DOI 10.5162/IMCS2012/P1.0.18

Fusing the Diagnostic Information Provided by a Gas Sensor Temperature-Modulated with Different Power Waveforms

Amir Amini[1], Mohammad ali Bagheri[2], Gholam ali Montazer[2], Faramarz Hossein-Babaei[3]*
[1] Sama Technical and Vocational Training College, Islamic Azad University, Tehran Branch, Tehran, Iran.
** Corresponding author's e-mail address: amir.amini.elec@gmail.com*
[2] Department of Information Technology, School of Engineering, Tarbiat Modares University, Tehran, Iran.
[3] Electronic Materials Laboratory, Electrical Engineering Department, K. N. Toosi University of Technology, Tehran, Iran.

Abstract:
Numerous voltage waveforms have been used for the operating temperature modulation of chemoresistors resulting in different amounts of analyte-related information. The massive amount of numerical information and high level of data redundancy increases the computation cost and complicates the signal processing algorithm. Here, we fuse the information contents of the responses recorded using different temperature-modulating waveforms with an ensemble classification strategy for obtaining higher rates in analyte recognition. 100% classification rates were achieved in the classification of three different target analytes each examined at different concentrations in air by combining the outputs of nine base classifiers each trained individually with different feature subsets.

Key words: gas sensor, metal oxide gas sensor, operating temperature modulation, information fusion, ensemble classification, gas recognition.

Introduction

The problem of high dimensional data in e-noses, also referred to as "the curse of dimensionality" in statistical pattern recognition, significantly increase the complexity of the classification algorithm, time and memory requirements. Many of these features of the recorded patterns are irrelevant or redundant due to the cross-selectivity of the responses of the array components or the outputs of the virtual components of the virtual array utilized [1]. A simple strategy to reduce the number of features is to select a subset of the available features, feature subset selection (FSS).

The goal in FSS is to find an optimal subset of features that maximizes prediction or classification accuracy. An exhaustive search of all possible subsets of features will guarantee that the optimal subset is found. However, this is computationally impractical even for a moderate number of features. The performance of different sensors and feature selection methods have been studied by various researchers in the electronic nose community [2-5], but the potential improvement in classification through feature fusion by ensemble-based approach [6-7] have remained unattended. While the feature selection seeks to find an optimal subset of features, the goal of classifier ensembles is to combine the outputs of diverse classifiers to achieve optimal accuracy. This approach generally belongs to the multiple classifier system which is explained in detail in the following section.

The responses of a chemoresistor temperature-modulated with a heating voltage waveform contain significant amount of information related to the nature of the prevailing analyte in the background atmosphere [8]. Different voltage waveforms, such as staircases, pulse trains, sinusoidals, and step functions have been applied to the microheater of these sensors resulting in different success levels in analyte recognition [9-13]. In this paper, the performance of an ensemble of nine classifiers, each trained on different feature sets produced from the response patterns obtained using different microheater waveforms, are evaluted.

DOI 10.5162/IMCS2012/P1.0.18

Multiple Classifier Systems

Combining multiple classifiers to achieve higher accuracy is one of the foremost research areas in machine learning. It is known under various names, such as multiple classifier systems, classifier ensemble, committee of classifiers, and classifier fusion. Multiple classifier systems can generate more accurate classification results than each of the individual classifiers [14]. In such systems, as shown in Fig. 1, the classification task can be solved by integrating different classifiers, leading to better performance. However, the ensemble approach depends on the assumption that single classifiers make errors on different samples, known as classifier diversity. The intuition is that if each classifier makes different specific errors, then the total errors can be reduced by an appropriate combination of these classifiers.

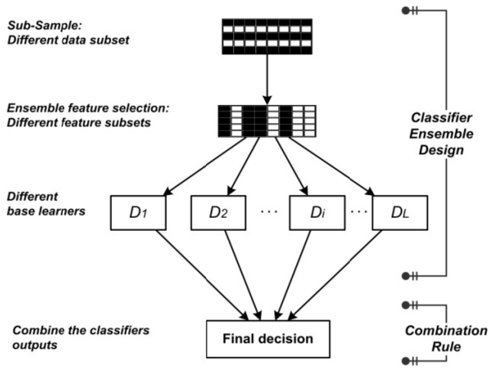

Fig. 1. The structure of a multiple classifier system.

There are three general approaches to create an ensemble of classifiers, among which the most straightforward approach is using different learning algorithms for the base classifiers or variations of the parameters of the base classifiers. For example, different initial weights or different topologies of a series of neural network classifiers can be utilized as different base classifiers. Another approach, is using different training sets to build different base classifiers. Such sets are often obtained from the original training set by re-sampling techniques [15-16].

The third approach, which is used in this work for classification of the response patterns of a thermally modulated gas sensor, is to train the individual classifiers with data that consist of different feature subsets, or so-called ensemble feature selection. While traditional feature selection algorithms seek to find an optimal subset of features, the goal of ensemble feature selection is to find different feature subsets to generate accurate and diverse classifiers. In the random subspace method [6] this ensemble is built by randomly choosing the feature subsets. These feature subsets are generated by randomly selecting *m* features from the *n*-dimensional feature space ($m < n$) . Then, each feature subset is fed into an individual classifier. Finally, all classifiers are aggregated by an appropriate combination rule. While the feature selection seeks to find an optimal subset of features, the goal of ensemble feature selection is to combine the outputs of diverse classifiers to achieve optimal accuracy.

Regardless of the base classification algorithm used, the diverse classifiers are then fused by a combination technique such as voting methods, fuzzy integral, Markov chains, Dempster-Shafer rule, behavior knowledge space, etc. [16].

Methods and Results

The sensor used is a generic tin oxide-based chemoresistor and the analytes are methanol, ethanol and 1-butanol. The response recording method is similar to those reported in [12] and [13], but no specific control was imposed or compensation measure was taken on the temperature and humidity level of the ambient air which is the background atmosphere in the experiments carried out. The voltage waveforms are simple rectangular pulses with different amplitude and durations. The responses recorded for methanol at different concentration levels using 6 different amplitude heating voltage pulses of constant duration (40 s) is given in Fig. 2. The heater is normally kept at a constant biasing of 2 V, when the pulses of different amplitudes are applied (Fig. 2). Similarly, responses were generated for three different pulse durations of similar general configurations. As a result a collection of 18 different pulsed responses were available for each target analyte at any concentration; examples are given in Fig. 3. Only nine out of these 18 responses were utilized in the analyte classification task described. The single pulse responses, similar to those presented in Fig. 3, are transformed by db2 wavelet. The obtained wavelet coefficients are used as the set of response features. The data processing flowchart is given in Fig. 4. In Table-1 the classification results of the individual classifiers are compared with those obtained from fusing the classifiers output by majority voting.

Conclusion

We showed that the uncorrelated information content of the responses of a temperature modulated gas sensor, generated with the application of different microheater voltage waveforms, can more efficiently be extracted by an ensemble classification strategy. The technique is cost effective and of general applicability for various gas analyses techniques.

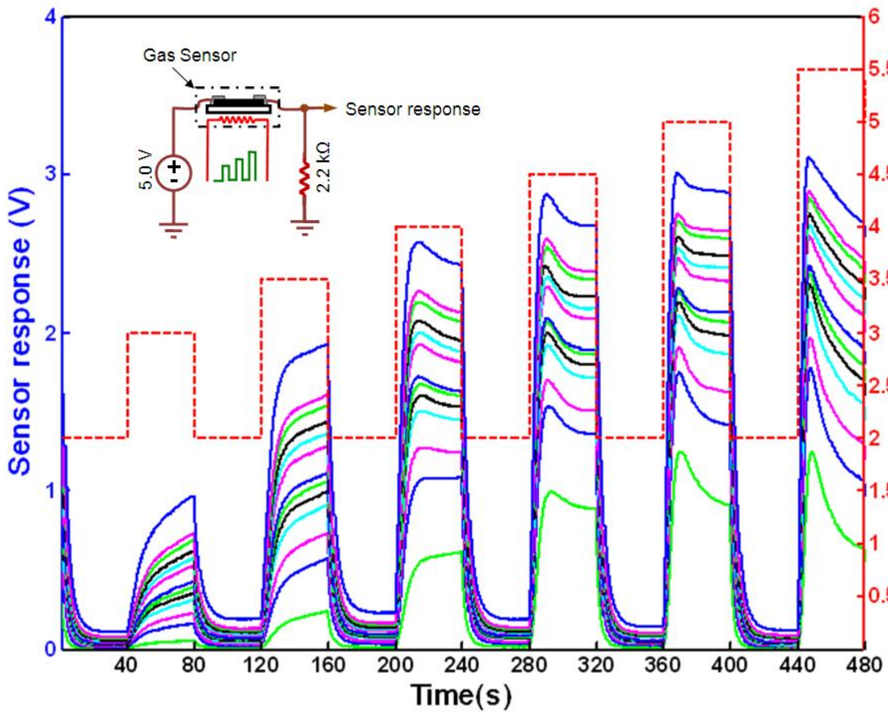

Fig. 2. One of the three heating voltage pulse trains (dotted line) used for the thermal modulation of the gas sensor along with the responses recorded for methanol at different concentrations in the 100 to 2000 ppm range in air. The inset indicates the way the sensor was connected to the response recording system.

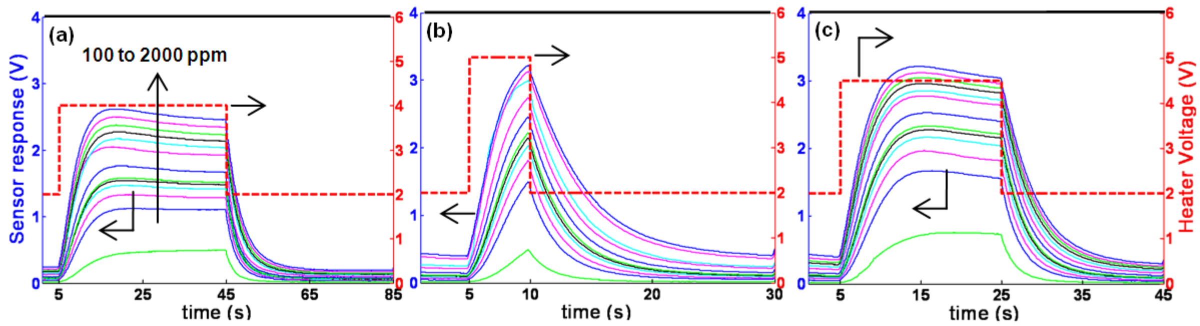

Fig. 3: (a,b and c) Three example microheater voltage waveforms are given along with their respective sensor responses. All the responses shown are related to methanol at different concentrations in the 100 to 2000 ppm range in air.

Tab. 1: The classification results of nine different base classifiers, each operating individually on the feature subsets extracted from the responses related to a specific microheater pulse, and the result of their fusion by the ensemble of all classifiers obtained by majority voting.

	Base classifiers									
Classifier #	*MLP 1*	*MLP 2*	*MLP 3*	*MLP 4*	*MLP 5*	*MLP 6*	*MLP 7*	*MLP 8*	*MLP 9*	***Fusion***
Accuracy %	98.5	92.3	90.8	96.9	93.8	93.8	95.4	96.9	92.3	**100**

DOI 10.5162/IMCS2012/P1.0.18

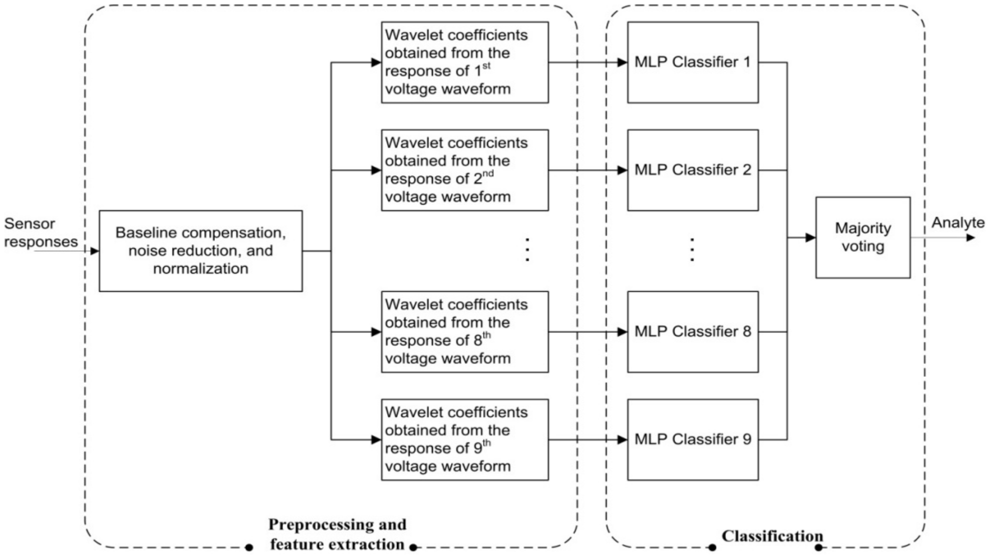

Fig. 4: The flowchart of the data processing carried out on the recorded responses of a sensor temperature modulated with nine different microheater voltage pulses. The goal is to discriminate between methanol, ethanol and 1-butanol.

References

[1] R. Gutierrez-Osuna, Pattern Analysis for Machine Olfaction: A Review, *IEEE Sens. J.* 2, 189-202 (2002); doi: 10.1109/JSEN.2002.800688

[2] M. Aleixandre, I. Sayago, M. C. Horrillo, M. J. Fernandez, L. Ares, M. Garcia, C. P. Santos, J. Gutearres, Analysis of Neural Networks and Analysis of Feature Selection with Genetic Algorithm to Discriminate Among Pollutant Gas, *Sens. Actuator B-Chem.* 103, 122-128 (2004); doi: j.snb.2004.04.044

[3] E. Phaisangittisagul, H. T. Nagle, Sensor Selection for Machine Olfaction Based on Transient Feature Extraction, *IEEE Trans. Instrum. Meas* 57, 369-378 (2008); doi: 10.1109/TIM.2007.910117

[4] J. W. Gardner, P. Boilot, E. L. Hines, Enhancing Electronic Nose Performance by Sensor Selection Using a New Integer-Based Genetic Algorithm Approach, *Sens. Actuator B-Chem.* 106, 114-121 (2005); doi: 10.1016/j.snb.2004.05.043

[5] T. Eklov, P. Martensson, I. Lundstrom, Selection of Variables for Interpreting Multivariate Gas Sensor Data, *Anal. Chim. Acta* 381, 221–232 (1999); doi: 10.1016/S0003-2670(98)00739-9

[6] T. K. Ho, *IEEE Trans. Pattern Anal. Mach. Intell,* The Random Subspace Method for Constructing Decision Forests 20, 832-844 (1998); doi: 10.1109/34.709601

[7] M. A. Bagheri, G. A. Montazer, Ensemble Classifier Strategy Based on Transient Feature Fusion in Electronic Nose, *14th ISOEN*, New York City, USA (2011); doi: 10.1063/1.3626375

[8] A.P. Lee, B.J. Reedy, Temperature modulation in semiconductor gas sensing, *Sens. Actuator B-Chem.* 60, 35-42 (1999); doi: 10.1016/S0925-4005(99)00241-5

[9] F. Hossein-Babaei, S.M. Hosseini-Golgoo, Analyzing the Responses of a Thermally Modulated Gas Sensor Using a Linear System Identification Technique for Gas Diagnosis, IEEE Sens. J. 8, 1837-1847 (2008); doi:10.1109/JSEN.2008.2006260

[10] A. Heilig, N. Bârsan, U. Weimar, M. Schweizer-Berberich, J. Gardner, W. Göpel, Gas Identification by Modulating Temperatures of Sno_2-Based Thick Film Sensors, *Sens. Actuator B-Chem* 43, 45-51 (1997); doi:10.1016/S0925-4005(97)00096-8

[11] A. Amini, S. M. Hosseini Golgoo, Rapid Recognition of Air Born Combustible Molecules with an Operating Temperature-Modulated Gas Sensor, *Sens. Lett.* In print (2012);doi:

[12] F. Hossein-Babaei, S.M. Hosseini-Golgoo, A. Amini, Extracting Discriminative Information from the Padé-Z-Transformed Responses of a Temperature-Modulated Chemoresistive Sensor for Gas Recognition, *Sens. Actuator B-Chem.* 142, 19-27 (2009); doi:10.1016/j.snb.2009.07.039

[13] F. Hossein-Babaei, A. Amini, A Breakthrough in Gas Diagnosis with a Temperature-Modulated Generic Metal Oxide Gas Sensor, *Sens. Actuator B-Chem.* In print (2012); doi:10.1016/j.snb.2012.02.082

[14] R. Polikar, Ensemble Based Systems in Decision Making, *IEEE Circuits Syst. Mag.* 6, 21-45 (2006); doi: 10.1109/MCAS.2006.1688199

[15] L. Breiman, Bagging Predictors, *Machine Learning* 24, 123-140 (1996); doi: 10.1007/BF00058655

[16] Y. Freund and R. E. Schapire, A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting, J. Comput. Syst. Sci. 55, 119-139 (1997); doi: 10.1007/3-540-59119-2_166