The calibration of the gas sensors can be conducted by comparing the sensor outputs sharing the same sites at a single moment. If at least some sensors moved, the others may be placed at fixed points. The same calibration procedures can also be applied.

In this paper, the calibration of dynamic gas sensor network is presented. The effect of proposed calibration method in an idealized case is evaluated by a simulation.

2. SIMULATION

2.1. Simulation setup

The simulation setup is shown in Figure 1. The field is meshed into 10 by 10 grids. Gas sensors and environmental monitoring stations are distributed in the field. Each sensor is allowed to move to one of the neighboring grid points at random in a step time. In this simulation, the movement of the gas sensors are restricted to only 4 directions (up, down, right, and left). The stations are fixed at their initial locations and play a role that the environmental monitoring stations will do in real-life situations. They provide accurate gas concentration values all the time. When a gas sensor comes to the location of a monitoring station, the concentration value at the station can be used for calibrating the sensor output.

Figure 2 shows the distribution of gas concentration in the simulation field. It is assumed for simplicity that the distribution does not change with time.

2.2. Gas sensor output model

The gas sensor output is influenced by many factors, e.g., temperature variation, humidity variation, the presence of an interference gas, and drift. From the view point of attaining the long-term stability, gas sensor drift is the most serious problem [3]. As a first step toward the dynamic calibration of the gas sensor network, here we deal with the drift problem. Since the dynamic gas sensor network under consideration consists of several types of gas sensors, it is expected that some of the sensors show positive drifts causing gradual increase of the sensor outputs and the others show negative drifts causing gradual decrease of outputs.

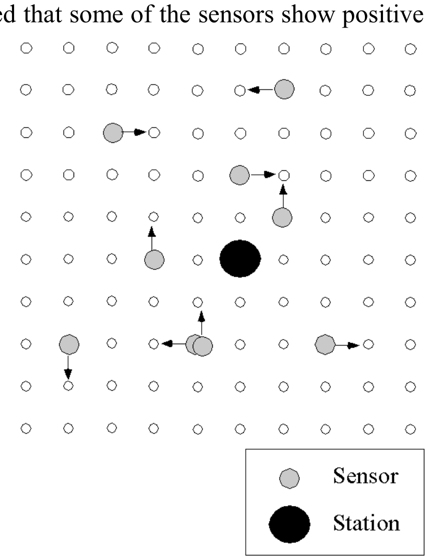


Figure 1. Simulation setup

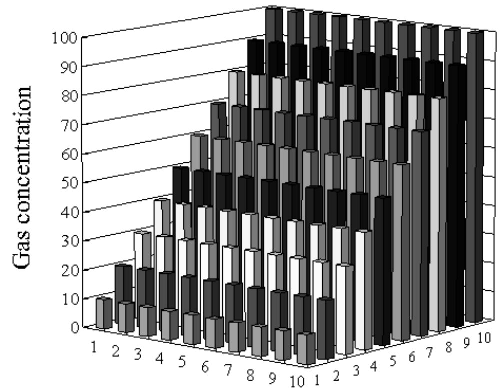


Figure 2. Distribution of gas concentration

In the simulation, each sensor output is assumed to show constant drift. A fixed drift rate is preset for each sensor by choosing a random number from a uniform distribution on the interval between -1 and 1. The raw output of gas sensor i at time t is represented as

$$C_m{}^i(t) = C_t + d^i \times (t-1), \qquad (1)$$

where C_t is a true concentration at the location of the sensor. d^i is the drift rate of gas sensor i. The error between the raw gas sensor output and the true concentration continues to increase when the time passes. To compensate for the gas sensor drift, a calibration term is added to the raw gas sensor output as

$$C_c{}^i(t) = C_m{}^i(t) + \alpha^i, \qquad (2)$$

where $C_c{}^i(t)$ is the calibrated output of gas sensor i, and α^i is the calibration parameter of gas sensor i.

2.3. Auto-calibration method

When sensors i_1, i_2, $\cdots$, i_k happen to encounter at the same grid, an estimate of the true concentration value has to be obtained from the outputs of those sensors. Here, the average value of those sensor outputs is calculated, and used as the estimate of the true gas concentration at that grid, $C_{estimated}(t)$.

$$C_{estimated}(t) = \frac{C_c^{i_1}(t) + \cdots + C_c^{i_k}(t)}{k} \quad (3)$$

On the other hand, when sensors happen to come the location of an environmental monitoring station, the true concentration value at the site is provided by the station. Therefore,

$$C_{estimated}(t) = C_r \quad (4)$$

Calibration parameter of each gas sensor can be updated using the estimated gas concentration as follows:

$$\alpha^i = C_{estimated}(t) - C_m^{\ i}(t) \quad (5)$$

3. RESULTS

The simulations were performed for various combinations on the number of gas sensors and the stations to evaluate the proposed auto-calibration method. MATLAB ver. 6 (The MathWorks, Inc.) was used for calculation. The gas sensors were moved for 500 step times. The simulation was done 10 times for each combination of the number of sensors and stations. Figure 3 shows one of the simulation results when fifty sensors and four stations were placed in the field. Although the raw gas sensor output increased gradually as a function time and the measurement accuracy was deteriorated, the calibrated gas sensor output kept good agreement with the true gas concentration.

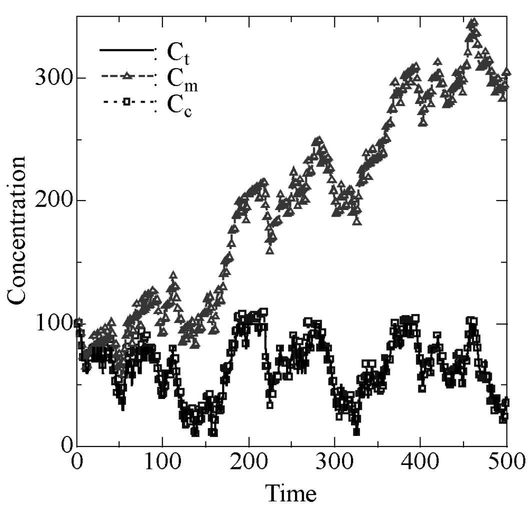


Figure 3. Comparison of the true concentration (C_t), raw sensor output (C_m), and calibrated sensor output (C_c). Fifty sensors and four stations were distributed in the field.

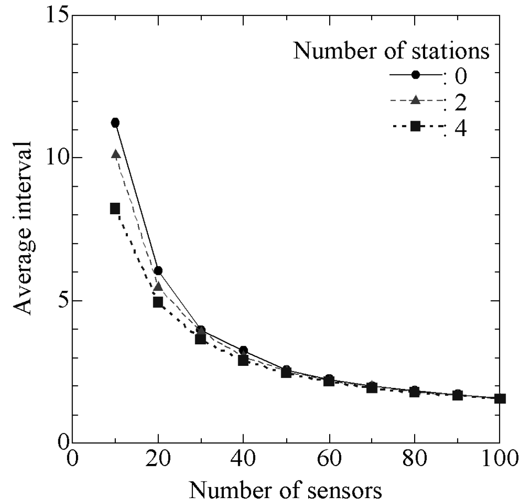


Figure 4. Relationship between the number of sensors and average time interval between two successive encounter with other sensors or stations.

An average time interval from an encounter of a sensor with other sensors or stations to the next encounter was calculated for each simulation setup, and the result is summarized in Figure 4. The increase of the number of sensors makes the encounter interval shorter. Adding the station into the field reduces the time interval only when the number of sensors is comparable with that of the stations.

The relationship between the number of sensors and the root mean square (RMS) error in the sensor outputs after the sensors were moved 500 times is shown in Figure 5. The RMS error in C_m and C_c were calculated as

$$RMSerrorinC_m = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_m^{\ i} - C_t^{\ i}\right)^2} \quad (6)$$

and

$$RMSerror\,in\,C_c = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_c^{\ i} - C_t^{\ i}\right)^2}\ , \quad (7)$$

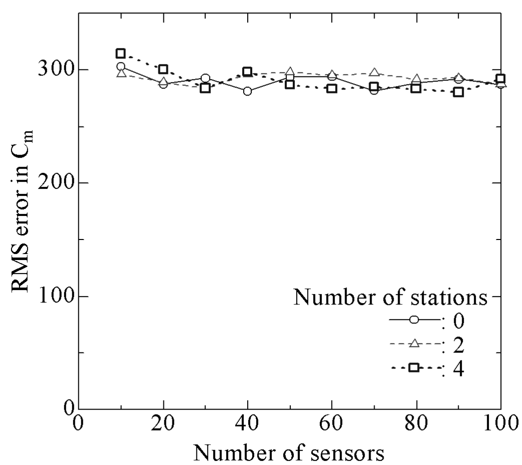
where N is the total number of the gas sensors. $C_t^{\ i}$ represents the true gas concentration at the location of gas sensor i .

Auto-calibration among the gas sensors was proved effective for reducing the RMS error. Although the RMS errors in the raw sensor outputs (C_m) are large for all simulations, the errors in the calibrated sensor outputs (C_c) are significantly small. Adding the stations further reduced the error in C_c . Even a small number of stations turned out to have a large impact on the measurement accuracy of the whole sensor network.

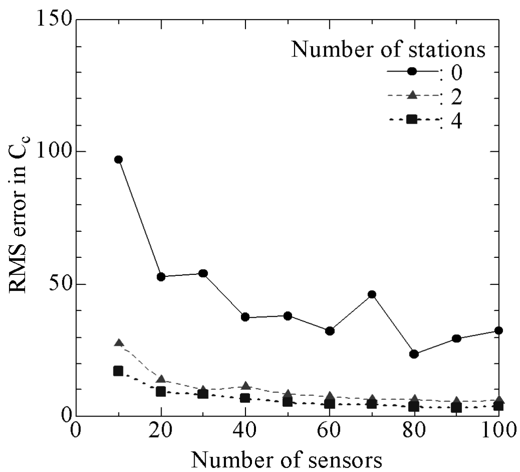
4. CONCLUSION

The dynamic gas sensor network for monitoring air pollutions was proposed. The auto-calibration of gas sensors by adjusting the sensor outputs to the average value of the sensors that share the same site was evaluated by the simulations. The results showed that the proposed calibration method was promising to accomplish maintenance-free operation of a number of gas sensors.

It should be noted that changes in the gas concentration distribution in the field has no effect on the proposed calibration method for the sensors showing baseline drifts. If the sensors also exhibit sensitivity deterioration, for example, different calibration scheme is required. The future work will be addressed to more complicated gas sensor models having more than two calibration parameters.



(a) RMS error in C_m



(b) RMS error in C_c

Figure 5. Relationship between the number of sensors and root mean square (RMS) errors in sensor outputs, after sensors were moved 500 times.

REFERENCE

[1] Y. Maruo, et al., "Measurement of local variations in atmospheric nitrogen dioxide levels in Sapporo, Japan, using a new method with high spatial and high temporal resolution", Atmospheric Environment, Vol. 37, pp. 1065–1074, 2003.

[2] T. Becker, et al., "Air pollution monitoring using tin-oxide-based microreactor systems", Sensors and Actuators B, Vol. 69, pp. 108–119, 2000.

[3] W. Tsujita, et al., "Sensor Network for Atmospheric Environmental Monitoring and its Auto-calibration", Proceedings, Int. Conf. Electrical Engineering, Vol. 3-1, pp. 132–135, 2004.

[4] J. Feng, et al., "Model-Based Calibration for Sensor Network", Proc. IEEE Sensors, Vol. 2, pp. 737–742, 2003.

[5] K. Whitehouse, el al., "Calibration as Parameter Estimation in Sensor Networks", Proc. ACM Int. Workshop Wireless Sensor Networks and Applications, 2002.

[6] B. Warneke, et al., "Smart Dust: Communication with a Cubic-Millimeter Computer", Computer, Vol. 34, No. 1, pp. 44–51, 2001

[7] A. Mainwaring, et al., "Wireless Sensor Networks for Habitat Monitoring", Proc. ACM Int. Workshop Wireless Sensor Networks and Applications, 2002.