CHEMICAL ENGINEERING TRANSACTIONS

VOL. 68, 2018

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Selena Sironi, Laura Capelli
Copyright © 2018, AIDIC Servizi S.r.l.
ISBN 978-88-95608-65-5; **ISSN** 2283-9216

DOI: 10.3303/CET1868031

Odor Identification and Data Transmission Method of Harmful Gas in Chemical Environment

Qiong Wu, Yunbo Shi*, Xinmiao Lu

The higher educational key laboratory for Measuring & Control Technology and Instrumentations of Heilongjiang Province, School of Measurement-Control Tech & Communications Engineering, Harbin University of Science and Technology, Harbin, 150080, China
yunbo_shi@126.com

In the petrochemical and coal chemical industries, in order to avoid production accidents caused by harmful gas leakage, this paper uses a kind of AlN-based semiconductor MEMS four-array sensor to identify the four kinds of harmful gases of Cl_2, CO, NO_2 and SO_2. Through wireless sensor network, it uses the iterative smoothing l_0 norm minimization algorithm to compress and reconstruct the odor identification data, and finally realizes the odor identification and data transmission in the chemical environment. The experimental results show that the method used in this paper reconstructs the odor identification data with less observations. While reducing the data collection cost of the wireless sensor network, it can effectively identify and detect harmful gases to achieve the purpose of risk warning.

1. Introduction

As is known to all, there are always various harmful gases in petrochemical production equipment. Once these gases leak and accumulate in the surrounding environment, they will form major potential risks, which may cause burning, explosion, damage to production equipment, personal poisoning and casualties, pollution to natural environment and other serious consequences (Wu et al., 2016).In the petrochemical and coal chemical industries, accidents and disasters caused by the leakage of harmful gases often occur, improper early prevention and later disposal would cause irreparable and serious consequences (Tjalvin et al., 2016).Therefore, in order to avoid the occurrence of production accidents caused by the leakage of harmful gases, it is necessary to set up harmful gas smell identification equipment at the place where gas leakage may occur at the production site, so as to timely discover the gas leakage and alert early warning to ensure personal safety and production safety and avoid causing serious dangerous accidents (Kalus et al., 2017).

In recent years, wireless sensor network technology has attracted the attention of researchers, and its most important application is the monitoring of the environment (Rawat et al., 2014). A large number of gas sensors based on odor identification can form a wireless sensor network, each sensor is taken as a node to perform odor identification, and the collected data is transmitted to the central node through multi-hop routing (Candes et al., 2006, Chen et al., 2018). This process needs to consume a lot of storage space and energy. Due to the limited computing, power supply and storage capabilities of sensor nodes, it is necessary to establish an efficient data collection and transmission model to extend the life of the sensors as much as possible and reduce the cost of information acquisition (Razzaque et al., 2014, Yin et al., 2016).

To this end, this paper uses an AlN-based semiconductor MEMS four-array sensor to identify the four kinds of harmful gases of Cl_2, CO, NO_2 and SO_2 which are common in the chemical environment. By using the compressed sensing theory, this paper adopts the iterative smoothing l_0 norm minimization algorithm to compress and reconstruct the odor identification data, so as to achieve the objective of harmful gas identification and alarm.

2. Odor identification based on MEMS four-array sensor

MEMS process makes it easy to fabricate gas sensors with the temperature sensing components to ensure the excellent performance of gas sensors (Wang et al., 2018, Adam et al., 2016; Barrozo et al., 2018). In this

Please cite this article as: Wu Q., Shi Y., Lu X., 2018, Odor identification and data transmission method of harmful gas in chemical environment, Chemical Engineering Transactions, 68, 181-186 DOI: 10.3303/CET1868031

paper, AlN-based semiconductor MEMS four-array sensors are used to identify the four harmful gases of Cl_2, CO, NO_2 and SO_2, which are common in the chemical environment. The heating electrodes and signal electrodes of the sensor are prepared by using laser to etch the Pt film. The structure of the MEMS four-array gas sensor is a symmetrical design, and its basic structure is shown in Figure 1.

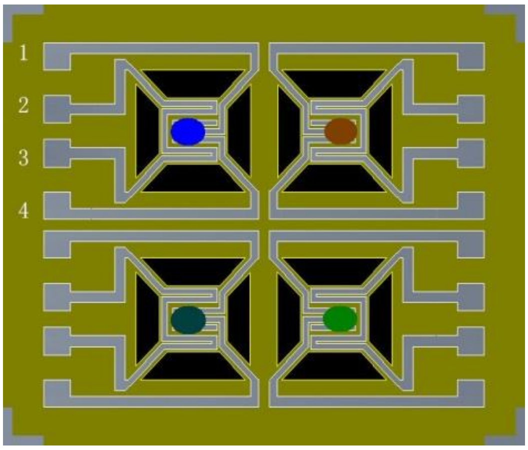

Figure 1: Diagram of MEMS-based four-array gas sensor

The SnO_2 nano gas sensing material selected in this paper is a resistance-controlled semiconductor gas sensing material. When the sensor is exposed to the gas to be tested, the oxygen adsorbed on the surface of the sensitive material will chemically react with the gases to be tested, and these chemical reactions will cause transfer of electric charges, which in turn leads to a change in the resistivity of the surface of the gas-sensitive material, by analyzing the change of resistivity we can achieve the detection of the gases to be tested.
Response time and recovery time of the sensor are important indicators to measure the pros and cons of the sensor. The gas sensing characteristics of the array unit a of the MEMS sensor used in this paper are shown in Figure 2. Taking CO as an example, the test uses 300ppm and 100ppm CO gas respectively. It can be seen from the figure that the response time of the sensor is about 8s, and the recovery time has a certain relationship with the gas concentration. For 300 ppm CO gas, the recovery time is more than 20s, while it only takes 15s to detach from 100 ppm CO gas. For the remaining array units, they all have the same characteristics.

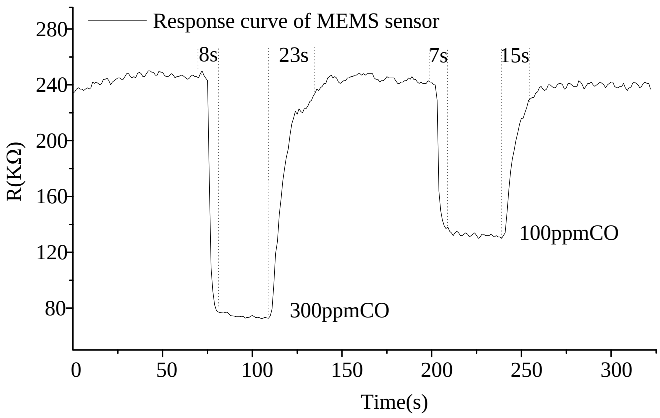

Figure 2: Response and recovery characteristic of MEMS sensor

The repeatability of the sensor directly affects the accuracy of the sensor, and is also an important technical indicator for determining the performance of the sensor. Taking NO_2 as an example, the MEMS sensor is tested for repeatability using the 13.3ppm and 80ppm NO_2 environments. The test results are shown in Figure 3. At 13.3 ppm concentration, the two test results were 178.2 kΩ and 182.7 kΩ, respectively. At 80 ppm concentration, the two test results were 410.2 kΩ and 413.6 kΩ, respectively. It can be seen from the figure that for the NO_2 gas, the MEMS sensor repeatability test curve is basically the same whether it is in a high concentration environment or a low concentration environment, and the repeatability is good.

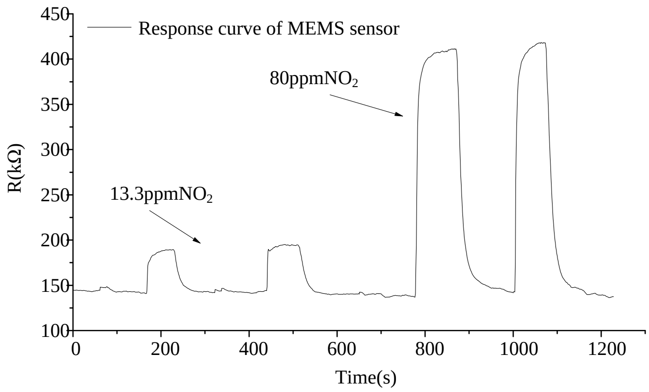

Figure 3: Curve repeatability of MEMS sensors in NO2 environment

3. Iterative smoothed l_0 norm minimization algorithm

In this paper, the ISL0 algorithm is used to realize the sensor node odor identification data collection reconstruction in the wireless sensor network.
The steps of the ISL0 algorithm are as follows:
(1) Enter: A,y
(2) Initialization: T is an empty set, $x^{(0)} = A^T\left(AA^T\right)^{-1} y$, the number of iterations is K, and the threshold value is $\beta = 2, k = 1$
(3) Algorithm iteration
Step 1 Solve the minimization problem using the descending iterative format $x^{(k+1)} = x^{(k)} - t^{(k)}\left(I - A^T\left(AA^T\right)^{-1}A\right)\nabla F_\delta(x)\Big|_{x=x^{(k)}}$ to obtain an estimate $x^{(k)}$
Step 2 Estimate the new support set based on $x^{(k)}$: $I^{(k+1)} = \left\{j\left|\left|x_j^{(k)}\right| \geq \left\|x^{(k)}\right\|\infty \middle/ \beta^k\right.\right\}$
Step 3 $T = \left(I^{(k)}\right)^C = \{1,2,\cdots,n\}/I^{(k+1)}$
Step 4 Let $k \leftarrow k = 1$, if $k \leq K$, then turn to step 1; otherwise, stop iterating
(4) Output: get estimated value $\hat{x} = x^{(K)}$

Generally, $\delta_j = \gamma\delta_{j-1}$, $j = 2,\cdots,J$, $\gamma \in (0.5,1)$ are taken. The selection of parameters δ_1 and δ_J will be discussed respectively as below. Make $\tilde{x} = \left\|x^{(0)}\right\|_\infty$. In order to make the algorithm converge faster, let the parameters δ_1 meet $f_\delta(\tilde{x}) = \frac{2}{\pi} arx\tan\left(\frac{\tilde{x}^2}{2\delta_1^2}\right) \leq \frac{1}{2} \Rightarrow \delta_1 \geq \frac{\tilde{x}}{\sqrt{2}}$

In order to save computing time, this study takes $\delta_1 = \left\|x^{(0)}\right\|_\infty / \sqrt{2}$. When $\delta_J \to 0$, $F_{\delta J}(x) \to \|x\|_0$, i.e., the smaller the δ_J is, the more the $F_{\delta J}(x)$ can reflect the sparsification of the vector x; however, at the same time, the more sensitive to noise it is. When there is noise, the δ_J value should not be too small so as to prevent hypersensitivity.

4. Experiment and result analysis

4.1 System model

The wireless sensor network system model is shown in Figure 4. Each node of the wireless sensor network performs odor identification, and the collected data is transmitted to the central node (sink) through multi-hop routing, and is uniformly aggregated to the server. On the server side, by running the iterative smoothing l_0 norm minimization data reconstruction algorithm, it achieves the reconstruction of data collected from each sensor node.

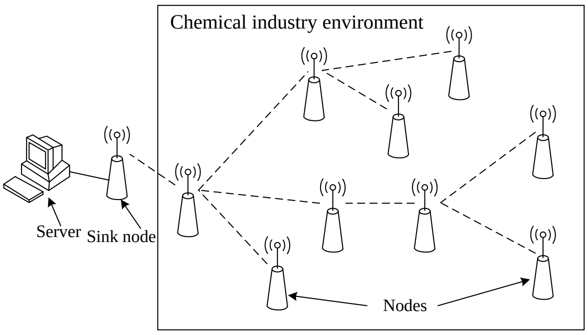

Figure 4: System model

4.2 Simulation implementation

In the simulation experiment, 256 sensor nodes are randomly arranged in a grid area of 100×100 in size, where the central sink node exists, and the target information source to be detected is randomly distributed. The experiment assumes that each sensor node collects signals for a period of time and performs sparse processing and compression sampling on the signals and then transmits them to the central node.
In order to analyze the performance of the ISL0 algorithm in the WSN more comprehensively, this study introduces BP, OMP, SP, and SL0 algorithms to compare and analyze the reconstruction accuracy of different algorithms. In order to more clearly demonstrate the recoverability of the ISL0 algorithm and other algorithms, this study uses the signal-to-noise ratio (SNR) of the reconstructed signal and the original signal to express the restoration effect. The definition is as follows:

$$SNR = 10\lg\left(\frac{\|x\|_2}{\|x-\hat{x}\|_2}\right) \tag{1}$$

where *x* denotes the original signal sent by the signal source, $\hat{x}$ denotes the reconstructed signal after compression sampling. The reconstruction probability *P* is defined as follows:

$$P = \frac{N}{M} \tag{2}$$

where *N* denotes the number of times for successfully reconstructing sparse signals, and *M* denotes the total number of simulations.
In Experiment 1, it is assumed that there is noise interference in the WSN. Let the number of dimensions of the sparse signal *x* be 256 and the sparse property *k* be 50. The number of iterations of the ISL0 algorithm is 3, and the threshold value is set to β=3, γ=0.5, *J*=7, $\delta_j=\gamma\delta_{j-1}$. With the same experimental parameters and environment, the experiment was repeated 300 times, and each experiment is independent of each other. The comparison of reconstruction performance under different algorithms with noise are shown in Figure 5 and Figure 6.

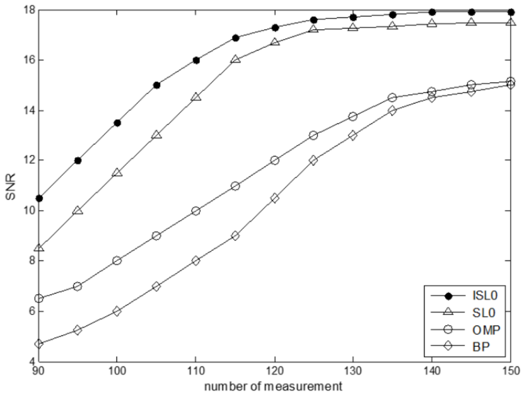

Figure 5: Different observations

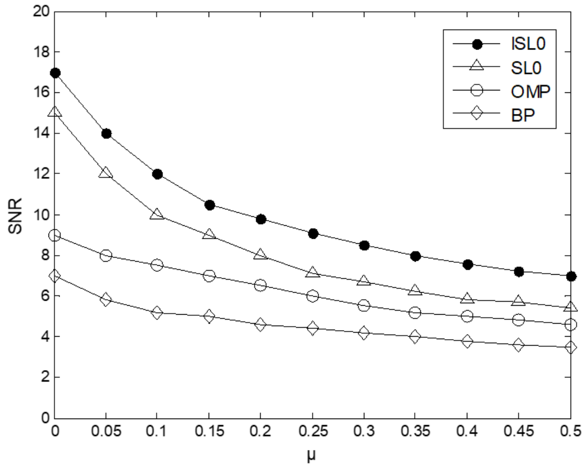

Figure 6: Different noise variances

In Figure 5, the noise mean-square error (MSE) value is set to 0.1. It can be seen that, with noise interference, ISL0 has a higher reconstructed SNR with the same number of observations and requires the least number of observations at a high reconstructed SNR. The observation value in Figure 6 is set to 128. It can be seen that ISL0 has a higher reconstruction SNR than other algorithms when MSE changes.
In Experiment 2, a simple WSN system based on practical application was established. The system consists of 20 gas sensor nodes randomly distributed in an area of 100×100, with data aggregation and reconstruction of the central node being completed by a computer.

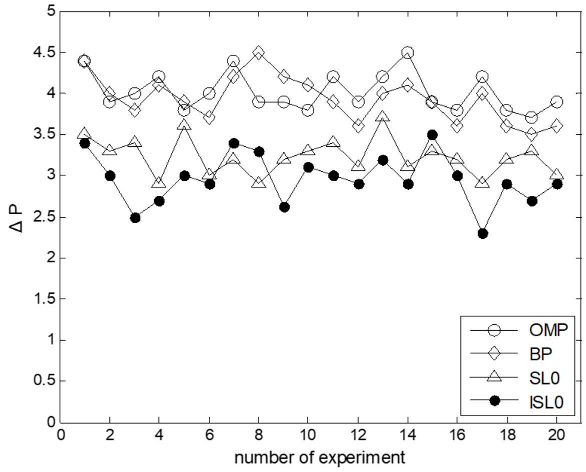

Figure 7: Comparison of gas sensor reconstruction accuracy based on compressed sensing

If we assume there is a stable gas source in the experimental environment, each sensor node detects the gas concentration, compresses and samples the data, and then transmits the processed gas concentration data to the central node that reconstructs the data. The reconstruction effects of BP, OMP, SL0, and ISL0 algorithms are compared while keeping the experimental environment unchanged, randomly changing the gas concentration values detected by each sensor and repeating 20 independent experiments.
As shown in Figure 7, the abscissa represents the number of independent experiments and the ordinate represents the reconstruction error ΔP. It can be seen that the ISL0 algorithm is better than the other three algorithms in terms of reconstruction effect, but slightly weaker than the BP and OMP algorithms in terms of data reconstruction stability.

5. Conclusions

In this paper, AlN-based semiconductor MEMS four-array sensor is used to identify the four harmful gases of Cl_2, CO, NO_2 and SO_2, and it's taken as the nodes to build a sensor network. Then through the iterative smoothing l_0 norm minimization algorithm, it achieves reconstruction of original odor identification data with fewer observations. The simulation results show that compared with BP, OMP, SL0 and other algorithms, the method adopted in this paper has better signal reconstruction performance, it improves the data collection efficiency of the wireless sensor network, and effectively identifies the harmful gas odors in the chemical environment.

References

Adam B., Nizar J., Omar Y., 2016, Nonlinear-Based MEMS Sensors and Active Switches for Gas Detection, Sensors, 16(6): 758, DOI: 10.3390/s16060758

Barrozo F., Valencia Ochoa G., Cardenas Y., 2018, Computational simulation of the gas emission in a biomass on grid energy system using homer pro software, Chemical Engineering Transactions, 65, 265-270, DOI: 10.3303/CET1865045

Candes E.J., Romberg J., Tao T., 2006, Exact signal reconstruction from highly incomplete frequency information, IEEE Transactions on Information Theory, 52(2):489-509, DOI: 10.1109/TIT.2005.862083

Chen Y., Jiao G., Zhang C., Qi Z., Chen X., 2018, Theoretical analysis on the bending springback of flattened oil and gas pipelines, Chemical Engineering Transactions, 66, 517-522, DOI:10.3303/CET1866087

Kalus K., Opalinski S., Maurer D., 2017, Odour reducing microbial-mineral additive for poultry manure treatment, Frontiers of Environmental Science & Engineering, 11(3): 7, DOI: 10.1007/s11783-017-0928-4

Rawat P., Singh KD., Chaouchi H., Bonnin J.M., 2014, Wireless sensor networks: a survey on recent developments and potential synergies, The Journal of Supercomputing, 68(1): 1-48, DOI: 10.1007/s11227-013-1021-9

Razzaque M.A., Dobson S., 2014, Energy-Efficient Sensing in Wireless Sensor Networks Using Compressed Sensing, Sensors, 14(2): 2822-2859, DOI: 10.3390/s140202822

Tjalvin G., Mageroy N., Bratveit M, 2016, Odour as a determinant of persistent symptoms after a chemical explosion, a longitudinal study, Industrial Health, 55(2): 127-1137, DOI: 10.2486/indhealth.2016-0155

Wang J., Yang J., Chen D., 2018, Gas Detection Microsystem with MEMS Gas Sensor and Integrated Circuit, IEEE Sensors Journal, 18(16): 6765-6773, DOI: 10.1109/JSEN.2018.2829742

Wu C., Liu J., Zhao P., 2016, Conversion of the chemical concentration of odorous mixtures into odour concentration and odour intensity: A comparison of methods, Atmospheric Environment, 127: 283-292, DOI: 10.1016/j.atmosenv.2015.12.051

Yin J., Yang Y.W., Wang L., 2016, An Adaptive Data Gathering Scheme for Multi-Hop Wireless Sensor Networks Based on Compressed Sensing and Network Coding, Sensors, 16(4): 462, DOI: 10.3390/s16040462