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Analyzing the response of a temperature modulated tin-oxide gas sensor using local linear neuro-fuzzy model for gas detection

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Abstract. A resistive gas sensor (RGS) under temperature modulation regime is considered as a system for gas detection. Five target gases including Methanol, Ethanol, 2-Propanol, 1-Butanol, and Hydrogen each at 11 concentration levels, were selected for diagnosis using a single commercial gas sensor. For modulating the sensor, a staircase containing five voltage steps each with 20s plateau is applied to micro-heater of the sensor. This, in turn, alters both the temperature and the resistance profiles of the sensing layer which are considered as the input and the output of the defined system, respectively. In this way, five systems corresponding to five steps of the system input can be distinguished. Next, each system under the influence of the examined target gases is modeled with neuro-fuzzy network. Local linear model tree (LOLIMOT) used as learning algorithm of the systems and weights of the trained networks utilized as the features of the sensor in presence of target gas. Mapping these feature vectors using linear discriminant analysis showed successful classification of all target gases.

Introduction

Resistive gas sensor (RGS) is cost effective, small, durable, and high sensitive. These sensors operate at high temperatures which are provided by micro heater placed in proximity of sensor sensitive layer. The response of these sensors to the presence of stimulus in air is appeared by shift in their electrical resistance [1-2]. The value of this shift is strongly depends on the operating temperature of the sensor. A single RGS is unable to discriminate among the different target gases (TGs). Use of multiple sensors in the form of sensor array is one of the most common methods which is utilized to enhance the selectivity in RGSs [3]. Modulating the sensor operating temperature is another most popular method which is presented to overcome non-selectivity problem in a single RGS [4-7]. It is believed that the dynamic sensor response due to the temperature changes of the sensing layer, includes enough information about the nature of the unknown TG [3]. The extraction and classification of distinction features available in dynamic sensor response to an unknown TG is mainly based on pattern recognition and system identification techniques.

Artificial neural networks (ANNs) based analysis is used extensively as a diagnosis tool for the gas sensing systems. In ANNs, the relation between inputs and outputs is determined by various training algorithms and correcting the network weights. In [8], e.g., a 4-component thick film sensor array used to identify seven alcohols and alcoholic beverages. Considering sensor responses as the input and type of the TGs as the output of the ANN, it was showed that RBFNN is more powerful, much faster, and less sensitive to learning parameters rather than MLPNN.

Although ANN methods have been successful in many cases, but the time consuming network training process makes them inappropriate for online applications. In addition to ANNs, Fuzzy systems have been used in modeling many nonlinear processes. One of the difficulties of fuzzy systems is related to production of the fuzzy rules. Combination of these two networks (ANN and

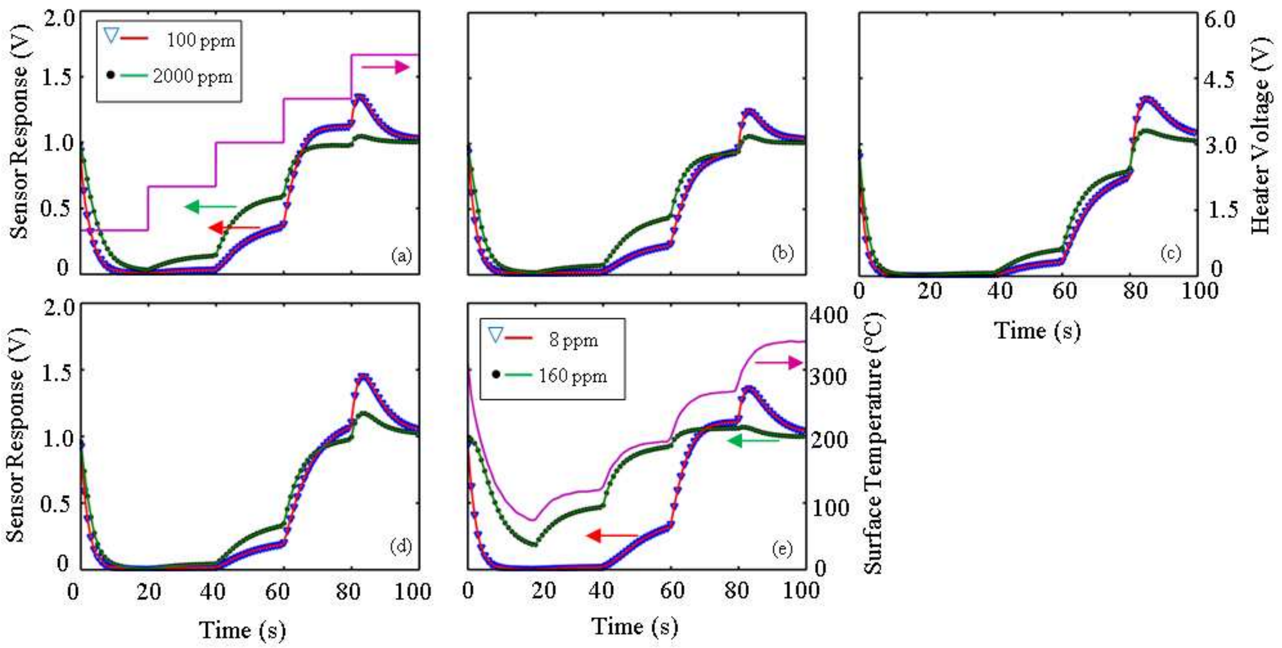

Figure1. The normalized responses for (a) Methanol; (b) Ethanol; (c) 2-Propannol; (d) 1-Butanol and (e) Hydrogen. The recorded and simulated responses are shown by point markers and solid lines, respectively. The heater voltage waveform and the corresponding changes of the sensing layer temperature are shown in Figs. (a) and (e), respectively.

Fuzzy) leads to neuro-fuzzy systems which have been used in electronic nose. In [9], neuro-fuzzy classifier is used for qualitative and quantitative classification of the data which was pre-processed by PCA algorithm.

In this work, we have applied a special neuro-fuzzy technique to analyze a thermally modulated RGS as a system and identify its discriminatory parameters. The diagnostic information was searched among the weights of the trained networks. This, in turn, has afforded the identification of the nature of the prevailing TGs. Good class separability in both training and verification data was obtained by dimension reduction.

Experimental

Five TGs including Methanol, Ethanol, 1-Propanol, 1-Buthanol and Hydrogen, each at 11 concentration levels, were selected for diagnosis using a single commercial gas sensor (SP3-AQ2, FIS Co., Japan) under temperature modulation mode. A resistive heater was used to evaporate the alcohol types of this group. A staircase voltage waveform with 5 steps, from 1 to 5 V, each with 20 s plateau was used to excite the sensor heater as depicted in Fig. 1c. It has been shown in previous works that 20s is the optimal time for modulating the utilized commercial RGS with this waveform configuration [5]. As the heater voltage is changed, the sensing layer temperature is accordingly altered as depicted in Fig. 1e. Details of the experimental procedure have been reported elsewhere [4], [5]. As a sample, two normalized recoded responses of each analytes are given in Fig. 1a-e with point marker.

System modeling and analysis

The discriminatory features contained in the response patterns of the sensor, which some of them given in Fig. 1, are exploited using single-input-single-output (SISO) modeling. The time varying temperature of the sensing layer is considered as the input, $u(t)$, and its corresponding transient response as the output, $y(t)$, of the system. Both variables are altered by applying staircase voltage to the sensor heater. So, the atmosphere polluted by examined TGs is defined as a part of the system. For each step of the staircase, a neuro-fuzzy model with the network architecture presented in Fig.2a was used to model the corresponding recorded temporal response. Network training was achieved by the *local linear model tree* (LOLIMOT) algorithm. The main approach with a local linear neuro-

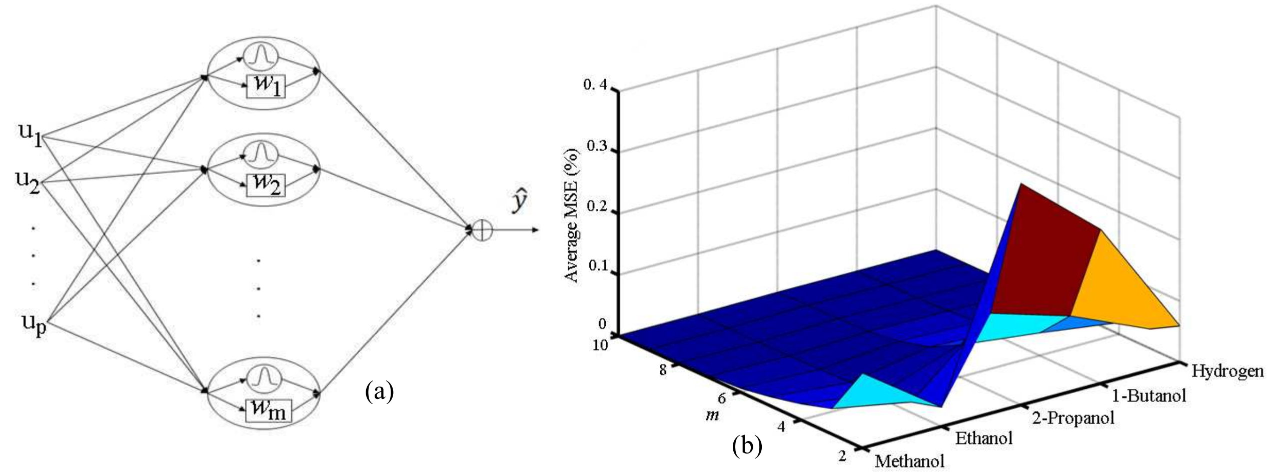

Figure 2. (a) Structure of a local linear neuro-fuzzy network. (b) the average MSE plot of the simulated sensor outputs versus the number of neurons in hidden layer, *m*, of neuro-fuzzy network and used for the modeling of step IV of the responses recorded for all the contaminants examined.

fuzzy model is dividing the input space into small linear sub-spaces with fuzzy validity functions. Any produced linear part with its validity function is described as a fuzzy neuron. So, the total model is a neuro-fuzzy network with one hidden layer and a linear neuron in the output layer which simply calculates the weighted sum of the outputs of local linear models. Details of the algorithm can be found in ref. [10]. Taking five steps of the heater voltage into account, five LOLIMOT trained networks is also obtained. Although from one system to another, the number of neurons in hidden layer can be different but, it is fixed in any five systems, individually. By changing the TG, weights of the networks will be changed. The mean square error (MSE) of the simulated outputs was utilized to determine the best number of the neurons in hidden layer of the networks, m, in each step. For instance, the average of MSE values computed over 11 concentration levels of each TGs by increasing m values and for step IV are shown in Fig. 2b. Once the m is known, each network can describe the system with the parametric vector given in Eq. 1:

$$\theta = (w_1 w_2 \cdots w_m)^T \tag{1}$$

in which, the w's are the weights of the trained network. Parametric vector components defined in Eq. 1 can be calculated by comparing measured output, $y(t)$, and the simulated output, $\hat{y}(t)$ computed from the trained networks. The best values for m in each of the five systems are $m = 7$ for steps I to IV of the staircase and $m = 8$ for the last step. The simulation results are compared with the experimentally recorded responses in Fig.1a-e. The close fitting of the simulated and the actual responses validates the model utilized here.

By combining parametric vectors of five different parts of a response pattern, the total parametric vector for each atmosphere contaminated TG is obtained by Eq. 2:

$$\Theta = (\theta_{\mathrm{I}}^{\mathrm{T}}\, \theta_{\mathrm{II}}^{\mathrm{T}}\, \theta_{\mathrm{III}}^{\mathrm{T}}\, \theta_{\mathrm{IV}}^{\mathrm{T}}\, \theta_{\mathrm{V}}^{\mathrm{T}})^T \tag{2}$$

Fisher's linear discriminant analysis (LDA) is utilized for mapping high dimension Θ vectors to low dimension vectors. Results of this mapping are shown in Fig. 3 in 3D space. In this figure, the unfilled markers show training data. In each case, the same LDA transformation matrix developed in the classification process of the training data was applied to feature vectors of the 25 verification experiments (5 of each TG). A successful classification of the five TGs, for both training and verification data, was achieved in a reduced feature space according to Fig. 3.

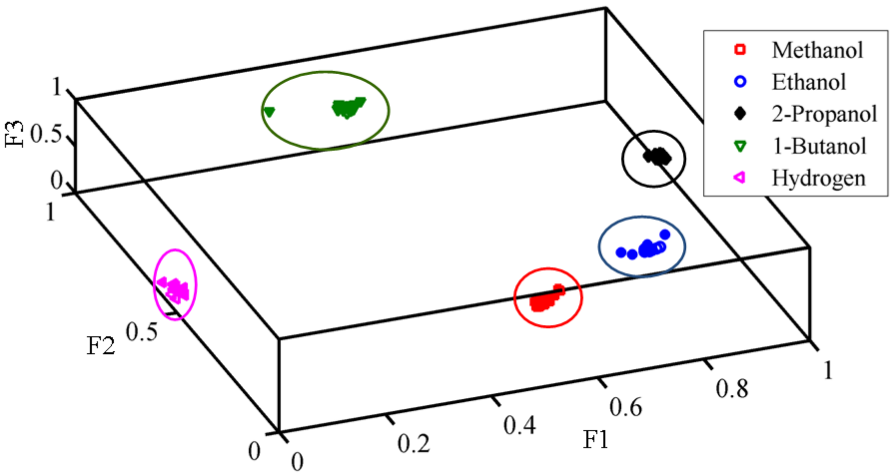

Figure 3. LDA mapping of the feature vectors of the sensor responses to the air polluted with the stated compounds in the 3D feature space. Unfilled and filled markers represent the vectors related to the training and the verification responses, respectively.

Conclusion

We demonstrated that the neuro-fuzzy network with LOLIMOT training method is robust instrument to extract the discriminative features from the responses of a temperature-modulated chemoresistor to the air polluted with methanol, ethanol, 2-propanol, 1-butanol, and hydrogen. A staircase heating voltage was used for temperature modulation. The feature vector of each segment of a recorded response was assigned by weights of LOLIMOT-trained NN which is used to fit it. Three dimensional LDA mappings were utilized for the classification of the feature vectors of the analytes which successfully classified all the analytes examined.

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