

Modified Multi-Gas Classification System Based on Fuzzy Min-Max

Young Wung Kim, Seung Hyun Paik, and Hong Bae Park

Abstract—In this paper, we propose a modified multi-gas classification system based on fuzzy min-max to classify effectively principle component of gases such as ammonia and hydrogen sulfide existing multiply in various environment. We obtain a modified DOC and design a classification system to apply the neural network based on fuzzy min-max algorithm. The proposed classification system using modified fuzzy min-max algorithm improves speed of the system with concise process and also its classification rate, 80.4%, is higher than using original fuzzy min-max.

Keywords—electronic nose, fuzzy min-max, gas sensor, multi-gas classification

I. INTRODUCTION

THE electronic nose has received attentions in such field as medical, manufacturing technology, and livestock. It is very important to classify multi-gas from the gas mixture in order that the electronic nose to be used in various environments [1]-[5]. Yet, multi-gas classification is very difficult because of interference among the gases. Especially ammonia and hydrogen sulfide interfere with the opposing sensors, so the gas classification is essential part in electronic nose with gas sensor array. To improve the performance of gas classification, many studies are progressed. There are several gas classification algorithms applied to the electronic nose [6]. To classify multi-gas, multilayer perceptron (MLP) and Fuzzy ARTMAP neural networks have been widely used in electronic noses. In restricted hardware resource such as wireless sensor node, the fuzzy ARTMAP can deliver more accurate classification and faster training process than MLP [7]-[9]. In previous works [10], [11], fuzzy min-max comes up with similar results of fuzzy ARTMAP. Moreover, in learning process training of the membership function parameters, fuzzy min-max performs less iteration than fuzzy ARTMAP.

In this paper we study multi-gas classification system using

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modified fuzzy min-max for performance improvement of classification accuracy. To analyze the performance, the proposed method is compared with the classification using original fuzzy min-max.

II. THE FUZZY MIN-MAX ALGORITHM

A. Fuzzy min-max classification

Pattern classification defines the classes and determines which input pattern is associated with the class. Classification system requires class boundaries for each class to be defined. Fuzzy min-max is a feedforward neural network classifier that uses min-max vector pairs to define hyperbox fuzzy sets. This neural network involves a supervised learning rule to make a set of classes. Class boundaries are the hyperbox fuzzy sets built by min-max vector pairs. So the learning is simple process that makes min-max vector pairs. A hyperbox defines a region of the n-dimensional pattern space, and the hyperbox has full class membership. The classification determines which class a pattern belongs by the membership with Degree of Classification (DOC). If an input pattern belongs to completely the hyperbox, then the input is a member of the class with degree 1. If the input falls completely outside the hyperbox, then the input is not a member of the class with degree 0. If the input pattern is neither completely within nor completely outside of hyperbox, then the input has DOC between 0 and 1. The DOC is computed as follows where $A_k = (a_{k1}, a_{k2}, \dots, a_{kn})$ is the k'th n-dimensional fuzzy input pattern; $V_j = (v_{j1}, v_{j2}, \dots, v_{jn})$ is the j'th class's min point; $W_j = (w_{j1}, w_{j2}, \dots, w_{jn})$ is the j'th class's max point, and j is the index of the class.

$$\text{DOC}(A_k, V_j, W_j) = \left[1 - \frac{\sum_{i=1}^n \max(0, v_{ji} - a_{ki})}{n_{\text{sub}}} \right] \left[1 - \frac{\sum_{i=1}^n \max(0, a_{ki} - w_{ji})}{n_{\text{sup}}} \right] \quad (1)$$

n_{sub} is the number of components of the fuzzy pattern where less than the min point, and n_{sup} is the number of components of the fuzzy pattern where greater than the max point [12].

B. Fuzzy min-max neural network

In figure 1, fuzzy min-max neural network is shown. Input nodes F_A are connected to hyperbox nodes F_B by two connections min and max point. The connections from F_B to class nodes F_C are used to represent DOC.

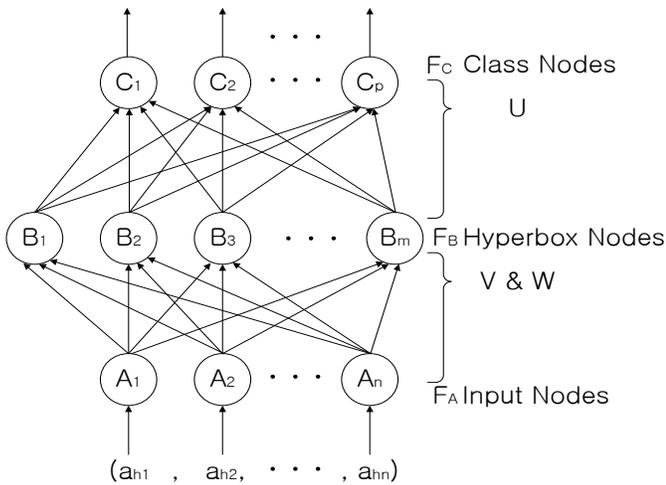


Fig. 1 Fuzzy min-max neural network

C. Modified fuzzy min-max

A marked characteristic of fuzzy min-max is depends on the DOC. In order to improve the performance of classification, DOC is multiplied by a coefficient vector (C_i). The modified DOC equation is the following.

$$DOC(A_k, V_j, W_j, C_i)^u = \left[1 - \frac{\sum_{j=1}^n \max(0, (v_{ji} - a_{ki}) C_i)}{n_{sub}} \right] \left[1 - \frac{\sum_{j=1}^n \max(0, (a_{ki} - w_{ji}) C_i)}{n_{sup}} \right] \quad (2)$$

III. EXPERIMENTAL DESIGN

A. Data acquisition

Ammonia and hydrogen sulfide are chosen as target gases, and experimental system for the data acquisition is prepared with the following three parts: gas flow control, a bubbler, and a test chamber. The gas flow control is composed of four gas bottles which contain H₂S, NH₃, and dry synthetic air (nitrogen: oxygen=4:1) and four mass flow controllers (MFCs). The synthetic air is injected through the bubbler into glass chamber and then intermixed with the target gas. The experiment conditions are maintained the temperature of experimental glass chamber as 27°C with 52% humidity. The total flow rates are set at 278cc/min, and the chamber capacity is 2250cc. This process is shown in figure 2.

Measurements of the target gases H₂S, NH₃, and mixture of the two gases are carried out at 30 different concentrations as shown in Table I. Concentration of H₂S, NH₃, and mixtures of the two gases are 10 different concentration levels. Each measurement was replicated 30 times for 33 samples, resulting in 990 measurements, including the reference air. One measurement cycle for each sample lasted 15 min after injection. 10 minutes was allowed for the sample to be saturated in the chamber and the responses stabilized, then 25 data sequences

were repeatedly recorded during the remaining 5min. One data sequence composes the sensor heater turn on period for 6s and turn off for 6s repeatedly, reading the output voltage changes of the SnO₂-CuO and SnO₂-Pt sensing films for 1.425μs with 57 ms interval, and collecting a 50-dimension data set extracted from the two sensing films. Eleven measurement cycles with different concentrations for each type of the gases are carried out successively by adjusting the concentrations through the MFC. Six measurement data sets out of eleven sets were used for calibration or training and the rest of data sets for estimation or prediction as indicated in Table II. The extracted data set are transmitted from sensor node to sink node and then, the sink node sends the received data to the host computer through a USB interface. For details, see the [13].

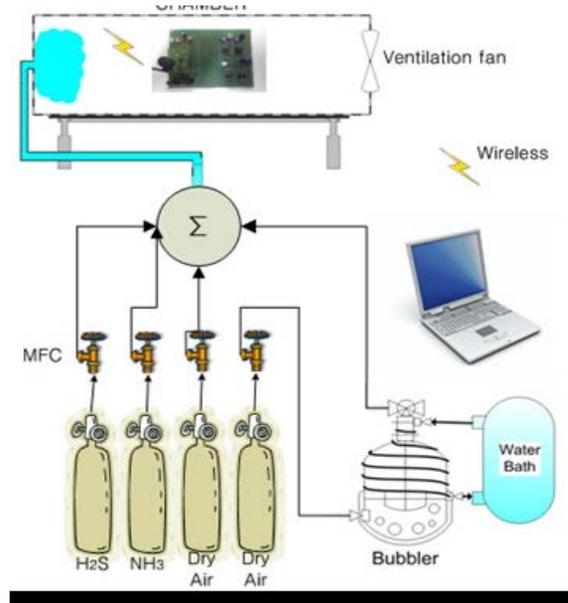


Fig. 2 Gas measurement experiment set-up for data acquisition

TABLE I
COMBINATION OF MULTI-GAS AND RESPECTIVE CONCENTRATIONS: TRAINING MARK 'T' AND ESTIMATION MARK 'E'

NH ₃ (ppm)	H ₂ S (ppm)										
	0	0.1	0.15	0.25	0.4	0.55	0.75	1	1.25	1.6	2
0	t ₁ /e ₁	t ₇	e ₇	t ₈	e ₈	t ₉	e ₉	t ₁₀	e ₁₀	t ₁₁	e ₁₁
3	t ₂	t ₁₂									
5	e ₂		e ₁₂								
8	t ₃			t ₁₃							
12	e ₃				e ₁₃						
20	t ₄					t ₁₄					
30	e ₄						e ₁₄				
40	t ₅							t ₁₅			
60	e ₅								e ₁₅		
80	t ₆									t ₁₆	
100	e ₆										e ₁₆

B. Fuzzy min-max classification system

To classify the gases and their mixture, the system is composed of data extraction, preprocessing, learning, and testing. This block diagram is shown in Figure 3.

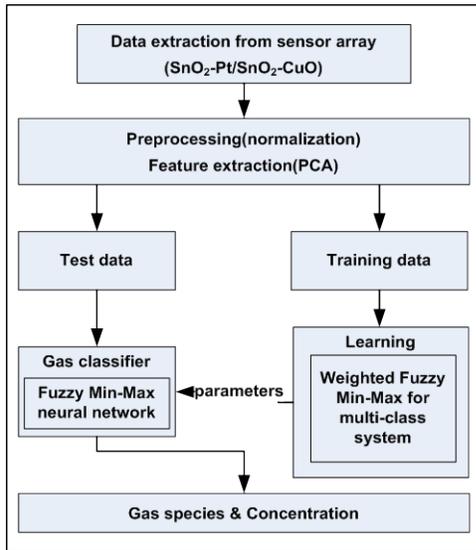


Fig. 3 Block diagram of classification

A neural network structure of the classification using fuzzy min-max is shown in figure 4. The hyperbox membership of input pattern is determined by DOC calculated by (2).

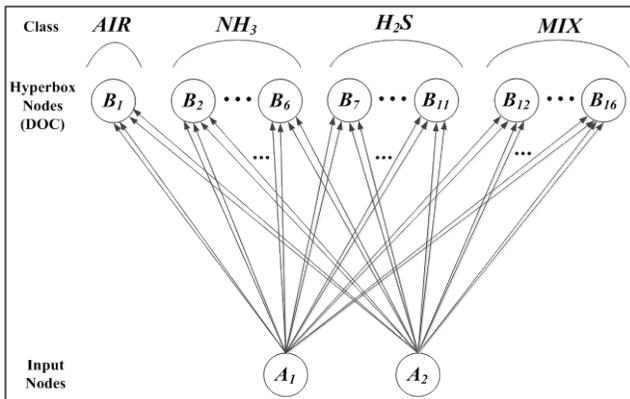


Fig. 4 Neural network structure

The fuzzy min-max classifier is a supervised learning classifier and the hyperbox node is already associated with a class. There are two connection neural networks from each input node to hyperbox node. These connections represent min and max point of a hyperbox, and their points are adjusted by the learning procedure. In equation (3) and (4), min point is updated by fuzzy intersection operation, and max point is updated by fuzzy union operation.

$$v_{ji}^{new} = v_{ji}^{old} \cap a_{ki} \equiv \min(v_{ji}^{old}, a_{ki}) \quad (3)$$

$$v_{ji}^{new} = v_{ji}^{old} \cup a_{ki} \equiv \max(v_{ji}^{old}, a_{ki}) \quad (4)$$

IV. RESULTS AND DISCUSSION

Firstly, the feature extraction results using PCA is shown in figure 5. From 50-dimension raw data set, the 2-dimension data set is extracted by PCA. As you see figure 5, the overlap region appears partially, and the information of PC1 variance is 95.9387%. So we can estimate the patterns are difficult to classify.

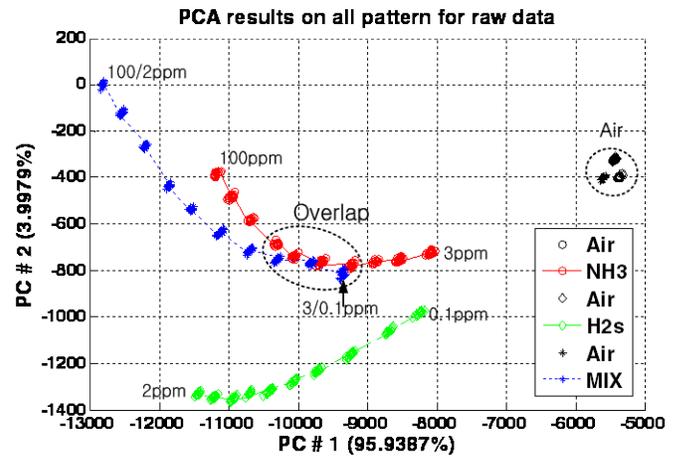


Fig. 5 PCA results on all pattern for raw data

In table II, we show the performance of the proposed classification system in comparison with original fuzzy min-max classifier. The modified fuzzy min-max classification rate is far better than the original fuzzy min-max. And iteration is just once, so learning process is fast by reducing unnecessary iteration.

TABLE II
THE COMPARISON BETWEEN ORIGINAL FUZZY MIN-MAX AND THE MODIFIED FUZZY MIN-MAX

Method	Original Fuzzy Min-Max	Modified Fuzzy Min-Max
Network Size	2/16(I/O)	2/16(I/O)
Iteration	1	1
Classification rate	53.3%	80.4%

V.CONCLUSION

In this paper, the modified multi-gas classification system based on fuzzy min-max was designed and evaluated. The simulation results with the real data showed that the proposed multi-gas classification system has high classification rate with few iteration. So the proposed multi-gas classification system has good performance with high classification accuracy and fast learning process in restricted hardware such as wireless sensor node.

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