An Embedded system for real time gas monitoring using an ART2 neural network

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Abstract: We propose a real time gas monitoring system for classifying various gases with different concentrations. Using thermal modulation of operating temperature of two sensors, we extract patterns of gases from the voltage across the load resistance. We adopt the relative resistance as a pre-processing method and an ART2 neural network as a pattern recognition method. The proposed method has been implemented in a real time embedded system with tin oxide gas sensors, TGS 2611, 2602 and an MSP430 ultra-low power microcontroller in the test chamber.

Keywords: Tin oxide gas sensor; Pattern extractor; ART2 Neural network; Gas classification; Embedded system

1. INTRODUCTION

There is an increasing interest in electronic nose applications [1-2]. Especially, gas monitoring is required by home as well as industry. In every life, there are sometimes accidents by leaking combustible or toxic gases-propane such as LNG, carbon monoxide, and so on. It is necessary for preventing a serious accident to implement a reliable detector system which can monitor these gases in real time. Semiconductor gas sensor arrays of the tin oxide type are widely used as detecting elements in measuring instruments for monitoring volatile organic compounds (VOCs) or inflammable gases.

The Taguchi gas sensors (TGS) have several advantages over alternative detection methods such as electrochemical gas sensor cells or absorption and fluorescence spectrometry methods. They have relatively small size with sensitivity and low price. But, their response can be widely influenced by drifts such as nonlinearities of sensors, humidity rate and temperature [3-4]. To solve these problems, researchers have focused their works on intelligent signal processing strategies and algorithms [5]. Neural networks are powerful signal processing tools in this area [6-7]. In this paper, we adopted an ART2 (Adaptive resonance theory) neural network. The neural network plays an import role in auto calibration in real time by adjusting its cluster centers which can give useful information about sensor output.

This study focuses on the implementation of the real time embedded system for gas discrimination. The experimental set-up is described in section 2. A pattern recognition method is explained in section 3. In section 4, experimental results are shown and discussed. Finally, section 5 contains conclusions.

2. EXPERIMENTAL

We decided to test four indoor environmental gases: propane, methane, carbon oxide, and hydrogen sulfide. To test these gases, our experimental system is composed of three parts: the gas lines, a humidity generator, and a test chamber (Fig. 1). The gas lines were composed of these gas bottles containing dry synthetic air and mass flow controllers (MFC's). The measurement procedure is as follows. First, the synthetic air is brought into the humidity generator and then mixed with the test target gas via gas lines controlled by MFC's. Then the mixture is introduced in the test chamber. Finally, the microcontroller with gas sensors mounted in a gas chamber measure periodically sensor output signals.

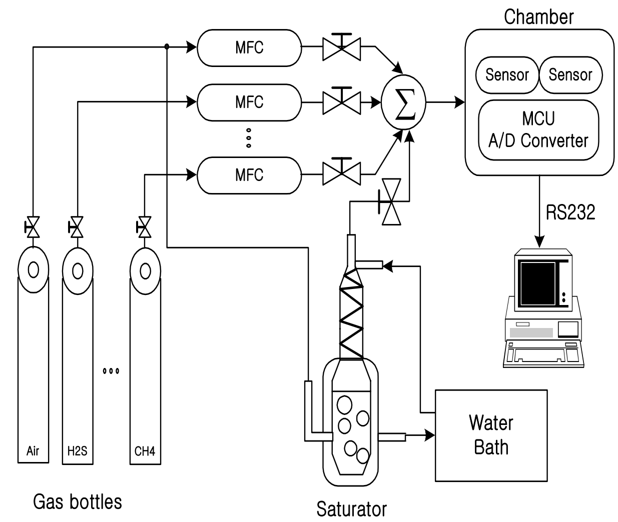

Fig. 1. Experimental set-up.

For our application, we use two commercially available gas sensors that were suggested by Figaro Engineering Inc. (TGS 2611, methane gas sensor, TGS2602, a general air contaminant sensor). These sensors have small size, high sensitivity and low price. They are widely used in many applications. In our application, the two sensors are connected to a microcontroller board to operate efficiently important factors of sensors that are the sensor resistance change in presence of the target gas. The output voltage of the sensor was read by a 12bit-ADC module of an MSP430 ultra-low power microcontroller from Texas Instruments.

Each data acquisition follows the same procedure. First, these sensors need to preheat during a period of one week to stabilize the sensitive layer. And then sensor output values are extracted by combination of heating control signal which operates temperature of sensor output and sensor control signal which is related to resistance change in every minute.

3. PATTERN RECOGNITION SYSTEM

3.1 Pattern extractor

We used thermal modulation method [8]. This method has some merits. One is simple because only one sensor is needed as compared to sensor array technology which is generally used. Another is reducing a deviation due to instability of material itself. Generally, various materials were used for sensor array. That means it has more possibility of instability due to materials. But, thermal modulation method has also a weak point. It was delay of response time. Recently, to compensate the delay, microsensor has been researched. As well known, very small active sensing area was equipped on the membrane of microsensor. Typically, thermal conductivity of the membrane is small, and the thickness of it is very shallow. Therefore, a thermal response is very quickly.

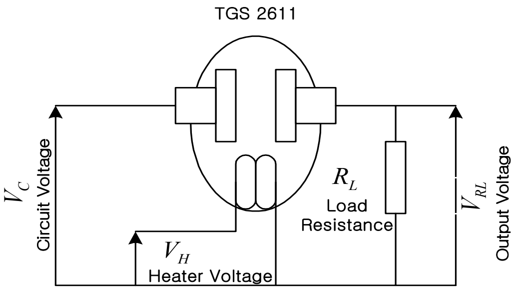

Fig. 2. Analog circuit to monitor the sensor response.

And, we used electronic circuit to extract electric signal from sensors. As shown in Fig. 2, load resistor is connected to sensor serially. The relationship between the sensor resistance and the monitored voltage is express by the following equation:

$$R_S = R_L \left(\frac{V_C}{V_{out}} - 1 \right) \tag{1}$$

3.2 Pre-processing of signal patterns

There are several interfering inputs, the most common being changes in temperature and relative humidity of odors. Usually, the heater of a chemoresistor is maintained at constant voltage but in reality the operating temperature varies due to any change in ambient temperature.

Humidity also has a strong effect on most sensors. The baseline resistances usually decrease as the humidity increase, although the exact slope depends from the operating temperature of sensors. Chemical sensors suffer from long-term stability, caused by physical changes in the sensors and the chemical background, which gives an unstable signal over the time. Attempts for drift counteraction have been made both in the pre-processing and recognition stage.

Several methods have been applied for an initial data reduction that is listed in [9]. for a metal-oxide sensor. The difference method is usually applied when there is an additive error both to the baseline and the steady-state response. In the case of multiplicative type of error, it is better to apply the relative method that represents the ratio of the steady-state response to the baseline so that the error will cancel out. The relative parameter is often used with metal-oxide gas sensor, due to the high sensitivity to concentration they have. However, the baseline of these sensors is usually referenced to a specific gas rather than air, since they are very sensitive in air to the presence of any gas by showing baseline stability problems. The pre-processing of this method has some limitations due to the quite restricted concentration range. To overcome this problem the fractional change has been proposed. This method has shown good results in odor recognition using neural networks for the discrimination of several coffees. The last method, the log parameter, is more suitable when the variation of concentration is very large. A log relative resistance parameter has the benefit of linearising the sensor output ant taking the value of zero in absence of an odor input.

In our paper, we adopted relative parameter. As we mention above, this method is suitable for TGS type sensor due to high sensitivity to concentration.

3.3 Pattern classifier

The ART2 neural network is designed for continuous-valued (e.g., real value) patterns. Let x and w_j denote the input vector and the weight of neuron j respectively. The criterion of selecting the winner is based on a minimum distance measure (e.g., Euclidean or other distance).

i) Given a new training pattern, a MINNET(Minimum Net) is adopted to select the winner, which yields the minimum distance $\|x - w_j\|$. The winner is denoted as j*.

ii) Vigilance Test: A neuron j* passes the vigilance test if and only if $\|x - w_{j^*}\| < \rho$ where the vigilance value ρ determines the radius of a cluster.

iii) If the winner fails the vigilance test, a new neuron unit k is created with weight $w_k = x$.

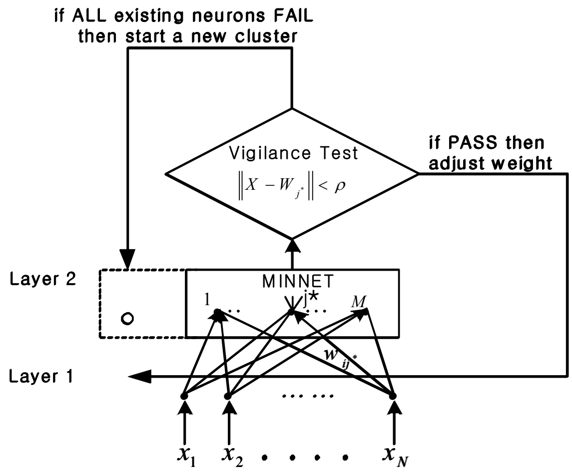

Fig. 3. A schematic diagram of an ART2 neural network.

iv) If the winner passes the vigilance test, adjust the weight of the winner j^*

$$w_{j^*}^{\,n+1} = \frac{x + w_{j^*}^{\,n} \|cluster_{j^*}^{\,n}\|}{\|cluster_{j^*}^{\,n}\| + 1} \tag{2}$$

where, $\|cluster_j\|$ denotes the number of members in cluster j.

4. RESULTS

First, we have studied the behavior of two TGS sensors for seven different concentrations. As their concentrations are increase, most elements of pattern are decrease as shown in Fig. 4, 5, 6. But in case of TGS 2602 sensor response to H_2S, their resistance values are increase in low concentration.

Fig. 7 shows relative resistance which is the ratio of gas resistance to air resistance. Each pattern is composed of ten-element data sets extracted from an ADC module in the microcontroller. These data sets are used as the inputs to the ART2 neural network.

Table 2 shows the simulation results for 90 sample data by an ART2 NN. As threshold value change, the ratio of correct matches is also change. From simulation results, we found that suitable threshold value is ranged from 0.16 to 0.20 to get high correct matches. Having this value, we test various gases and

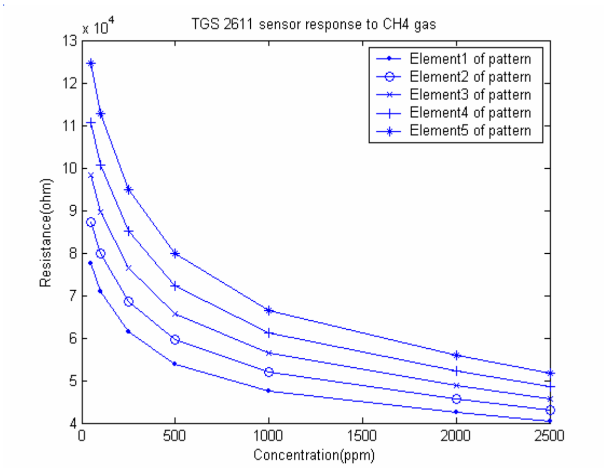

Fig. 4. TGS 2611 sensor steady-state response in CH_4 gas.

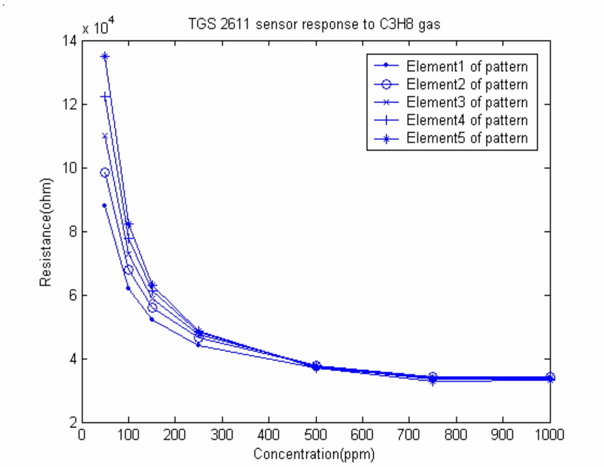

Fig. 5. TGS 2611 sensor steady-state response in C_3H_8 gas.

their concentration we mention above in real time. Our embedded system is evaluated during twenty minutes after gas injection for each target gases. Unlike simulation, in real time there some fail to classify the gas. It may be result from short-term and long-term drift influenced by humidity, temperature and sensor's nonlinearity. To be more stable classification, we need to additional method which can compensate these drift efficiently in accordance with our application. And also we found it is difficult to discriminate low concentration gases.

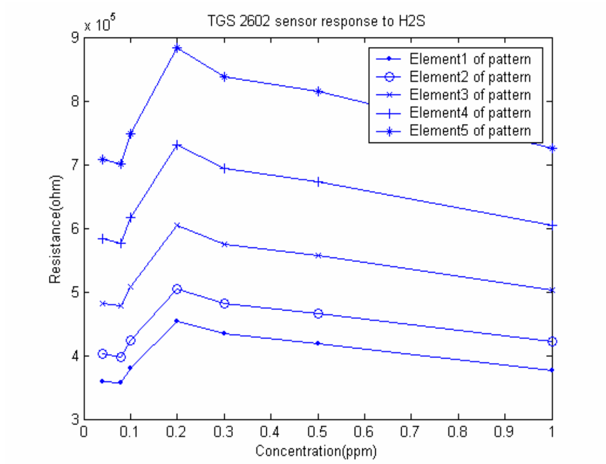

Fig. 6. TGS 2602 sensor steady-state response in H_2S gas.

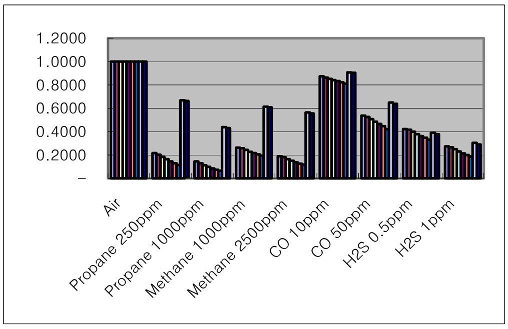

Fig. 7. Patterns of relative resistance.

Table 2 Simulation results by an ART2 NN.

ρ	% correct matches
0.15	86.67
0.16-0.20	98.89
0.21	86.65

Table 3 Experimental results in real time by an ART2 NN.

Cluster Number	Test Gas	# of success	# of fail	% of success
1	C_3H_8 250ppm	18	2	90
2	C_3H_8 1000ppm	20	0	100
3	CH_4 1000ppm	17	3	85
4	CH_4 2500ppm	19	1	95
5	CO 10ppm	4	16	20
6	CO 50ppm	15	5	75
7	H_2S 0.5ppm	20	0	100
8	H_2S 1ppm	20	0	100

5. CONCLUSION

In this paper, we propose a real time embedded system with tin oxide sensors and a one-chip-microcontroller for classifying various gases of various concentrations. Sensor output signals are extracted from thermal modulation method. To improve the performance of classification, a pre-processing method of relative resistance and an ART2 neural network are used. From the simulation and experimental results, we conclude that the system is necessary for the stable use in the fields.

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