Diagnosis and Detection Method of Critical Equipment Failure Based on Electronic Nose Technology

Ying Zhang

School of Optoelectronic Engineering, Xi'an Technological University, Xi'an 710021, China
zhangying_1102@163.com

In the manufacturing process of modern space and aeronautics industry, chemical industry, industry and manufacturing industry, the safe and efficient operation of equipment has played an increasingly important role. In order to realize the early diagnosis of critical equipment failure, this paper uses the e-nose gas sensor technology to qualitatively and quantitatively analyze the odor volatilized by the oil generated by equipment failure and the odor emitted by the wire during the heating process. The experimental results show that the linear discriminant analysis and artificial neural network method can be applied to the e-nose gas sensor array to perform accurate qualitative separation of the odor. The curve change of the response stability amplitude is in accordance with the related law of the gas sensor output stability and concentration change. With the increase of the gas concentration, the larger the stability amplitude K, the smaller the response time constants \( T_{P1} \) and \( T_{P2} \), and the higher the confidence. By establishing a mixed gas response model, it is conducive to the separation of the gas sensor array signals of the mixed gas.

1. Introduction

The development and application of technologies such as manned spaceflight, deep sea exploration, and large aircraft have placed increasing demands on the safe operation of equipment systems (Bhattacharya and Dan, 2014). If the air in the cabin is slowly accumulating or sudden accidents have caused air pollution, it will pose serious threats to personnel safety (Zou and Huang, 2015; Rusinov et al., 2013). For large equipment with extremely high sealing requirements, their requirements for safety and reliability are increasing, e-nose gas sensors or gas sensing arrays can analyze and determine the type and concentration of odors and convert the information into electrical signals and output in the form of frequency (Zhou et al., 2014). The e-nose system consists of a gas sensor array, a signal preprocessing unit and a pattern recognition unit (Qin et al., 2017). The gas sensor commonly used in e-noses includes metal oxide type, which has high sensitivity, fast response time, low price, low power consumption, high operating temperature, but it is sensitive to humidity, in actual application process, humidity must be strictly controlled (Yin and Zhao, 2016).

The signal preprocessing of the e-nose system is a converter of the whole process, and the process includes the extraction of feature parameters, feature extraction and selection of recognition modes (Yang et al., 2016; Li et al., 2013). At home and abroad, a large number of research results have been obtained in the application process of e-nose technology, which has been widely used in food, chemical and medical fields. In terms of qualitative and quantitative identification of odors, its technology has gradually matured, and some research has also applied artificial neural networks to the e-nose gas sensor arrays and used a nonlinear modelling method to identify the mixed odors (Feipe et al., 2018; Jiang et al., 2012; Gu et al., 2011). There are few studies on the application of e-nose technology to the diagnosis and detection of critical equipment failure. The only research abroad has applied it to the diesel engine exhaust gas detection, there is still a lot of research content to be further explored (Zhou et al., 2010; Xiong et al., 2016). In this paper, the e-nose technology is applied to the odor detection of equipment abnormal state, and the signal of the gas sensor array is analyzed in-depth for the early warning of the test equipment failure.

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2. Equipment abnormal odor simulation experiment and response analysis

The power transmission device is the core part of the equipment, long-term damage or aging is easy to cause oil leakage or oil spill, which not only causes environmental pollution, but also may even cause fire or other accidents (Mortellec et al., 2013). In order to simulate the response of the e-nose gas sensor array to the oil volatile gases, the diesel oil, engine oil, gear oil and equipment wires that are commonly used in the power transmission system are taken as test objects, 10 e-nose gas sensors were used to detect the odors volatilized by three kinds of oil and the odor emitted during heating of the wire respectively (Bai et al., 2016; Lima et al., 2015). The working steps of the e-nose gas sensor include sampling-sample washing-desorption-injection-cleaning-cooling, etc., and the maximum working temperature is 300 °C. By analyzing the response value of the sensor, it is found that the 2# sensor's response value signal is much larger than the other 9 sensors, which is very sensitive, and the 2# sensor is removed from the odor recognition process of equipment abnormal state.

3. Qualitative identification of equipment abnormal state odors

3.1 E-nose gas sensor array signal data preprocessing

The data preprocessing of the sensor array signals is the most important environment for the odor identification process (Mao, 2018). The acquired odor response is converted into electrical signals or digital signals, and the main content includes baseline correction and normalization of the data. Baseline correction of the data can compensate for the error caused by temperature to the sensitivity of the gas sensor. Normalization can achieve dimensionality reduction and convert the spatial data of the higher dimension into the surface data of the lower dimension. Figure 1 shows the load matrix obtained by the singular value decomposition method. The figure shows the singular value decomposition of the modeled sample set X_{model} during data processing. The interpretation rate of the first four principal components of the load matrix P to the original variables is obtained. The state of the gases volatilized by diesel oil and gear oil are relatively stable and the identification effect is optimal.

![Figure 1: The load matrix obtained by the singular value decomposition algorithm](image)

3.2 Qualitative identification of abnormal odor based on linear discriminant analysis and artificial neural network

Linear discriminant analysis can transform the linear inseparable problem into a linear separable problem, and the decrease or increase of the dimension can find a linear separable problem with better separation. Figure 2 shows the linear discriminant analysis (LDA) of four kinds of odors. It can be clearly seen that the four-sample aggregation are quite dispersed, and the four different kinds of odors can be clearly distinguished. Aggregation of the same odor samples is concentrated, by LDA we can effectively characterize the four kind of gases, and the identification effect is optimal. It has been found that the application of artificial neural networks to e-nose gas sensor arrays can greatly improve the predictive ability of fault diagnosis of critical equipment, so that early detection and early processing can be achieved. The gas sensor array can be composited several times by a simple nonlinear function, and any continuous function can be realized at any
precision to accurately perform qualitative separation of the odors. In order to achieve the qualitative identification of the four kinds of odors, we selected a total of 36 gas sample sets of the three kinds of gases with different concentrations. By using 9 gas sensors to identify the three kinds of gases, input the gas sensor array data into the neural network, the output of the network is the identification result, the expected output is: Diesel oil: \([I_a, I_b, I_c] = [1, 0, 0]\)
Gear oil: \([I_a, I_b, I_c] = [0, 1, 0]\)
Heating wire gas: \([I_a, I_b, I_c] = [0, 0, 1]\)

**Figure 2:** LDA linear discriminant analysis of four kinds of odors

### 4. Application of e-nose technology in equipment fault detection

#### 4.1 Quantitative analysis of equipment abnormal state odor

According to existing researches, it is difficult to express the abnormal odor of the equipment fault itself with a single signal value, and it is necessary to establish a mathematical model for the gas sensor array signals. From the analysis in Section 2, it is found that the 2# gas sensor is much more sensitive to gas than other sensors, but the response of the sensor is relatively smaller than others. For quantitative analysis, we only use the 2# sensor for experiments. Figure 3 shows the response curve of 2# sensor for gas volatilized by diesel oil with different concentrations, it can be seen that the growth curve with time shows a trend of rapid growth first and decline later. The main reason is that the concentration of volatile gases in the sealed bottle is continuously reduced due to the replenishment of clean air. Figure 4 is a comparison of the sensor response fitting results with the actual response. The sensor array curve is similar to the sensor transfer function curve, and the fit of the two curves exceeds 94%, which can better reproduce the sensor response process. Table 1 shows the identification results and confidence of 2# sensor transfer function model with different odor
concentrations. As the gas concentration increases, the larger the stability amplitude \( K \), the smaller the response time constants \( T_{P1} \) and \( T_{P2} \), and the higher the confidence. Figure 5 shows the reconstructed response signal curve, it can be seen that the reconstructed response signal better reflects the odor response characteristics of the gas sensor. Figure 6 is a graph showing the response stability amplitude \( K \) varies with the gas sampling volume \( L_0 \), and the curve conforms to the related law between the gas sensor’s steady state output value and the concentration change. Figure 7 shows the curve of response time constant \( T_{p1} \) varies with gas sampling volume \( L_0 \), the response time decreases with the increase of odor concentration, when the concentration \( L_0 > 10 \text{ml} \), the response time decreases linearly with the increase of concentration.

**Table 1:** Identification results and confidence of 2# sensor transfer function model with different odor concentrations

<table>
<thead>
<tr>
<th>( L_0 ) (ml)</th>
<th>( K )</th>
<th>( T_{P1} )</th>
<th>( T_{P2} )</th>
<th>Confidence degree/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40.003</td>
<td>12.438</td>
<td>2.480</td>
<td>88.84%</td>
</tr>
<tr>
<td>5</td>
<td>184.518</td>
<td>12.017</td>
<td>2.200</td>
<td>90.83%</td>
</tr>
<tr>
<td>10</td>
<td>262.001</td>
<td>12.013</td>
<td>2.788</td>
<td>91.45%</td>
</tr>
<tr>
<td>20</td>
<td>353.363</td>
<td>11.782</td>
<td>3.256</td>
<td>92.32%</td>
</tr>
<tr>
<td>50</td>
<td>519.730</td>
<td>11.422</td>
<td>2.233</td>
<td>94.02%</td>
</tr>
<tr>
<td>100</td>
<td>724.624</td>
<td>10.753</td>
<td>2.060</td>
<td>94.28%</td>
</tr>
</tbody>
</table>

**Figure 5:** Reconstructed response signal curve  
**Figure 6:** Response stability amplitude \( K \) varies with gas sampling volume \( L_0 \)  
**Figure 7:** Response time constant \( T_{p1} \) varies with gas sampling volume \( L_0 \)

### 4.2 Blind separation of equipment abnormal state mixed odor

The oil gas volatilized by abnormal equipment and other odors are mixed together, it’s often a mix of gases, and we need to establish a mixed gas response model for it. Assume that there is no chemical reaction
between the gases volatilized by the abnormal equipment, and the gas distribution is uniform, and the concentration between the gases is not dependent, use an e-nose gas sensor to perform independent analysis. Figure 8 shows the response curve of the sensor array of one experimental sample. By analyzing the correlation coefficient matrix between the nine sensors, the correlation coefficient is between 0.3387-0.9877, and the linear correlation between the nine sensors is large. Figure 9 is a response curve of an e-nose gas sensor array to the diesel oil gas, it can be seen that the response of the gas sensor to the diesel oil gas is not much different. Figure 10 is the response curve of the diesel/gear oil mixed gas of the e-nose gas sensor array, it can be seen that the response curve of the diesel/gear oil mixed gas and the diesel oil gas response curve are different, which is conductive to the separation of the gas sensor array signals of the mixed gas.

5. Conclusion

In this paper, the e-nose technology is applied to the odor detection of equipment abnormal state, and the signal of the gas sensor array is analyzed in-depth. The specific experimental conclusions are as follows:
(1) The linear discriminant analysis can realize the aggregation degree analysis of four odor samples, which can effectively identify the four gases qualitatively and the identification effect is optimal. The artificial neural network is applied to the e-nose gas sensor array to realize any continuous function at any precision, so as to accurately perform qualitative separation of the odor.
(2) With the increase of gas concentration, the larger the stability amplitude K, the smaller the response time constants $T_{P1}$ and $T_{P2}$, and the higher the confidence. The response time decreases with the increase of odor concentration. When the concentration $L_0>10\text{ml}$, the response time decreases linearly with the increase of concentration.
By analyzing the correlation coefficient matrix between the nine sensors, it is found that the linear correlation is large, and the response of the gas sensor to the diesel oil gas is not much different, but the response curve of the diesel/gear oil mixed gas and the response curve of diesel oil gas are different, which is conductive to the separation of the gas sensor array signals of the mixed gas.

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