CHEMICAL ENGINEERING TRANSACTIONS
VOL. 62, 2017

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

Guest Editors: Fei Song, Haibo Wang, Fang He

ISBN 978-88-95608- 60-0; **ISSN** 2283-9216

DOI: 10.3303/CET1762138

Gas Detection Software Based on Sensors

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Subject to serious gas pollution in the environment, this paper developed a gas detection system based on porphyrin chemical sensor. The reaction between porphyrin and organic gas will cause color change, so the images of the porphyrin chemical sensor array before and after the chemical reaction with the target gas were collected automatically by CCD. The feature information of the target gas was obtained using the image processing technology. The target gas was detected using the proper pattern recognition algorithm. The system was used to detect nine kinds of common VOCs and ammonia, and the experiment showed its effectiveness in qualitative identification of VOCs and quantitative identification of ammonia. It is concluded that the detection and control of VOCs is vital on indoor air quality evaluation and control and can detect harmful gases to prevent infection and gene mutation.

1. Introduction

At present, all kinds of low quality decoration materials are the main causes of indoor air pollution in China. With the improvement of people's living standards, indoor pollution caused by decoration becomes prominent (Bhat et al., 2013). Long-term living and working in a polluted indoor environment is prone to discomfort. The symptoms are headache, runny nose, sore throat, nausea, dizziness, slowness of movement and memory loss, a serious threat to human health (Chiang et al., 2016). The WHO called this "sick building syndrome". In the composition of deteriorated indoor air, Volatile Organic Compounds (VOCs) gas has the most serious impact on human health (Darabpour, 2015). It is reported that there are about 300 kinds of common harmful substances in a newly decorated house, including VOCs such as benzene, toluene, xylene, ethylbenzene, etc. Formaldehyde concentrations up to 0.1 ppm can cause damage to the pharynx and the upper lung; patients and children with asthma can experience breathing difficulties at concentrations up to 0.25 ppm; long time exposure can cause discomfort and even nasal cancer (Hou et al., 2015).
The main components of VOCs have an impact on immunity of the human body, leading to the disorder of mmunity, such as enhanced humoral immunity and weakened cellular immunity, resulting in various immunological diseases including skin diseases; Both benzene and formaldehyde can inhibit the immunity of the body; VOCs can act directly or indirectly on DNA, resulting in mutations in the gene. Therefore, it is vital to evaluate and control the indoor air quality, especially the detection and control of VOCs (Jamalabadi and Alizadeh, 2017).

2. Function of gas detection software

2.1 Hardware communication

The PC software system needs to communicate with the hardware system to control the hardware system and data acquisition. There are 4 units for hardware communication: image acquisition, lighting control, air pump control and flow/humidity/temperature monitoring (Karacali et al., 2013).
Image acquisition unit: Acquire the images of sensor array chip before and after the reaction by control of CCD, display in real time and save to the hard disk; including manual/auto acquisition. Output data: the images of sensor array chip before and after reaction (Liu et al., 2013).

Lighting control unit: Control on/off of the LED by sending a command to control the illumination of the reaction chamber during the image acquisition.

Air pump control unit: control on/off of the gas pump by sending commands, and control the gas pump flow via control the motor speed with PW. (Manchukutty et al., 2015)

Flow/humidity/temperature monitoring unit: Acquire the data of the temperature sensor, humidity sensor and flow sensor read from the serial port to monitor and display the reaction conditions in real time.Output data: chamber temperature, humidity and gas flow after the reaction (Martin et al., 2012).

2.2 Image processing

The acquired image is processed. In the detection system, the system does not identify the chemical sensor array image, but the color change information before and after reaction of the porphyrin-sensitive point in the sensor array with the gas to be identified (Mishra et al., 2015). In the image signal processing unit, the color information of the sensitive points in the image of the chemical sensor array before and after reacting with the target gas is extracted using image processing technology. The color change caused by the reaction between the sensor and the gas to be identified is obtained through subtraction (Pourbabaee et al., 2016). The color change information is the sensor response to the gas to be identified. In the porphyrin sensor chip, the porphyrin points with valid information are arranged in an image with an array of m × n. The system locates each of the porphyrin points by a grid and then separates the porphyrin points from the image background using an image segmentation algorithm (Sekhar and Brosha, 2015). Through segmentation of the grid and porphyrin points, Ye Lin points in Ye Lin chip sensor can be identified and the number is located. Figure 1 shows the diagram of image processing:

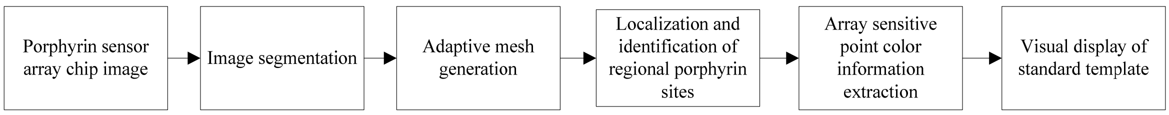

Figure 1: Diagram of image processing

2.3 Pattern recognition

Input data: 108 color components of 36 points in the array extracted by image processing.

The pattern recognition unit consists of three modules: feature extraction, qualitative identification and quantitative identification. The feature extraction module extracts the classification and concentration components that distinguish the target gas from 108 color components as input for subsequent pattern recognition. (Shu et al, 2016)

Qualitative identification module can perform qualitative identification of target gas by observing the visual difference spectrum on the standard template. The quantitative identification module performs quantitative identification of concentration of target gas of the known category with a well-trained network using a suitable neural network algorithm, and the feature extracted by the feature extraction module as the input of neural network. (Shu et al, 2016)

3. Pattern recognition

Gas sensor array pattern recognition includes three steps: feature extraction, classification and identification. Feature extraction and classifier design are the critical two steps in most pattern recognition systems, which are directly related to the recognition effect.

The main methods of feature extraction are Principal Component Analysis (PCA), feature extraction based on wavelet transform, genetic algorithm, Partial Least Squares (PLS), K Nearest Neighbor (KNN) algorithm and KW test. The Principal Component Analysis (PCA) and its improved methods are typical methods of feature extraction (Zhou et al., 2017). The system was used to conduct experiments and preliminary data analysis of nine common volatile organic compounds (VOCs) and ammonia (NH_3) etc.

3.1 Dynamic response of sensor array to NH3

In the automatic image acquisition, set total 14 collection times for each experiment: 0.1, 0.15, 0.2, 0.25, 0.3, 0.33, 0.4, 0.43, 0.5, 0.6, 1.8, 1, 1.5 and 2min. The image is processed using the sequence image processing mode. The reaction of 30ppb NH_3 is shown below. It can be seen from Figure 2 that there are three points in the chemical sensor array that have obvious reaction with NH_3: {(1, 4), (1, 5), (4, 3)}. An adjustable difference threshold T is set in order to reduce the noise introduced by the image sensor and operation during the image processing. For each point in the sensor array, if ΔB + ΔG + ΔR ≤ T, the color change for this point is set to ΔB = 0, ΔG = 0, ΔR = 0 and T is set to 10 in the experiment.

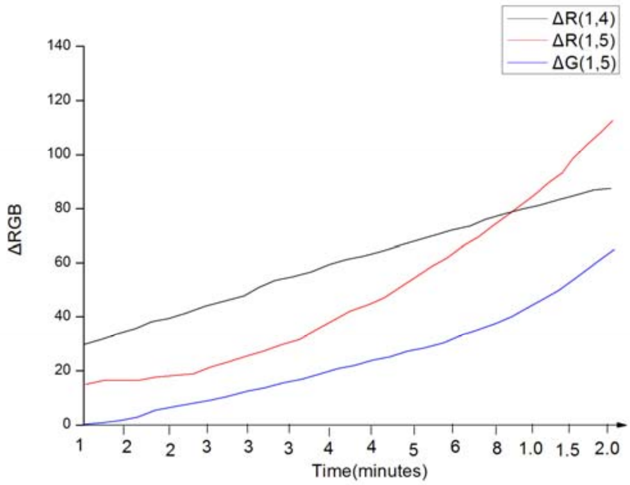

Figure 2: Typical colorimetric sensor array response to NH3 concentration (30 ppb)

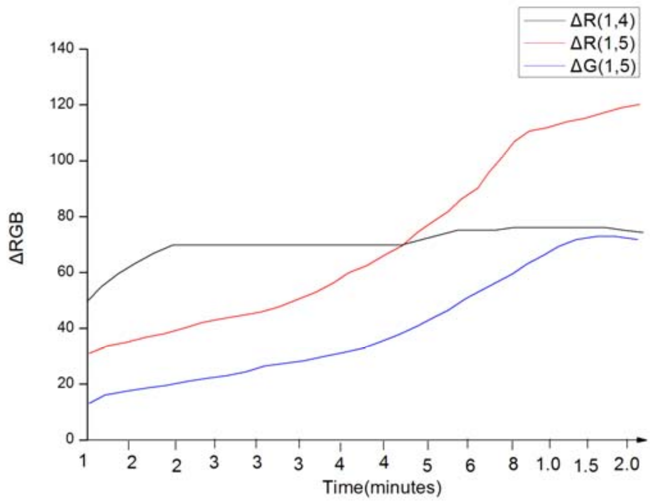

Figure 3: Typical colorimetric sensor array response to NH3 concentration (150 ppb)

The color change over time can be intuitively represented by a curve. Each line in Figure 5.4 and Figure 5.5 represents a certain color component of a point at which a color change occurs in the array, namely ΔR (1,4), ΔG (1,5), ΔR (1,5), that is, the green and red components of these three points: {(1, 4), (1, 5), (4, 3)}. For 30ppb and 150ppb NH3, the three color components increased with the increase of exposure time; The trend of ΔG (1,5), ΔR (1,5) increasing at the two concentrations of 30ppb and 150ppb was similar. ΔR (1, 4) tended to be saturated at exposure time of 0.5 min and concentration of 150 ppb. It can be found that for different concentrations at the same exposure time, the color change of higher concentration is larger.

3.2 Sensor array response to different NH3 concentration

Figure 4 shows the three color components of ((1, 4), (1, 5), (4, 3)} changes with the concentration. The exposure time is 0.25 min. Similar results were obtained with 0.1, 0.1 5, 0.2, 0.3, 0.33 and 0.4 min respectively. At the same exposure time, ΔR (1,4), ΔG (1,5), ΔR (1,5) increased with increasing concentration.

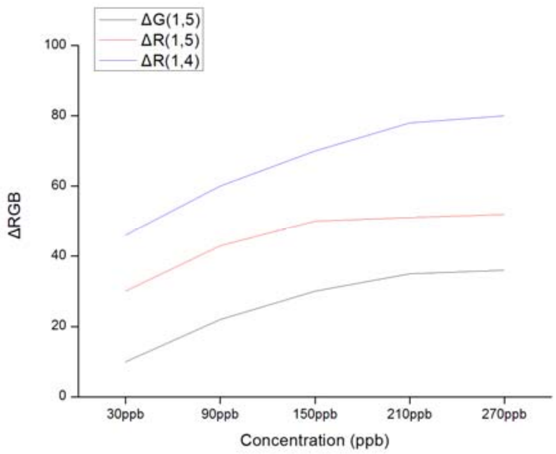

Figure 4: Typical colorimetric sensor array response to NH3 with various concentrations (at an exposure time of 0.25 minute)

3.3 Feature extraction

Different sensors respond differently to the target VOCs, we use pattern recognition techniques to analyze the data, including two steps: signal preprocessing and pattern recognition. In the signal preprocessing step, the data is normalized, and Principal Component Analysis (PCA) is used for feature extraction and cluster. The extracted features serve as input to neural network pattern recognition. The PCA method is also used for clustering, which divides target VOCs into different groups. The selection of features has a great influence on the accuracy of classification and recognition. The magnitude of the color change caused by the reaction and the reaction kinetics model will provide useful information for determination of the concentration.
Figure 4 shows the PCA 2D scores plot of 20 samples of 4 concentrations of NH3. The first two principal components represent the variance contribution of 86.205%, and the first four principal components represent the variance contribution of 97.499%. The PCA results show that the eigenvector V can distinguish 4 concentrations of NH3.

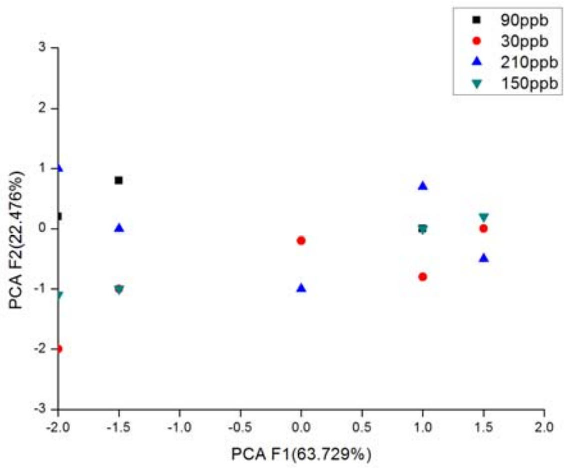

Figure 5: PCA scores plot for several concentrations of NH3 resulting from analysis of time-stacked vectors

Combining all color components of all points in the array with those similar to the 3 color components of the above 3 points followed by PCA, we get an unacceptable clustering result. These results were discarded. This method is not used for subsequent neural network processing. Therefore, the optimized sensor array will help improve the recognition performance of chemical sensor array.

3.4 BP neural network identification

Figure 6 shows the neural network pattern identification. Artificial neural network is a kind of algorithm that approaches human brain thinking method, which forms a complex network system by extensively interconnecting a large number of simple processing units, namely neurons, and can learn the external environment through training. It has good effect in function mapping and function approximation, and has strong self-adaptive characteristics for nonlinear classification problems such as gas analysis. Feedforward neural network is a kind of supervised learning based artificial neural network, which can know the unknown samples by learning the known samples and gaining experience. The learning algorithm of feedforward neural network usually adopts back propagation (BP) algorithm. Therefore, this kind of network is also called BP network.

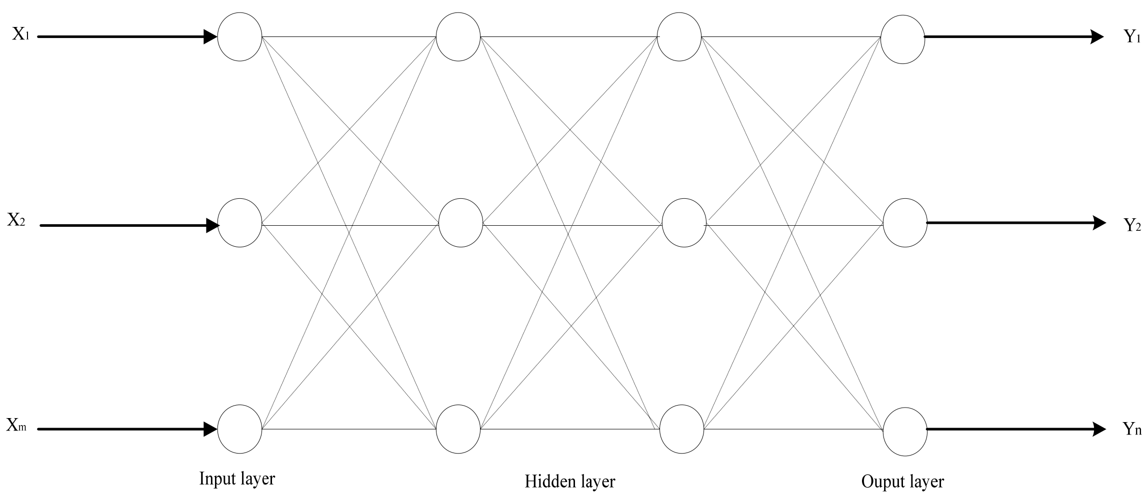

Figure 6: Structure diagram of BP neural network

The entire network is divided into input layer, hidden layer and output layer. There may be more than one hidden layer (Figure 6). The neurons in adjacent layers of the network are connected to each other, and the neurons in each layer are not connected. The output of the neurons of previous layer is used as the input of the neurons of the next layer. The properties of the entire network are determined by the connection rights between neurons in adjacent layers and the thresholds on neurons.

4. Conclusion

A novel gas detection system was constructed based on the rapid cross recognition of gas by the porphyrin chemosensing array chip. The system identifies the gas by converting the gas feature information into the image information of porphyrin sensor. A detection software system has been developed for the gas detection system, integrating signal acquisition, signal processing & analysis and data management. The following functions are realized. First, signal acquisition, including manual/auto image signal acquisition; real-time acquisition and display of reaction chamber temperature, humidity and flow. Second, signal processing and analysis, and two signal processing modes are used for two image acquisition modes: processing of single image before and after reaction and sequence image processing. Processing of single image before and after reaction includes opening images before and after reaction, rotating at the same time or separately, cutting, automatic processing and result printing etc.

Acknowledgments

The paper is supported by the follow project:
Project: National Power Grid Corp science and technology project (5216A01600VZ).
Project Name: Based on cloud platform and RFID to achieve the closed-loop mode of intelligent meter life cycle management key technology research and development of complete sets of equipment.

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