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A Rapid Monitoring Method for Natural Gas Safety Monitoring

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***Abstract*—The quick leakage alarm and the accurate concentration prediction are two important aspects of natural gas safety monitoring. In this paper, a rapid monitoring method of sensor data sharing, rapid leakage alarm and simultaneous output of concentrations prediction is proposed to accelerate the alarm speed and predict the possible impact of leakage. In this method, the Dempster-Shafer evidence theory is used to fuse the trend judgment and the CUSUM (cumulative sum) and the Gauss-Newton iteration is used to predict the concentration. The experiment system based on the TGS2611 natural gas sensor was built. The results show that the fusion method is significantly better than the single monitoring method. The alarm time of fusion method was more advanced than that of the CUSUM method and the trend method (being averagely, 10.4% and 7.6% in advance in the CUSUM method and the trend method respectively). The relative deviations of the predicted concentration were the maximum (13.3%) at 2000 ppm (parts per million) and the minimum (0.8%) at 6000 ppm, respectively.**

***Keywords*—trend judgment, CUSUM, Dempster-Shafer evidence theory, Gauss-Newton nonlinear fitting, fast alarm monitoring, concentration prediction**

I. Introduction

As an important clean energy, natural gas is widely used in the world [1], [2]. It would bring great danger to people's life and property once the gas leakage occurs, for the special physical and chemical properties [2], [3]. Strengthening effective monitoring, preventing and reducing the occurrence of disaster accidents have attracted wide attention [4]–[9]. Xia, Long et al. studied new types of detection sensors [4], [5]. Xiao et al. studied a small leak detection method based on variational mode decomposition adaptive de-noising and ambiguity correlation classification intended for natural gas pipelines [6]. Zhou et al. studied natural gas pipeline leakage through the method of experiment and simulation [7]. He et al. proposed a new method of gas identification monitoring for sensor signal processing to get high identification accuracy [8], [9]. As a leisure and entertainment place, tourist attractions are usually crowded, and safety monitoring is crucial and essential [10]. Natural gas in the scenic area mainly comes from restaurants and natural gas vehicles [11], [12]. The consequences of natural gas leakage might be even worse. At the same time, leakage may cause environmental problems and will have a far-reaching influence. Information processing is an important part of the development for smart scenic spots [13]. Gas safety monitoring has been studied on many occasions using information system technology [14], [15]. However, the monitoring in scenic spots has not been reported yet [16], [17]. The traditional method for monitoring natural gas is threshold comparison method and the main step is to compare the gas concentration with the threshold value. This method is difficult to detect mild dangers and cannot provide target concentration and it cannot satisfy the rapid and predictive monitoring requirements in scenic spots.

In the application of scenic spot monitoring, quick response is needed to leave time for disposal. It is also necessary to predict and assess the possible consequences. In the present paper, the rapid monitoring method for sharing sensor data, leaking quick alarms and simultaneously outputting concentration prediction is proposed to speed up the alarm speed and predict the concentration of the leakage. The transient response data is used to alarm and predict the concentration.

II. Methods

The gas sensor converts the concentration information into response electrical signal and a typical sensor output curve is shown in Fig. 1. The response slope of the sensor decreases with increasing concentration. Considering the measurement of the gas sensor response process, it is expressed as a discrete time signal with sampling period. The traditional method is to compare the measured value with the threshold. The response signal below the threshold cannot be monitored and the response rate of the sensor gradually decreases resulting in slow response. The threshold value comparison method uses a single point of the measured value for comparison and cannot predict the ambient gas concentration. The transient response signal of the sensor contains abundant information and the comprehensive usage of sensor transient response information can help make up for the shortcomings of the threshold comparison method [9].

In order to compatible with the response speed and concentration prediction, the system needs to be designed with both considerations in mind. Different from the traditional monitoring system, the signal processing subsystem is designed for an integrated method. Signal acquisition consists of the front

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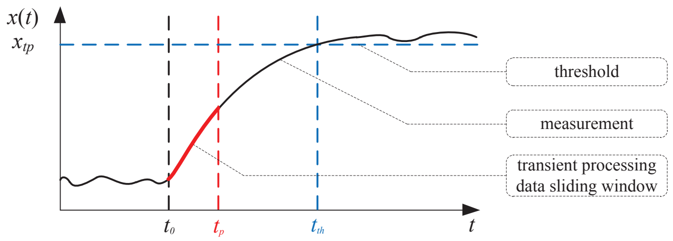

Fig. 1. The measurement $x(t)$ of the process variable x with a variation from normal condition to abnormal one at the time instant t_0 .

end sensor and signal collection modules. Generally, the signal collection module converts the analog signal of the sensor into digital signal. The output data of the signal collection module is provided to the signal processing module.

To improve the speed and accuracy of fast detection, the integrated method combines sensor raw for anomaly detection and change rate for slope detection. Based on the fusion results, the concentration prediction module is triggered. The threshold comparison is used as supplemental information for the monitoring method. The fusion detection module fuses anomaly detection and slope detection, as shown in Fig. 2. The anomaly detection module provides the ability to quickly identify changes of the sensor and the slope detection module monitors the severity of signal changes.

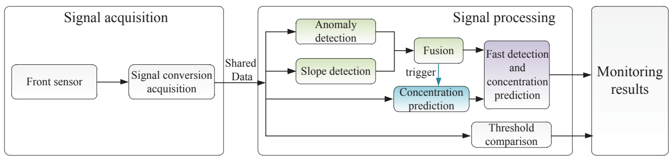

Fig. 2. Fast detection and concentration prediction structure in this study.

In this study, the anomaly detection uses commonly used CUSUM (cumulative sum) detection algorithm, the slope detection uses the trend judgment method based on least square method, the information fusion uses Dempster-Shafer evidence theory algorithm and the concentration prediction uses Gauss-Newton method based nonlinear fitting algorithm. Compared with the traditional monitoring method, this method has two characteristics: the first is that the data is shared which does not increase the amount of signal acquisition equipment; the other is that it makes full use of the sensor information and gives multi-dimensional information.

The CUSUM detection algorithm is a commonly used algorithm in statistical process control [18]. The algorithm accumulates small offsets in the process to achieve the effect of amplification, so that changes in parameters can be quickly identified and detection sensitivity improved. The CUSUM detection algorithm is more effective in detecting small shifts in the mean. According to the degree of data point shift, the mean change can be detected intuitively and conveniently, which is defined as

$$y(n) = y(n-1) + x(n), y(0) = 0, n = 1, 2, \cdots \tag{1}$$

where $x(n)$ is the observation sequence; $y(n)$ is the cumulative value.

Therefore, when $x(n)$ is transformed from a negative value to a positive value, the cumulative value $y(n)$ increases and the change in $x(n)$ can be detected.

When the measured gas concentration changes, the gas sensor output response fluctuates with the concentration change. In order to detect the gas concentration trend, it is necessary to make a judgment on the gas concentration trend. The direct method is to linearly fit the sensor signal. In order to process the sensor's output data in real time, the data needs to be sliding window processed. Using linear fitting can help quickly detect the trend of the sensor signal.

Assume that the observations are (x_1, y_1), (x_2, y_2), ..., (x_n, y_n). The mathematical expression for the straight line is

$$y = a_0 + a_1 x + e \tag{2}$$

where a_0 and a_0 are the coefficients representing the intercept and the slope, respectively. The parameter e is the error or residual between the model and the observations, which can be represented by rearranging as

$$e = y - a_0 - a_1 x \tag{3}$$

Thus, the residual is the discrepancy between the true value y and the approximate value $a_0 + a_1 x$, predicted by the linear equation.

A strategy is to minimize the sum of the squares of the residuals

$$S_r = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - a_0 - a_1 x_i)^2 \tag{4}$$

To determine values for a_0 and a_1, equation (5) finds partial derivatives about a_0 and a_1 respectively. Setting these derivatives equal to zero will result in a minimum S_r. The analytical solution of a_1 when S_r takes the minimum value can be obtained as [19]

$$a_1 = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n \sum_{i=1}^{n} x_i^2 (\sum_{i=1}^{n} x_i)^2} \tag{5}$$

As the slope of the signal, a_1 is a key parameter to measure the trend of the sensor signal.

Dempster-Shafer evidence theory which is a mathematical theory of evidence, is one of the most widely used because it has a unique advantage in expressing uncertainty [20]. As an extension of Bayesian reasoning, Dempster-Shafer evidence theory does not need to know the exact data about the prior probability and conditional probability in order to perform evidence fusion. On the basis of establishing a one-to-one correspondence between propositions and sets, the problem of uncertainty of propositions is transformed into the problem of uncertainty of sets for processing [21].

The basic concept of evidence theory is the identification framework, Let Θ be a finite set of possible hypothesis. This set is referred as the frame of discernment and its powerset denoted by 2^{Θ}. A basic belief assignment function m assigns a value between 0 and 1 to every subset A of the frame of discernment. Then m function is defined to satisfy the following conditions

$$m(\emptyset)=0, \sum_{A\subseteq 2^{\Theta}} m(A)=1 \tag{6}$$

Assume that the basic probability distributions of the two evidence amounts are m_1 and m_2 respectively. Using the Dempster-Shafer synthesis rule, they can be fused into a new basic probability distribution as

$$m(A)=\frac{1}{N}\sum_{A_i\cap B_j\neq A} m_1(A_i)m_2(B_j) \tag{7}$$

where the constant $N=\sum_{A_i\cap B_j\neq\emptyset} m_1(A_i)m_2(B_j)>0$.

In this paper, the recognition framework consists of two processing, namely alarm, no alarm. The CUSUM method and the trend method are the basic probability distribution functions m_1 and m_2 respectively.

The dynamic response characteristics of the gas sensor meet the exponential function([9], [22]) and the response model to be fitted can be written in the universal form

$$f(x)=a_0(1-e^{-a_1 x})+e \tag{8}$$

In a short form, it can be expressed as

$$y_i=f(x_i)+e_i \tag{9}$$

where y_i is the measured value of the dependent variable and $f(x_i)$ is the measurement equation, which is a function of the independent variable x_i.

The parameter values are determined based on the criterion of minimizing the sum of squared residuals and the solution process is performed iteratively [19]. At the parameter value, expand by Taylor series and omit the terms after the first derivative

$$y_i-f(x_i)_j=\frac{\partial f(x_i)_j}{\partial a_0}\Delta a_0+\frac{\partial f(x_i)_j}{\partial a_1}\Delta a_1+e_i \tag{10}$$

Represented as a matrix, that is

$$\{D\}=\{Z_j\}\{\Delta A\}+\{E\} \tag{11}$$

The expressions of $\{D\}$,$\{Z_j\}$,$\{\Delta A\}$ and $\{E\}$ are as follows

$$\{D\}=\begin{bmatrix} y_1-f(x_1)\\ y_2-f(x_2)\\ \vdots\\ y_n-f(x_n)\end{bmatrix},\qquad \{Z_j\}=\begin{bmatrix} \frac{\partial f_1}{\partial a_0} & \frac{\partial f_1}{\partial a_1}\\ \frac{\partial f_2}{\partial a_0} & \frac{\partial f_2}{\partial a_1}\\ \vdots & \vdots\\ \frac{\partial f_n}{\partial a_0} & \frac{\partial f_n}{\partial a_1}\end{bmatrix},$$

$$\{\Delta A\}=\begin{bmatrix}\Delta a_0\\ \Delta a_1\end{bmatrix}, \{E\}=\begin{bmatrix} e_1\\ e_2\\ \vdots\\ e_n\end{bmatrix}$$

and n is the number of data points.

The normal equation is obtained as follows

$$\{Z_j\}^T\{Z_j\}\{\Delta A\}=\{Z_j\}^T\{D\} \tag{12}$$

By solving Equation (12), $\{\Delta A\}$ is obtained, and the parameter value after iteration is

$$a_{0,j+1}=a_{0,j}+\Delta a_0, a_{1,j+1}=a_{1,j}+\Delta a_1 \tag{13}$$

Repeat the above process until the iteration process converges.

III. Results

A. The experiment system

In order to validate the rapid monitoring method and simulate the operating environment, the experimental system was built. The main component of natural gas is methane, so the methane sensor is used to study natural gas monitoring. The metal oxide semiconductor methane sensor TGS2611 and supporting test circuit were placed in a 10-L volume test chamber. The gas sensor resistance was installed in a half-bridge configuration and the matching resistance R_L is 7.5 kΩ. The measuring circuit was supplied with a DC power supply by the Agilent E3631A. The voltage V_{out} was measured by the Agilent 34410A Multimeter and the result was uploaded to the computer in real time. For the explosive limit for methane is 5 to 15 percent, a concentration less than 1 percent was selected in order to study the early warning of methane leakage. The gas sensor was placed in the middle of the chamber, and a pair of fans in the side wall was used for the balance of concentration in the chamber. The high concentration gas enters the chamber through the gas injection device and the wanted gas concentration was diluted by pure methane and air. The system composition is shown in Fig. 3

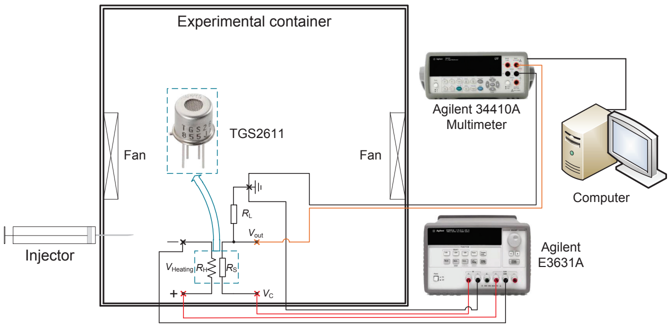

Fig. 3. Experimental set-up used in this study.

The real-time program embedded signal processing runs on the computer and the fast detection and concentration prediction algorithm runs when data is received.

B. Fast detection

When there is no methane in the experimental chamber, the sensor outputs a low concentration value close to 0. When the gas concentration is set to 5000 ppm (parts per million), with the injection of methane, the output response starts to rise rapidly and then slows down as shown in Fig. 4. After about 200 seconds, the sensor response increases slowly and it is close to the preset concentration value. If the alarm concentration is set slightly above 5000 ppm, it will take more than 200 seconds to trigger the alarm signal. For a gas hazard warning signal, the alarm is given earlier, the more disposal time is left for people.

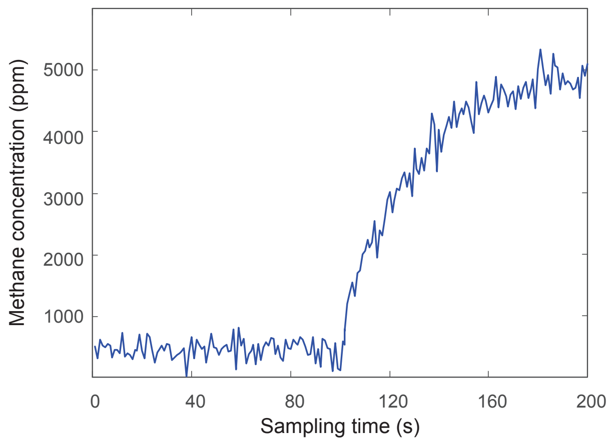

Fig. 4. The gas sensor output at the preset 5000 ppm.

In order to fuse the sensor's transient information, the CUSUM method and the trend method need to be uniformly expressed as an alarm probability form. The CUSUM of concentration and the probability of alarm are shown in Fig. 5(a). With the gas injected, CUSUM gradually rises. In order to calculate the alarm probability of the CUSUM method, the buffer length is set to be 10 seconds and the number of deviations from the mean 3 times the standard deviation in the buffer is used as the comparison value. Therefore, the quotient of the comparison value and the buffer length is taken as the probability of alarm, as shown in the blue curve in Fig. 5(a). The probability of the CUSUM method gradually increases from 0 to 1. In 131 seconds, the alarm probability of CUSUM method reaches 90%. The rate of concentration change and the probability of concentration change rate are shown in Fig. 5(b). The upward trend is particularly pronounced in the early stages of gas injection and this is reflected in the gradual increase in the slope of the sensor output curve. Similarly, the number of concentration growth rate continuously greater than 10 ppm/second is taken as a reference value. The quotient of the comparison value and the buffer length is taken as the probability of alarm, as shown in the blue curve in Fig. 5(b). In 129 seconds, the alarm probability of trend method reaches 90%.

The results of Dempster-Shafer fusion method are shown in Fig. 5(c). The alarm probability of the Dempster-Shafer fusion algorithm rises at a faster rate. This is because both the CUSUM method and the trend method take full advantage of the sensor's transient response to help increase alarm speed. The Dempster-Shafer algorithm integrates the information of the two methods, which is helpful to further improvement. In 118 seconds, the alarm probability of the Dempster-Shafer fusion method reaches 90%, which is significantly earlier than the CUSUM method and the trend method.

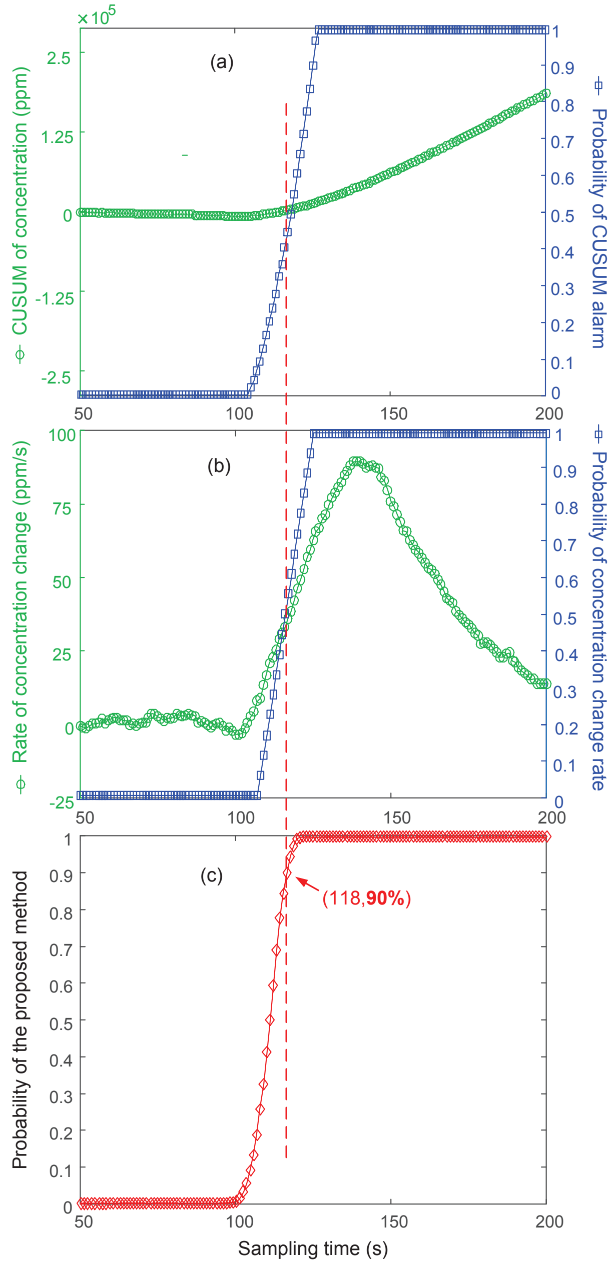

Fig. 5. The output of rapid monitoring method. (a) The CUSUM of concentration and the probability of CUSUM alarm. (b) The rate of concentration change and the probability of change rate. (c) The fusion curve of the proposed method.

C. *Concentration prediction*

The steady-state concentration of methane is an important reference to determine whether there is a risk of combustion or explosion. Gas diffusion, space size and other factors affect the speed of the response and the time to reach a stable concentration. It takes a large number of sampling points to reach the steady-state concentration of the sensor, as shown in Fig. 4. As a reference for the alarm signal output, the slow rise of the sensor signal is not conducive to the rapid perception of the gas concentration. When the fusion signal triggers the start of concentration prediction, the software automatically fetches the buffered data to fit the target concentration value.

The injected methane concentration was 5000 ppm and Fig. 6 shows the methane concentration curves in 20, 40, 60 and 80 seconds after the signal is triggered. It can be seen that as the number of sampling points increases, the prediction curve becomes closer to the actual measurement value. Since the cache is already used when the trend is detected, it helps more data to participate in the fitting and improves the fitting accuracy. In 80 seconds, the difference between the predicted concentration and the actual measurement value is 190 ppm.

D. *Fast detection and concentration prediction*

In order to study the relationship between alarm and concentration, the alarm experiments were conducted at 2000, 4000, 6000, 8000 and 10000 ppm. The CUSUM method, trend method and Dempster-Shafer evidence theory based fusion method were applied to the alarm judgment respectively. Figure 7 is the change curves of alarm time with concentration and it can be seen that the trend method is faster than CUSUM method to give the alarm signal. With the increase of gas concentration, the alarm time of CUSUM method and trend method decreased and the difference between the output of gas sensor and that of pure air becomes more obvious. This helps to distinguish between normal and alarm state. The Dempster-Shafer evidence theory based fusion method utilizes the information of CUSUM method and trend method to improve the alarm speed. When the threshold is lower than the set value, the alarm state can be predicted by the fusion algorithm. It can be seen from the experimental results that the alarm judgment result of the fusion method is significantly faster than that of CUSUM method and trend method. With the increase of gas concentration, the alarm advance of the fusion method decreases slightly. It can be concluded that the fusion method is 10.4% ahead of the CUSUM method and 7.6% ahead of the trend method on average.

In this experiment, in order to give consideration to the accuracy of prediction and the rapidity, the detection trigger probability is selected as 90%. This implies that when the Dempster-Shafer output alarm probability is not less than 90%, the concentration prediction is turned on. Under the above five different concentrations, the concentration prediction was analyzed as shown in Fig. 8. The predicted concentration error fluctuated with different methane concentrations and the relative deviation of the predicted concentration was the maximum (13.3%) at 2000 ppm and the minimum (0.8%) at 6000 ppm.

IV. Conclusions

The monitoring of combustible gas leakage has a great influence on the safety of tourists, the environment and the reputation of scenic spots. In this paper, the integrated rapid monitoring method is established to accelerate the alarm speed and predict the concentration. By sharing sensor data, multi-source information fusion and nonlinear prediction, the alarm status is given quickly and the steady state concentration is predicted accurately.

The CUSUM and the trend judgment are processed based on the gas sensor data. The two methods give the alarm probability respectively and then enter the data fusion processing to

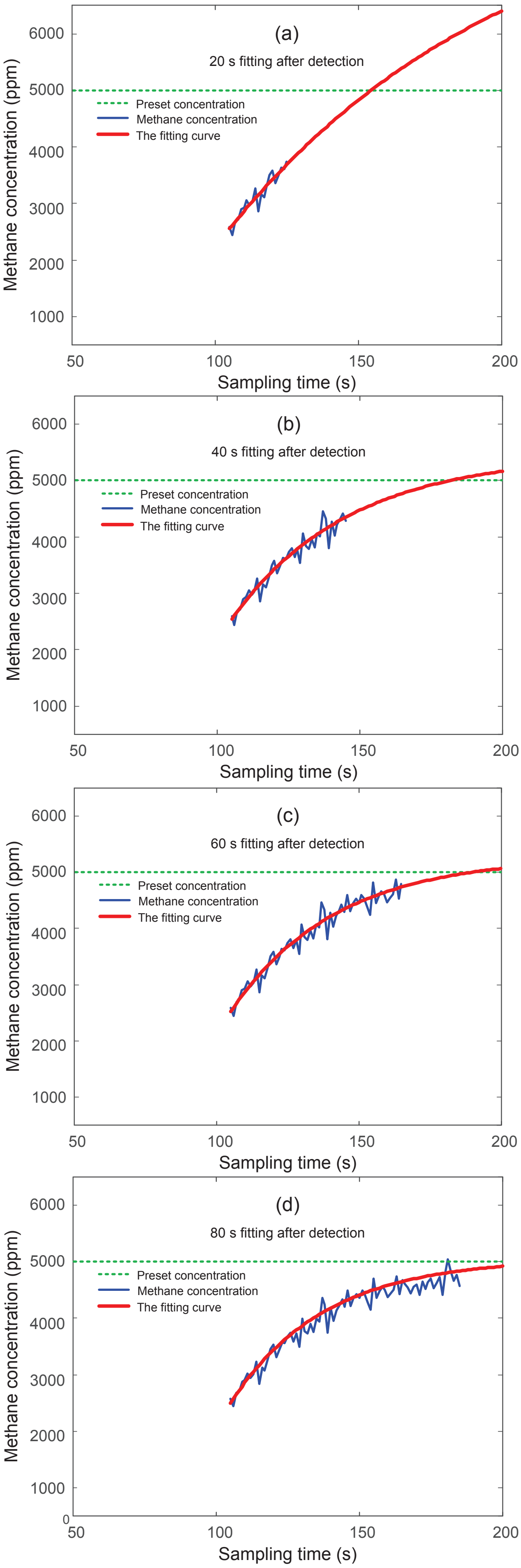

Fig. 6. Final concentration prediction at different seconds. (a) 20 s, (b) 40 s, (c) 60 s and (d) 80 s fitting after detection.

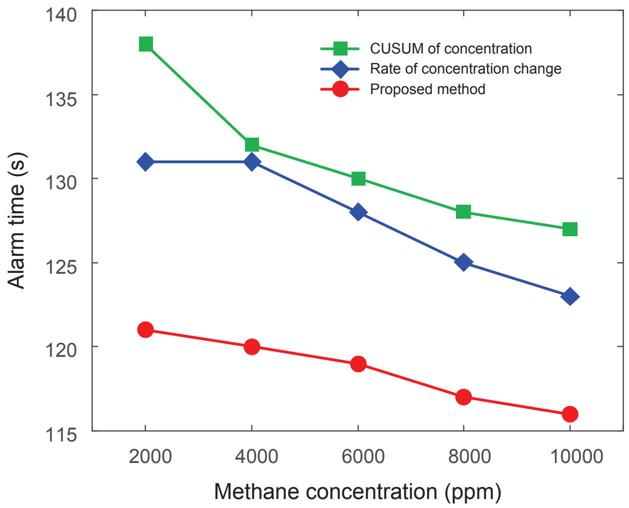

Fig. 7. Comparison of alarm time at different concentrations.

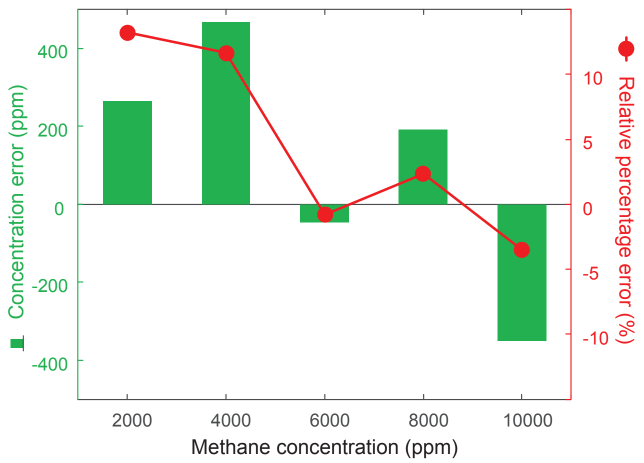

Fig. 8. Predicted concentration error and relative percentage error at different concentrations.

accelerate alarm judgment. Based on transient data, the steady state concentration is predicted by nonlinear fitting method. In order to improve the fitting accuracy, the data is stored in the cache in advance to assist in improving the fitting accuracy.

A simulation test system was set up, containing the gas sensor TGS2611, whose data was processed according to the fast detection and concentration prediction structure. Compared with the separate CUSUM method and the trend prediction method, the fusion method can alarm the judgment earlier (being averagely, 10.4% and 7.6% in advance in the CUSUM method and the trend method respectively). The fitting method can predict the concentration earlier and the relative deviations of the predicted concentration were the maximum (13.3%) at 2000 ppm and the minimum (0.8%) at 6000 ppm, respectively.

References

[1] P. Lustenberger, F. Schumacher, M. Spada, P. Burgherr, and B. Stojadinovic, "Assessing the performance of the European natural gas network for selected supply disruption scenarios using open-source information", *Energies* 12, 1–28 (2019). https://.org/10.3390/en12244685

[2] S. Kakuma, and K. Noda, "Practical and Sensitive Measurement of Methane Gas Concentration Using a 1.6 μm Vertical–Cavity–Surface–Emitting–Laser Diode", *Sensors and Materials* 22 (7), 365–375 (2010).

[3] K. L. Su, Y. L. Liao, S. W. Shiau, and J. H. Guo, "Bayesian-Estimation–Algorithm-Based Gas Detection Modules", *Sensors and Materials* 25 (6), 397–402 (2013).

[4] Y. Xia, J. Wang, L. Xu, X. Li, and S. J. Huang, "A room-temperature methane sensor based on Pd-decorated ZnO/rGO hybrids enhanced by visible light photocatalysis", *Sensors and Actuators B:Chemical* 304, (2020). https://doi.org/10.1016/j.snb.2019.127334

[5] T. Long, E. Li, L. Yang, J. F. Fan, and Z. Z. Lian, "Analysis and design of an effective light interference methane sensor based on three-dimensional optical path model", *Journal of Sensors* Article ID 1342593, 1-11 (2018). https://doi.org/10.1155/2018/1342593

[6] Q. Xiao, J. Li, Z. Bai, J. Sun, N. Zhou, and Z. Zeng, "A small leak detection method based on VMD adaptive de-noising and ambiguity correlation classification intended for natural gas pipelines", *Sensors* 12, 1-16 (2016). https://doi.org/10.3390/s16122116

[7] Z. M. Zhou, J. Zhang, X. S. Huang, and X. S. Guo, "Experimental study on distributed optical-fiber cable for high-pressure buried natural gas pipeline leakage monitoring", *Optical Fiber Technology* 53, Article ID 102028 (2019). https://doi.org/10.1016/j.yofte.2019.102028

[8] T. Jia, T. Guo, X. Wang, D. Zhao, C. Wang, Z. Zhang, S. Lei, W. Liu, H. Liu, and X. Li, "Mixed Natural Gas Online Recognition Device Based on a Neural Network Algorithm Implemented by an FPGA", *Sensors* 19 (9), 1-16 (2019). https://doi.org/10.3390/s19092090

[9] A. X. He, J. Yu, G. F. Wei, Y. Chen, H. Wu, and Z. A. Tang, "A. Short-time fourier transform and decision tree-based pattern recognition for gas identification using temperature modulated microhotplate gas sensors", *Journal of Sensors* Article ID 7603931, 1-12 (2016). https://doi.org/10.1155/2016/7603931

[10] Z. Y. Yang, M. Yin, J. G. Xu, and W. Lin, "Spatial evolution model of tourist destinations based on complex adaptive system theory: a case study of Southern Anhui, China", *Journal of Geographical Sciences* 29 (8), 1411–1434 (2019). https://doi.org/10.1007/s11442-019-1669-z

[11] L. W. Tian, D. J. Moschandreas, J. H. Hao, "The impact of kitchen activities on indoor pollutant concentrations", *Indoor and Built Environment* 17 (4), 377–383 (2008). https://doi.org/10.1177/1420326x08094626

[12] N. Hu, S. D. Liu, Y. Q. Gao, J. P. Xu, X. Zhang, Z. Zhang, and X. H. Lee, "Large methane emissions from natural gas vehicles in Chinese cities", *Atmospheric Environment* 187, 374–380 (2018). https://doi.org/10.1016/j.atmosenv.2018.06.007

[13] Y. Li, C. Hu, C. Huang, and L. Duan, "The concept of smart tourism in the context of tourism information services", *Tourism Management* 58, 293-300 (2016). https://doi.org/10.1016/j.tourman.2016.03.014

[14] P. Zhao, R. Zhuo, S. Li, C. Shu, B. Laiwang, Y. Jia, Y. Shi, and L. Suo, "Analysis of advancing speed effect in gas safety extraction channels and pressure-relief gas extraction", *Fuel* 265, Article ID 116825 (2020). https://doi.org/10.1016/j.fuel.2019.116825

[15] E. R. S. Jaclyn, N. N. A. Franz, C. M. J. Fernando, and M. D. Fabian, "Developing a chemical and hazardous waste inventory system", *Journal of Chemical Health and Safety* 18 (6), 15–18 (2011). https://doi.org/10.1016/j.jchas.2011.05.012

[16] F. Mehraliyev, Y. Choi, and M. A. Koseoglu, "Progress on smart tourism research", *Journal of Hospitality and Tourism Technology* 10, 522-538 (2019). https://doi.org/10.1108/jhtt-08-2018-0076

[17] F. Mehraliyev, I. C. C. Chan, Y. Choi, and M. A. Koseoglu, "A state-of-the-art review of smart tourism research", *Journal of Travel and Tourism Marketing* 37 (1), 78–91 (2020). https://doi.org/10.1080/10548408.2020.1712309

[18] M. Pastell, J. Hietaoja, J. Yun, J. Tiusanen, and A. Valros, "Predicting farrowing of sows housed in crates and pens using accelerometers and CUSUM charts", *Computers and Electronics in Agriculture* 127, 197–203 (2016). https://doi.org/10.1016/j.compag.2016.06.009

[19] S. C. Chapra, "Applied Numerical Methods with MATLAB for Engineers and Scientists", McGraw-Hill, New York, 2001.

[20] Q. Liu, Y. Tian, and B. Kang, "Derive knowledge of Z-number from the perspective of Dempster–Shafer evidence theory", *Applications of Artificial Intelligence* 85, 754–764 (2019). https://doi.org/10.1016/j.engappai.2019.08.005

[21] D. Su, Q. Shi, H. Xu, "Nonintrusive Load Monitoring Based on Complementary Features of Spurious Emissions", *Electronics* 8 (9), 1-13 (2019). https://doi.org/10.3390/electronics8091002

[22] Y. S. Chen, "Research on Self-Validating Methods for Metal Oxide Semiconductor Gas Sensor Arrays", Doctor's Thesis, Harbin Institute of Technology, Harbin, China, (2017).