ART2 Neural Network Applications for Diagnosis of Sensor Fault in the Indoor Gas Monitoring System

In-Soo Lee*, Jung-Hwan Cho**, Chang-Hyun Shim***, Duk-Dong Lee**, and Gi-Joon Jeon**

* School of Electronics and Electrical Engineering, Sangju National University, Sangju, Korea
(Tel : +82-54-530-5324; E-mail: islee@sangju.ac.kr

** School of Electrical Engineering and Computer Science, Kyungpook National University, Daegu, Korea
(Tel : +82-53-940-8824; E-mail: mrjoe20@palgong.knu.ac.kr)

*** Sense & Sensor Co., Ltd. Technopark of Kyungpook National University , Daegu, Korea
(Tel : +82-53-953-4233; E-mail: shim933@s-s.co.kr)

Abstract: We propose an ART2 neural network-based fault diagnosis method to diagnose of sensor in the gas monitoring system. In the proposed method, using thermal modulation of operating temperature of sensor, the signal patterns are extracted from the voltage of load resistance. Also, fault classifier by ART2 NN (adaptive resonance theory 2 neural network) with uneven vigilance parameters is used for fault isolation. The performances of the proposed fault diagnosis method are shown by simulation results using real data obtained from the gas monitoring system.

Keywords: Fault diagnosis, sensor fault, ART2 neural network, gas monitoring system

1. INTRODUCTION

There is an increasing interest in electronic nose applications. Especially, gas monitoring is required by home as well as industry [1, 2]. However, sensor fault degrades reliability and performance of gas monitoring system. Therefore fault diagnosis of sensor is very important in the gas monitoring system.

There have been many methods for FDI (fault detection and isolation) of the system. These methods fall into two major groups [3]: 1) model free methods, 2) model based methods. The model based FDI methods rely on the idea of analytic redundancy [4]. However, these methods are dependent on finding a system mathematical model that defines the relationship between the system inputs and outputs. In practice, however, the mathematical description of the relationship is not easy to obtain due to nonlinearities. To overcome this problem, it is necessary to find the modeling tool of presenting any nonlinear relationship approximately.

Model free methods include limit checking, expert systems and neural network-based schemes. In recent years, neural network models have been studied considerably for the optimum production and control strategy as problem-solving tools. Extensive research efforts have been devoted to the use of fault diagnosis problem [5-8]. Main advantages of the neural network model for fault diagnosis applications can be represented by approximating the nonlinear functions and by adaptive learning and parallel processing. It has been noted that neural network model consists of a suitable structure for representing the unknown nonlinear function generally. Hence this model can be used as a powerful tool for handling nonlinear problems. However, these methods are difficult to isolate new unencountered faults.

Srinivasan et al. [8] proposed an FDI algorithm using the Hopfield and ART1 NN. However, the ART1 NN is used for classification of the binary patterns. Therefore, ART2 NN is suitable for classification because the estimated parameters are analog patterns. Usually, the estimated parameters have widely varying magnitudes. Therefore, the parameter with a large magnitude will greatly affect the classification result as compared to a parameter with a smaller magnitude. For this reason, when the conventional ART2 NN [9] is used for the fault isolation, the isolation accuracy deterioration of the classifier is occurred.

This paper presents a neural network-based fault diagnosis method to diagnose of sensor in the gas monitoring system (Figure 1). In the proposed method, the signal patterns are extracted from the voltage of load resistance using thermal modulation method. The proposed algorithm is based on ART2 NN with uneven vigilance parameters [10]. Since ART2 NN with uneven vigilance parameters is an unsupervised neural network the proposed fault classifier does not require the knowledge of all possible faults to isolate the faults occurred in the system. The performances of the proposed fault diagnosis method are shown by simulation results using real data obtained from the gas monitoring system.

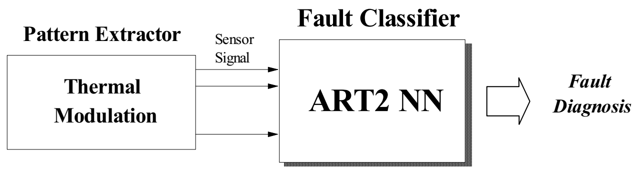

Fig. 1 Block diagram of the proposed ART2 NN-based sensor fault diagnosis method.

2. GAS MONITORING SYSTEM

Our experiment setup, for indoor gas monitoring and fault diagnosis of sensor, is composed of gas line, saturator (humidity generator), and testing chamber, as shown in Figure 1. Gas lines consist of various gas bottles including mixture air and MFC's (mass flow controllers). And in chamber, there are TGS2611 (methane gas sensor) sensors and an MSP430 ultra-low power microcontroller to measure gases. 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 and transfers its value to host computer.

Fault causes of TGS2611 are categorized with following three types. First case is that oil stain absorb into sensor. Second, high voltage passes into sensor heater. Third, humidity is exposed to sensor. We extract sensor output data to diagnose of sensor through breaking down sensor by intention.

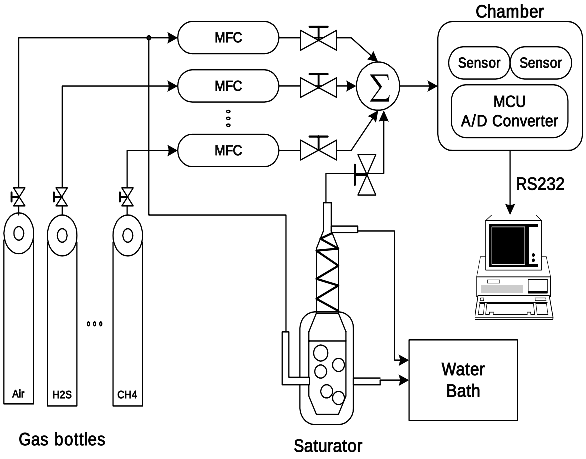

Fig. 2 Experimental setup.

3. ART2 NN-BASED SENSOR FAULT DIAGNOSIS

3.1 Pattern extraction for fault diagnosis of sensor

Sensor output signals are extracted from thermal modulation method [11]. This method has some merits. One is simple because only one sensor is needed as compared to sensor array technology that 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.

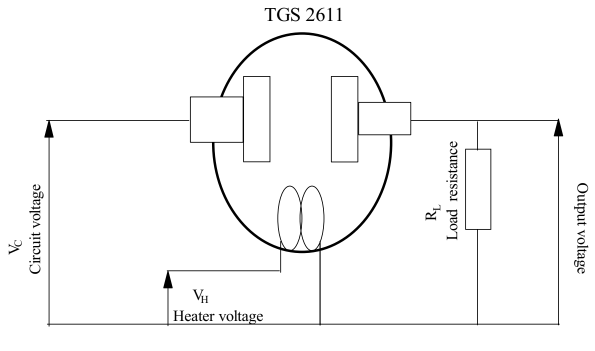

Fig. 3 Analog circuit for extracting sensor signals.

And, we used electronic circuit to extract electric signal from sensors. As shown in Figure 3, load resistor is connected to sensor serially. The relationship between the sensor resistance and the monitored voltage is express by the following equation:

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

where R_S is the sensor resistance, R_L is the load resistance, V_C and V_{out} are circuit voltage and output voltage respectively.

The heater resistance is heated by control signal of microcontroller for 10 seconds. As soon as turn off, the output voltage of the sensor is read by a 12bit-ADC module of microcontroller every 100ms. On the other hands, with heating heater of sensor, the pattern data are extracted by same interval. The total of 20 pattern data is used to input of an ART2 neural networks for classifying sensor faults.

We conduct fault experimental of TGS2611 sensor for following three fault types of sensor.

First, oil stain, it can be generated in kitchen room, is exposed to sensor so sensitivity of sensor drop and finally sensor is not operating well. The TGS2611 sensor is heated by alcohol lamp with fixing to a test tube and exposed to evaporating oil stain for 20 minutes. After then we get a pattern data from air condition.

Second, high voltage is passed to heat resistance. In case of taking high voltage to operate heater of sensor, heater will be damaged and aged easily. After high voltage 7V is passed to heater for 10 minutes, pattern data are extracted.

Third, sensor is exposed to humidity, which can affect operation of semiconductor. After sensor is exposed to hot vapor for 20 minutes, we get pattern data as same method.

We experiment repeatedly above three cases until they result in breaking down. We assume single fault which generate one sensor fault at that time.

3.2 ART2 NN with uneven vigilance parameters

In the proposed method, the ART2 NN with uneven vigilance parameters isolates the sensor faults of the indoor gas monitoring system using the sensor signal patterns. Architecture of the ART2 NN is shown in Figure 4. The ART2 NN with uneven vigilance parameters has the same architecture of the general ART2 NN [7]. But, in the proposed network new vigilance test is used to classify the input patterns.

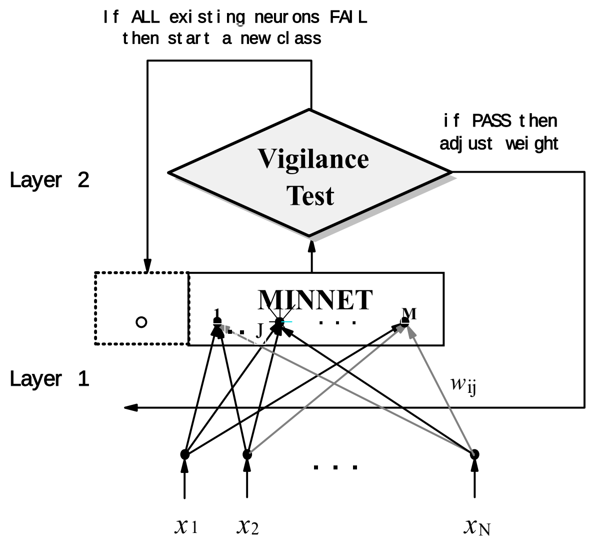

Fig. 4 Architecture of the ART2 NN.

The distance between the input patterns and j-th output node (fault class) is computed as follows:

$$d_j = \left\| W_j - X \right\|_{\infty}^{E} \underline{\Delta} \max_i \left| \frac{1}{\varepsilon_i}(w_{ij} - x_i) \right|, \quad j = 1, 2, \ldots, M \tag{2}$$

where x_i is the input of the input node i, $i=1,2,\ldots, N$, N is the number of input nodes, w_{ij} is the weight from output node j to input node, M is the number of the output nodes (created classes). And $\|\bullet\|_{\infty}^{E}$ is the weighted infinite norm, $E = diag(\frac{1}{\varepsilon_1}, \frac{1}{\varepsilon_2}, \ldots \frac{1}{\varepsilon_N})$ is the $N \times N$ diagonal weighted matrix, ε_i is the i-th vigilance parameter for i-th input node. In order to improve the classification accuracy, the vigilance parameter for the parameter with a large magnitude variation is selected large. On the other hand, the vigilance parameter for the parameter with a large magnitude variation is selected small.

If the distance between the input patterns and the J-th output node (class) is minimum, then the class J is selected winner node. Verification is done whether input pattern X really belongs to the winner class J by performing the vigilance test as follows:

$$\textit{Vigilance test condition :} \quad \|W_J - X\|_{\infty}^{E} < 1 \tag{3}$$

If the winner class J passes the vigilance test, adjust the weights of the class J, W_J by

$$W_J^{new} = \frac{X + W_J^{old}[class_J^{old}]}{[class_J^{old}] + 1} \tag{4}$$

where $[class_i]$ is the number of the patterns in the class i.

On the other hand, if the class J fails the vigilance test, a new class (output node) is created with weight $W_{M+1} = X$.

4. SIMULATION RESULTS AND DISCUSSION

Simulations are carried out to evaluate the performance of the ART2 NN-based sensor fault diagnosis system using real data obtained from the gas monitoring system. The data was collected from TGS 2611 gas sensor and converted to digital signal patterns for fault isolation using 12bit-ADC module. We choose vigilance parameters of the ART2 NN as $\varepsilon = 10 * [10,7,7,7,5,5,5,5,5,4,4,5,6,6,6,6,6,5,6,5]$.

To verify the proposed diagnosis algorithm, three types of sensor (TGS 2611) faults are introduced to the gas monitoring system at the 150-th sample number and measurement board for fault diagnosis experiment is shown in Figure 5. The faults that were introduced into the fault diagnosis experiment are summarized in Table 1.

Table 1 List of faults.

Fault	Description
Fault #1	Contaminated with cooking oil vapor
Fault #2	Increase sensor heater voltage
Fault #3	Exposed to humidity

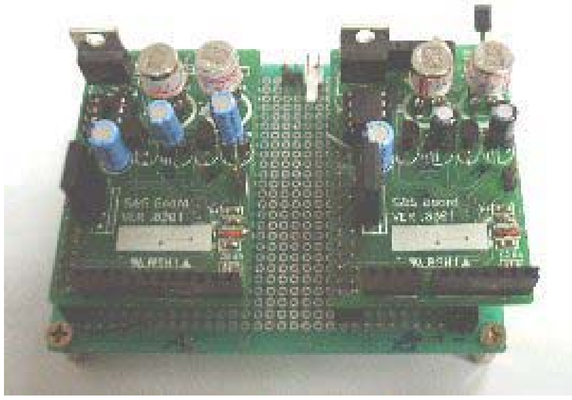

Fig. 5 Measurement board for sensor fault diagnosis.

Table 2 lists the sensor signal patterns for fault diagnosis. The simulation results for the fault #1, fault #2 and fault #3 are shown in Figure 6, Figure 7 and Figure 8 respectively. Figure 6 shows the output of the ART2 NN with uneven vigilance parameters. The simulation results showed that the proposed classifier successfully classifies the fault #1(P11) as new fault class 2. Also, Figure 7 and 8 show the results of fault isolation for new sensor fault #2(P21) and #3(P31) respectively. From the results, we can see that the ART2 neural network creates a new fault class 3 (fault #2) and 4 (fault #3). Table 3 shows the simulation results for 40 real sensor signal patterns by ART2 NN with uneven vigilance parameters and the neural network classifies the fault very well.

Table 2 Sensor signal patterns for fault diagnosis.

Fault	No. of patterns	Sensor signal patterns (ART2 NN inputs)
Normal	P01	2099 2333 2309 2239 2163 2088 2016 1946 1877 1812 0520 0877 1126 1300 1428 1525 1602 1666 1721 1771
Fault #1	P11	1904 2251 2294 2263 2211 2157 2102 2049 1998 1948 0422 0764 1039 1259 1432 1569 1676 1761 1832 1888
Fault #2	P21	2260 2482 2460 2404 2340 2277 2218 2160 2106 2054 0773 1224 1495 1658 1764 1836 1891 1937 1980 2017
Fault #3	P31	1739 2073 2117 2084 2032 1970 1910 1852 1796 1740 0403 0702 0926 1095 1224 1326 1409 1478 1537 1588

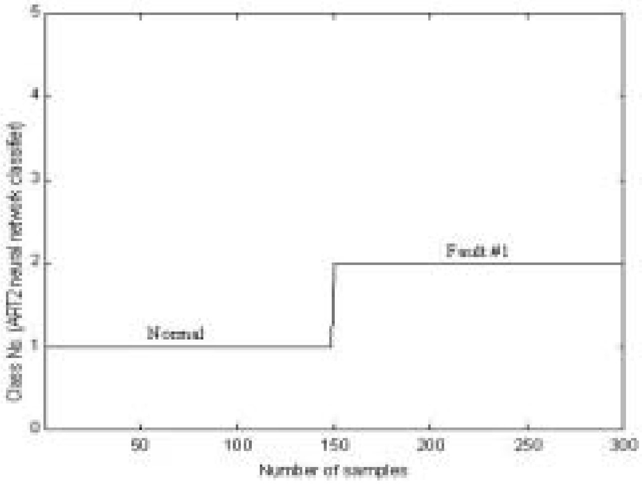

Fig. 6 Result of fault diagnosis for fault #1.

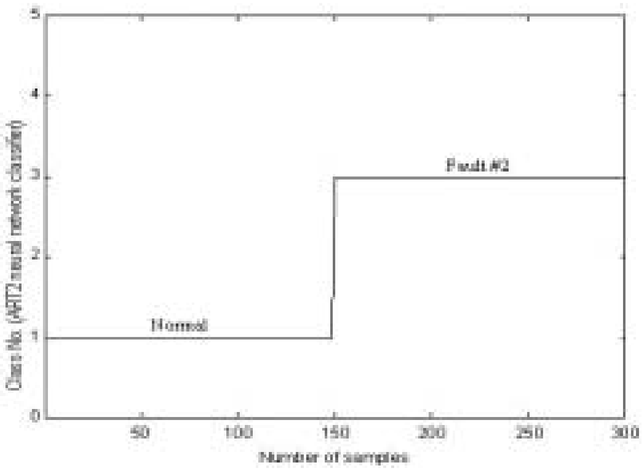

Fig. 7 Result of fault diagnosis for fault #2.

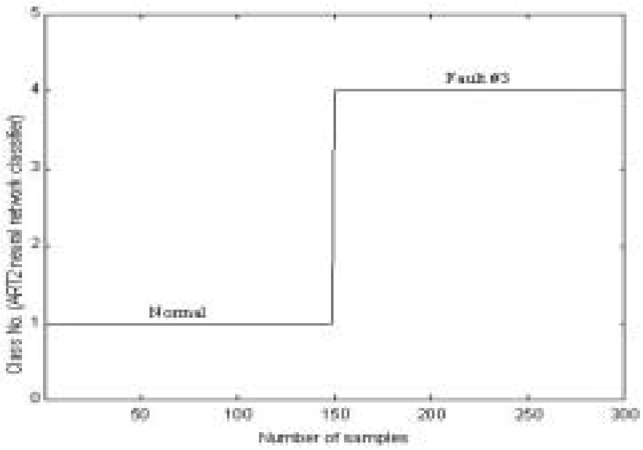

Fig. 8 Result of fault diagnosis for fault #3.

Table 3 Sensor signal patterns and fault diagnosis results.

Fault	No. of patterns	# of success	% of success
Normal	10(P01-P10)	10	100
Fault #1	10(P11-P20)	10	100
Fault #2	10(P21-P30)	10	100
Fault #3	10(P31-P40)	10	100

5. CONCLUSIONS

In this paper, we propose an ART2 NN with uneven vigilance parameters based diagnosis method to diagnose of sensor fault in the indoor gas monitoring system. In the proposed method the thermal modulation method is used to extract the signal patterns from the voltage of load resistance. The proposed algorithm is based on ART2 NN with uneven vigilance parameters. Since the ART2 NN is an unsupervised NN it can adaptively learn and classify input patterns without a priori knowledge of classes. Therefore, the fault classifier does not require the knowledge of all possible faults to isolate the faults occurred in the system. In particular, the proposed fault classifier can isolate the fault more flexibly because it uses uneven vigilance parameters to classify the fault patterns. From the simulation results using real data collected from the real system, it is verified that the proposed ART2 NN-based fault diagnosis method is successfully applied to diagnose problem in the gas monitoring system.

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