Multi-agent Systems for Classification of E-Nose Data

Yoshinori Ikeda, Sigeru Omatu, Pablo Chamoso, Alberto Pérez and Javier Bajo

Abstract Metal Oxide Semiconductor Gas Sensors are used to measure and classify odors. This kind of system requires both advanced sensor design and classification techniques. In this paper we present a MOGS (Metal Oxide Gas Sensor) specifically designed to classify the breath of humans. We propose an architecture that incorporates new sensing technology and a classification technique based on multi-agent systems. The proposal is evaluated using samples from Asian and European participants. The results obtained are promising.

Keywords Odor classification · Electronic nose · Multi-agent systems · Virtual organizations

1 Introduction

In recent years, odor sensor systems, also known as EN (Electronic Nose) systems have progressed significantly. The EN systems try to reproduce the sensation produced in humans when smelling certain odors. To do that, techniques like sensor arrays or pattern recognition systems are used [1].

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In this document we are proposing an agent-based architecture for odor classification. These odors are taken with MOGSs, which are detailed in Sect. 4.

There are different kinds of MOGS, each one of them dedicated to certain specific odors. For instance, in [2] a fire detector is presented and, in [3], a tea classifier.

In our case, specifically designed sensors are going to be used to obtain human breath. To classify it, we will analyze data obtained by the sensors applying different classification techniques. Different specialized agents will apply these techniques and we will take as the final result the best one proposed by each agent [4].

2 Related Work

The "electro nose" term is generally associated to odor detection or the attempt to "smell" with technological devices. The most common technique is based on chemical gas sensors [5] and it will be used when developing this study. However, there are many advances in the developing of electro noses with other kind of sensors systems, such as optical sensor systems, mass spectrometry, ion mobility spectrometry, infrared spectroscopy, etc.

These systems have been used for different unalike tasks. For instance, in [6], a few applications of an EN system based on solid-state sensor arrays are presented to measure the air quality. In [7] ENs are applied to develop analysis in the food area, for example, to control the quality or to evaluate the freshness of products. More recently, and also related food odors, a system to differentiate between types of coffee has been presented in [8] and a system to develop a rapid diagnosis of enterobacteriaceae in vegetable soups in [9].

Nevertheless, during last recent years, the application of EN systems to analyze breath is increasing and important work with rats or even with human patients with chronic lung infections is being done [10] trying to detect the acute liver failure [11].

3 Measurement Method

In this paper, we have used a new device, shown in Fig. 1, to measure odor. This device is small size one and therefore, it is portable. Measurement system is shown Fig. 2.

Fig. 1 Measurement device

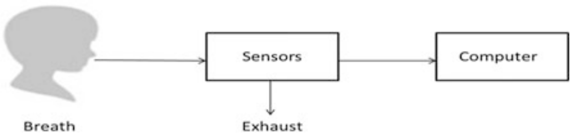


Fig. 2 Measurement system

Odor was measured by using the following procedure:

(i). Find out about subject's health.
(ii). Initiate the device.
(iii). Wait 10 s in order to stabilize it.
(iv). After that, measure subject's breath during 10 s.
(v). Finally finish measurement, stop the device and transmit the measurement results to the computer.

4 Principle of Metal Oxide Semiconductor Gas Sensors (MOGS)

We have used MOGSs to measure and classify odors. There are five kinds of sensor made by FIS Co. LTD (Japan). The characteristics of sensors are shown in Table 1. We have combined these sensors and classify various odors.

Table 1 Used sensors

Sensor number	Model number	Application
1	SB-AQS	VOC (volatile organic compound)
2	SB-15-00	Flammable gas (propane, butane)
3	SB-30-04	Alchol detection
4	SB-42A-00	Refrigerant gas (freon)
5	SB-31-02	Solvent detection

The working principle of MOGSs is explained in Fig. 3.

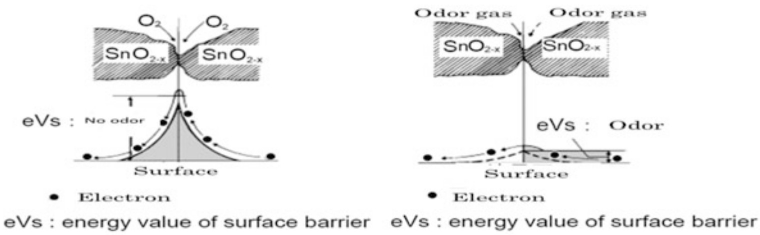
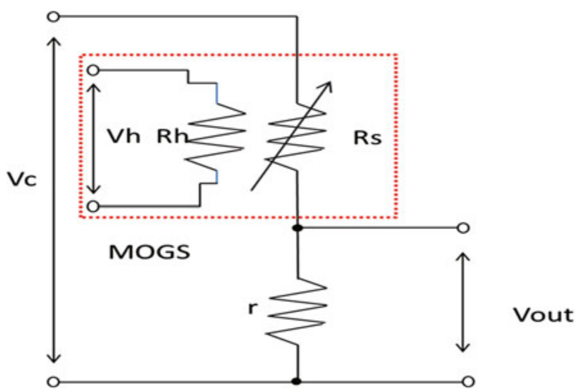


Fig. 3 The principle of MOGS

This kind of sensor makes good use of oxidation-reduction reactions. As shown in Fig. 3, the potential barrier changes attending to the existence or absence of gas. As a result, variable resistance becomes higher or lower.

Since the output voltage changes to low or high, we can measure odor information by using a measurement circuit as shown in Fig. 4.

Fig. 4 Odor measurement circuit



5 Classification Technique: Error Back-Propagation Type Neural Network (BPNN)

We have used the BPNN, as shown in Fig. 5, to classify odors. This classifier is one of the multi-layered neural networks. This method uses the error between an output value and a desired value to the given input. Connection weights are changed so that output error becomes the minimum based on the gradient method.

The error back-propagation algorithm is given by following steps.

Step 1: Set connection weights (W_{ji}, W_{kj}) to random numbers and set η (>0) as an initial value.
Step 2: Designate desired values of output $\{d_k, k = 0, 1, \ldots, K\}$, corresponding to the input data $\{X_i, i = 0, 1 \ldots, \mathrm{I}\}\}$ in the input layer.
Step 3: Calculate outputs in the hidden layer by the following formula:

$$net_j = \sum_{i=0}^{I} W_{ji}X_i - \theta_j, O_j = f\left(net_j\right), f(x) = \frac{1}{1 + e^{-x}}$$

Step 4: Calculate outputs in the output layer by the following formula:

$$net_k = \sum_{j=0}^{J} W_{kj}O_j - \theta_k, O_k = f(net_k), f(x) = \frac{1}{1 + e^{-x}}$$

Step 5: Calculate the error e_k and the generalization errors by the following formula:

$$e_k = d_k - O_k$$

$$\delta_k = e_k O_k (1 - O_k)$$

$$\delta_j = \sum_{k=1}^{K} W_{kj}\delta_k O_j (1 - O_j)$$

Step 6: Calculate half of root mean square error of all outputs by the following formula:

$$\mathrm{E} = \frac{1}{2}\sum_{k=1}^{K} e_k^2$$

Step 7: If E becomes a minimum, finish the learning, otherwise, connection weights should be changed by the following formula:

$$\Delta W_{kj} \equiv W_{kj}(t + 1) - W_{kj}(t) = \eta\delta_k O_j$$

$$\Delta W_{ji} \equiv W_{ji}(t + 1) - W_{ji}(t) = \eta\delta_j X_i$$

After changing the connection weights, go to Step 3.

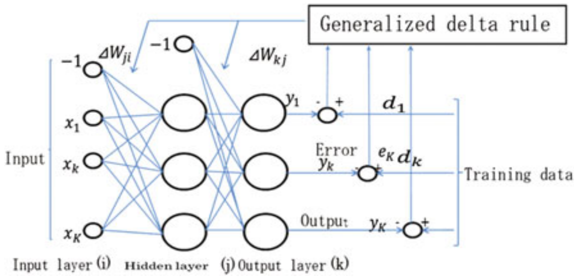


Fig. 5 BPNN

6 Case Study

6.1 Multi-agent Architecture

The proposed multi-agent architecture is based in a series of virtual organizations deployed in PANGEA platform [12]. This platform offers different tools for data base access, definition and creation of virtual organizations and integration with other platforms [13], which allow a simpler development. This architecture is based on the proposal from [4], with some modifications to adapt it to the specific case.

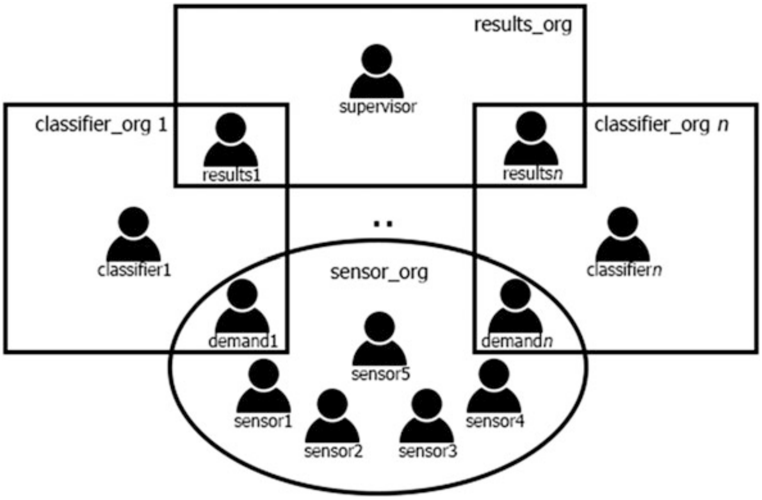


Fig. 6 Agent's organization scheme

Agents are structured in virtual organizations, with at least three of them necessarily and adding one by any other new classification method to be applied. Down below, the structure shown in Fig. 6 is described detailing each agent's functionality in the present system:

Sensor organization: there is an agent associated to each one of the 5 sensors (for this specific case), which will be the one in charge of getting the data offered by the sensor they represent and applying the necessary transformations to serve the data to the other organization participants. These participants are completed with the inclusion of a type of agent known as 'demand agent' and it will have an instance for every kind of classifier to be used. This agent is the one in charge of controlling that correct values are obtained from each one of the sensors participating in the analysis.

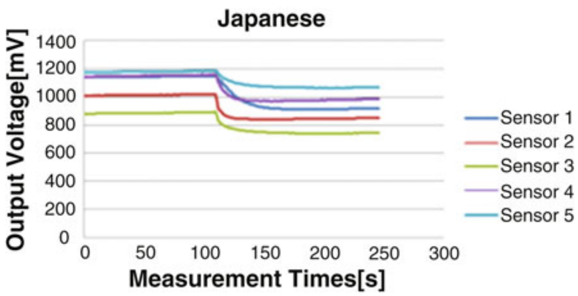
Classifier organization: it represents the virtual organization in which specialized agents are, in the application of the necessary techniques to develop classifications. To avoid the existence of a complex organization differing from the rest of organizations, the system has been structured in such a way that a virtual organization is generated by each kind of classifier. On each one of them, besides the necessary specialized agents to develop the classification, the 'demand agent' will have to exist as well as it exists on the 'sensor organization'. This time, its function will be to provide to the classifier agents the input data when they are ready. To receive classifiers output, the 'results agent' will also be required on each organization.

Results organization: on this organization we can find all the 'results agents' to provide data associated to each classifier output. The inclusion of a supervisor agent establishes the output provided to the final user according to the percentage indicated by the reliability grade on the response generated by the classifiers. In the case there are different results with the same reliability, the conflict gets resolved by returning the first response that gets to the supervisor agent. In any case, there will always have to exist a quicker-than-others result due to the fact that messages throughout PANGEA are delivered one by one.

6.2 *Measurement of Odor Data*

For this case study we have measured the breath of experimental participants from different precedence, precisely from Japan, China and Spain. When we measured the members' breath, we asked them about their health condition attending to a three-stage scale (good, usual, bad). These measurements were made several times to each subject and the average of the sample path of these data was used for each sensor. In Fig. 7, we show the measurement data of Japanese subjects. X-axis is the measurement of time and Y-axis is the output voltage.

Fig. 7 Measurement data



We used the minimum values from each sensor as the feature value and then, normalized these data. In this normalization, the maximum value is 1 and the minimum one is 0. We used neural networks as classification technique and then performed the classification.

7 Case Study

We classified the following case and showed conditions and results of these classifications. First, we explain about classification using by BPNN. η is set as 0.3.

After doing some classifications, we are showing the results and conclusions of them by explaining the classification using BPNN. η is set as 0.3.

(1) Japanese
We classified two persons. The total number for each data was 10. The training data and the test data are 5. The network was trained to learn until the error become less than, or equal to 1.0 × 〖10〗^(-3). Test data used 50 by changing parameters of neural networks and changing the test data and training data. The results are shown in Table 2.

Table 2 Classification results of Japanese (A, B)

Odor data	A	B	Total
A	26	24	50
B	29	21	50

In this classification, average classification rate was 46.5 %.

(2) Japanese, Chinese and Spaniard
We classified Japanese, Chinese and Spaniard. We also made a classification with subjects from Japan, China and Spain. The number of each data is four. The training data and the test data are 2. The network was trained to learn until the error become less than, or equal to 1.0×10^{-3}. Test data were 100 by changing parameters of neural networks and changing the test data and training data. The result is shown in Table 3.

Table 3 Classification result of Japanese (A), Chinese (B) and Spanish (C)

Odor data	A	B	C	Total
A	54	29	17	100
B	9	84	7	100
C	0	3	97	100

In this classification, average classification rate was 78.3 %.

(3) Health condition
We classified health condition of usual and good. We made another classification attending to the values usual and good of the health condition of the subjects. The number of A's data was 93, B's data was 35, C's data was 6 and D's data was 10.

The number of test data is 3 and that of training data is remaining data. The network performed learning until the error become less than, or equal to 5.0×10^{-3}. This classification performed 10 by changing parameters of neural networks and changing the test data and training data. The result is shown in Table 4.

Table 4 Classification result of usual (A, B, C) and good (D)

Odor data	A	B	C	D	Total
A	262	121	45	472	900
B	29	234	39	18	320
C	0	0	30	0	30
D	26	0	0	44	70

In this classification, average classification rate was 66.3 %.

In addition, we used Weka, which was developed by the University of Waikato, to classify cases (1) and (2). We used RBF network, SMO and Logistic as the classifiers to obtain the classification results. In case (1), SMO improved the average classification rate against the BPNN. The average classification rate was 68.4 %. In case (2), Logistic improved the average classification rate against the BPNN. The average classification rate was 90.9 %.

In case (2), classification rate was high. In case (1) and (3), classification rate was bad or usual. Therefore, we think that it isn't sufficient.

In order to improve classification results, we need to introduce a new classifier by using Weka. Regarding measurement condition, we think that it is ambiguous and isn't quantitative. Therefore, we need to think a better measurement condition.

References

1. K. El Hedhli, J.C. Chebat, M.J. Sirgy, Shopping well-being at the mall: construct, antecedents, and consequences. J. Bus. Res. **66**(7), 856–863 (2013)
2. J.E. Lane, Method, theory, and multi-agent artificial intelligence: creating computer models of complex social interaction. J. Cogn. Sci. Relig. **1**(2), 161–180 (2014)
3. Z. Fan, W. Duan, B. Chen, Y. Ge, X. Qiu, Study on the method of multi-agent generation algorithm within special artificial society scene. In Control (CONTROL), 2012 UKACC International Conference on (pp. 1076–1081). IEEE (2012)
4. P. Schreinemachers, T. Berger, An agent-based simulation model of human–environment interactions in agricultural systems. Environ. Model Softw. **26**(7), 845–859 (2011)
5. C. Zato, G. Villarrubia, A. Sánchez, J. Bajo, J.M. Corchado, PANGEA: a new platform for developing virtual organizations of agents. Int. J. Artif. Intell. **11**(A13), 93–102 (2013)
6. A. Mas, Agentes software y sistemas multiagente: conceptos, arquitecturas y aplicaciones (Prentice Hall, 2005)

7. G. Boella, J. Hulstijn, L. Van Der Torre, Virtual Organizations as Normative Multiagent Systems. In System Sciences, 2005. HICSS'05. Proceedings of the 38th Annual Hawaii International Conference on (pp. 192c–192c). IEEE (2005)
8. S. Rodriguez, V. Julián, J. Bajo, C. Carrascosa, V. Botti, J.M. Corchado, Agent-based virtual organization architecture. Eng. Appl. Artif. Intell. **24**(5), 895–910 (2011)
9. V. Julian, M. Rebollo, E. Argente, V. Botti, C. Carrascosa, A. Giret, Using THOMAS for Service Oriented Open MAS. In Service-Oriented Computing: Agents, Semantics, and Engineering (pp. 56–70). Springer Berlin Heidelberg (2009)