Multi-agent Technology to Perform Odor Classification

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Abstract. Quartz crystal microbalance (QCM) sensors are used to measure and classify odors. In this paper, we use seven QCM sensors and three kinds of odors. The system has been developed as a virtual organization of agents using the agent platform called PANGEA (Platform for Automatic coNstruction of orGanizations of intElligents Agents), which is a platform to develop open multi-agent systems, specifically those including organizational aspects. The main reason that justifies the use of the agents is the scalability of the platform; that is, the way in which it models the services. The functionalities of the system are modeled as services inside the agents, or as SOA (Service Oriented Approach) architecture compliant services using Web Services. In this way, it is possible to improve odor classification systems with new algorithms, tools and classification techniques.

Keywords: Odor sensing, odor classification, multi-agent systems, virtual organizations, QCM sensors.

1 Introduction

During the last years, major advances have been made in the field of Ambient Intelligence [1], [2], which has come to acquire significant relevance in the daily lives of people [5], [6], [7]. Ambient Intelligence adapts technology to people's needs by proposing 3 concepts: ubiquitous computing, ubiquitous communication and intelligent user interfaces. The development of new frameworks and models to allow information access, independently of the location, is needed in order to achieve these targets. Wireless sensor networks [3], [4], [22], provide an infrastructure, which is able to distribute communications in dynamic environments by incrementing mobility and efficiency independently of the location. Sensor networks interconnect a large amount of sensors and manage information in the intelligent environment. Many times information management is done in a distributed way. However, it is necessary to have distributed systems with enough capabilities to manage sensor networks in an efficient way and to include elements with some degree of intelligence that can be embedded in the devices and act both autonomously and in coordination with the distributed system. Multi-agent systems are a suitable alternative to perform this type of systems.

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There are several proposals to build smart environments that combine multi-agent systems and sensor networks [8], [9], [10], [11], [12], [13] , [14], [15], [16], [17], [18], [19], [20], [21]. New approaches are needed to support evolutional systems and to facilitate their growth and runtime updates. The dynamics of open environments have promoted the use of Virtual Organizations of Agents (VOs). A VO [25], [26], [27], [28], [29] is an open system designed for grouping; it allows for the collaboration of heterogeneous entities and provides a separation between the form and function that define their behavior. However, it is not possible to find an existing multi-agent architecture to work on the concept of virtual organizations and to provide agents capable of working with any type of sensor or device. This article considers different types of odor sensors and aims to classify odors according to sensing data by using quartz crystal microbalance (QCM) sensors. QCM sensors are sensitive to odors and allow the precise measurement of odor data. Using many QCM sensors, we will attempt to classify various kinds of odors based on neural networks. To model the system, virtual organizations of agents, which are capable of bringing a greater number of possibilities, are presented. These agents are connected with PANGEA [23], a multi-agent platform designed on the basis of virtual organizations, aimed at the creation of intelligent environments.

Over the last decade, odor-sensing systems (called electronic nose (EN) systems) have undergone important developments from a technical and commercial point of view. EN refers to the ability to reproduce the human sense of smell by using sensor arrays and pattern recognition systems [30].

The authors in [31] present a type of an EN system to classify various odors under the various densities of odors based on a competitive neural network by using learning vector quantization (LVQ). The odor data were measured by an odor sensor array made of MOGSs. We used fourteen MOGSs of FIGARO Technology Ltd in Japan. We considered two types of data for classification in the experiment. The first type included four types of teas, while the second included five types of coffees with similar properties. The classification results of teas and coffees were approximately 96% and 89% respectively, which was much better than the results in [32], [24].

The article is structured as follows. First, the PANGEA platform is described in section 2, detailing the structure of the virtual organizations used in the odor classification case study. Both the platform and virtual organizations are evaluated in a case study consisting of an intelligent environment for odor recognition. Finally the results of the case study and the conclusions reached from this research are presented.

2 Case Study: Development of a VO for Odor Classification

This central section of the article presents the integration of the system and the sensors used in the multi-agent architecture, and explains the main concepts of QCM sensors. In addition, an overview of the odor sensing system and the measures of odor data used are described.

2.1 Integration in a Multi-agent Platform (PANGEA)

With the development of ubiquitous and distributed systems, it is interesting to have new agent platforms that facilitate the development of open agent-architectures that can be deployed on any device. PANGEA [23] is an agent platform based on organizational concepts. It can model and implement all kinds of open systems, encouraging the sharing of resources and facilitating control of all nodes where the different agents are deployed.

It is essential to have control mechanisms that enable new devices to be included in a single platform where they can be easily integrated, managed and monitored. In this case PANGEA, with its model of agents and organizations, provides the necessary features to function as the base platform when developing a comprehensive system.

In order to facilitate control of the organization, PANGEA has several agents that are automatically deployed when starting the platform operation: OrganizationManager and OrganizationAgent are in charge of the management of the organizations and suborganizations; InformationAgent is in charge of accessing the database containing all pertinent system information; ServiceAgent is in charge of recording and controlling the operation of services offered by the agents; NormAgent is in charge of the norms in the organization; and CommunicationAgent is in charge of controlling communication among agents, and recording the interaction between agents and organizations.

In addition to the intrinsic PANGEA agents, the organizations developed in the present system are the following:

- *Odor-recognition sensors organization.* In this organization all agents belonging to an individual odor recognition system is deployed. Such agents may also be of different types (sensor agents, interface agent and identifier agent).
- *Sensor control central organization.* In this organization the agent interface type is included, representing each of the odor-recognition sensors organizations together with an adapter agent.

Communication in this case is restricted only to the existing agents in the same organization, in addition to the control agents that the PANGEA platform offers (as is the case of the Information Agent, which accesses the database).

Each type of agent is engaged in a well-defined task, as explained below:

- *Sensor agent.* It is exclusively dedicated to performing sensor readings and providing the latest value when an authorized agent requires such data.
- *Identifier agent.* Its function is to perform the necessary calculations for the identification of odors. It makes use of the ability to communicate with the sensor agents, which require the data needed to perform these calculations.
- *Interface agent.* This kind of agent is present in the two types of virtual organizations cited. It is responsible for providing a communication link with the agents outside their own organization of odor-recognition sensors that are authorized to establish two-way communications using the appropriate communication format.

– *Classifier agent.* This agent performs classification services that implement the algorithms described in the following section. To perform the classification, a Classification Method of Odor Data (e-BPNN) is used and implemented on the platform. We can say that the classifier agent could use new methods for the classification of odors by making the system scalable in terms of functionality.
– *Adapter agent.* This type of agent is in the central organization of the sensor control. Its function is to try to correct the differences between the measurements of each of the associated sensors to the sensor agents. Thus, a joint database among all recognition systems participating in the architecture is achieved, expanding the source of knowledge.

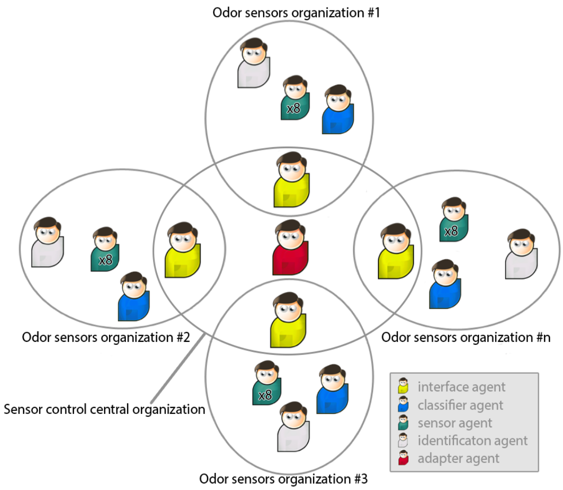

Fig. 1. Structure of virtual organizations of the case study in PANGEA

2.2 Algorithms: Classification Method of Odor Data (e-BPNN)

We will show two types of neural networks: one is a multi-layered neural network based on error back-propagation method and the other is a learning vector quantization (LVQ).

First, we will explain the multi-layered neural networks. In order to classify the odors, we adopt a three-layered neural network based on the error back-propagation method, as shown in Fig.2. The error back-propagation algorithm, which is based on the gradient method, is given by the following steps.

- *Step* 1. Set the initial values of $w_{ji}, w_{kj}, \theta_j, \theta_k$, and $\eta(>0)$.
- *Step* 2. Specify the desired values of the output $d_k, k = 1,2,\cdots,K$ corresponding to the input data x_i, i= 1,2, . . . , I in the input layer.
- *Step* 3. Calculate the outputs of the neurons in the hidden layer by

$$net_j = \sum_{i=1}^{I} w_{ji}x_i - \theta_j \,, O_j = f(net_j), f(x) = \frac{1}{1+e^{-x}}$$

- *Step* 4. Calculate the outputs of the neurons in the output layer by

$$net_k = \sum_{k=1}^{K} w_{kji} O_j - \theta_j \, , O_k = f(net_k), f(x) = \frac{1}{1+e^{-x}}$$

- *Step* 5. Calculate the error *en* and generalized errors by

$$e_k = d_k - O_k$$

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

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

- *Step* 6. Use the following formula to calculate half of the sum of the squares of the errors in the output of all.

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

- Step 7. If E is sufficiently small, exit the learning. Otherwise, modify the weight by the following equation:

$$\Delta w_{kj} \equiv w_{kj}(t+1) - w_{kj}(t) = \eta \delta_j O_{jk} \qquad \Leftarrow w_{kj} + \Delta w_{kj}$$

$$\Delta w_{ji} \equiv w_{ji}(t+1) - w_{ji}(t) \quad = \eta \delta_i O_j \qquad \Leftarrow w_{ji} + \Delta w_{ji}$$

- Step 8. Go to *Step* 3.

Using the above recursive procedure, we can train the odor data.

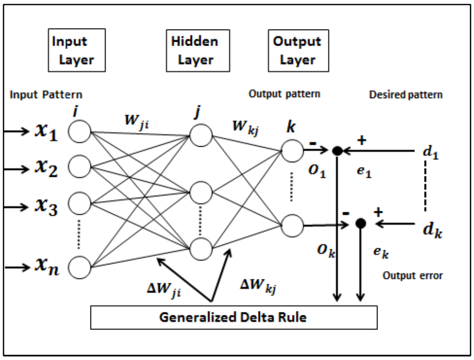

Fig. 2. Three layered neural network with the error back-propagation

The neural network (Fig. 2) consists of three layers: input layer i, hidden layer j and output layer k. When the input data $x_i, i = 1,2,\ldots,I$, are applied in the input layer, we can obtain the output O_k in the output layer, which is compared to the desired value d_k which has been assigned in advance. If the error $e_k = d_k - O_k$

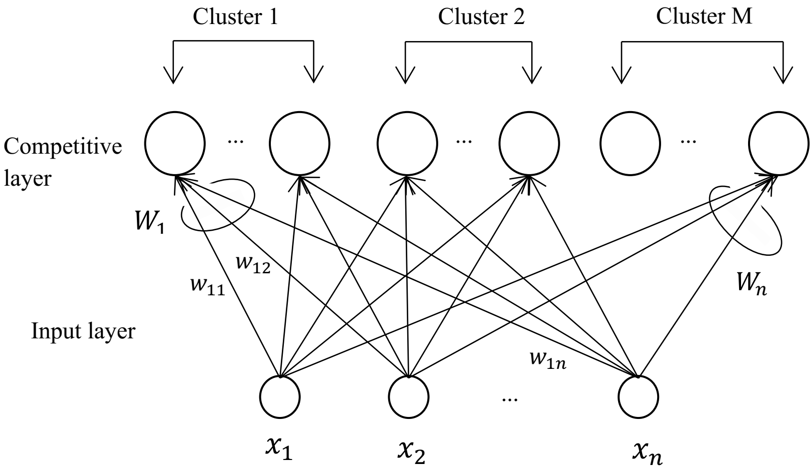

Fig. 3. LVQ structures

occurs, then the weighting coefficients w_{ji}, w_{kj} are corrected so that the error becomes smaller based on the error back-propagation algorithm.

Next, we will show the LVQ:

The structure of LVQ is two layered, consisting of an input layer and a competitive layer as shown in Fig. 3.

In order to classify the odors we adopt a two-layered neural network based on the learning vector quantization method as shown in Fig. 3. Learning vector quantization is a supervised learning method for the purpose of pattern classification for input data. The learning method is given by the following steps:

Step 1. Set the initial values of w_{ij} $(j=1,2,\ldots M,\ i=1,2,..,n)$, T, *and* α_0 (> 0) where T is the total iteration number for learning, n is the number of input, M is the number of neurons in cluster j, and α_0 is the initial value of the learning rate.

Step 2. First, calculate proximity to the coupling coefficient vector WJ of the input vector x and neuron j in the sense of Euclidean distance. The neuron with the closest coupling coefficient in the sense of Euclidean distance in the competitive layer neuron is detected by following equation for the input pattern.

$$d_j = \| \mathrm{x} - w_j \| = \sqrt{\sum_{i=1}^{n} (x_i - w_{ji})^2}$$

$$d_c = \| \mathrm{x} - w_c \| = \min_j d_j$$

Step 3. If the input vector and winning neuron c belong to the same class, then change $w_j(t)$ by using the following equation:

$$w_j(t+1) = w_j(t) + \alpha(t)\left(x - w_j(t)\right), j = c$$
$$w_j(t+1) = w_j, j \neq c$$

where

$$\alpha(t) = \alpha_0 \left(1 - \frac{1}{T}\right).$$

If the input vector and neuron c belong to the different class, then change $w_j(t)$ by using the following equation:

$$w_j(t+1) = w_j(t) - \alpha(t)\left(x - w_j(t)\right), j = c$$

$$w_j(t+1) = w_j, j \neq c.$$

Step 4. If t<T, Go to *Step 2*

Using the above recursive procedure, we can train the odor data.

2.3 Principle of QCM Sensors

The QCM has been well-known to provide very sensitive mass-measuring devices in nanogram levels. Synthetic polymer-coated QCMs have been studied as sensors for various gas works as a chemical sensor. The QCM sensors are made by covering the surface with several kinds of a very thin membrane with about 1 mm, as shown in Fig. 4. The QCM sensor is integrated into a resonance circuit. If the film absorbs the odor molecules, the oscillation frequency is reduced since the mass of the vibrator is changed.

Therefore, the frequency (of the QCM) will change according to the deviation of the weight due to the adsorbed odor molecular (odorant). In this paper we have used the materials shown in Table 1. The basic approach used here is a sol-gel method. The process is a wet-chemical technique used for the fabrication of both glassy and ceramic materials. The manufacturing of a film was done by the following procedure.

MTMS (1): Trimethylsilane, ethanol, water and nitric acid. (2) Once stirred, 2-ethyl acrylate (PFOEA) was added to a solution of 1.

Here, HTMS: $CH_3S_i(OCH_3)_3$ and PFOEA: $F(CF_2)_8CH_2CH_2 - OCOCH = CH_2$

Table 1. Chemical materials used as the membrane.We used seven sensors using a solution of three types of in this paper.

$\alpha = C_4H_{12}O_3Si(0.5g), C_{16}H_{19}F_{17}O_3Si(0.015g)$, 30%$HNO_3(10\mu L), H_2O(0.30ml), etanol(3.0ml)$
$\beta = C_4H_{12}O_3Si(0.5g), C_{16}H_{19}F_{17}O_3Si(0.030g)$, 30%$HNO_3(10\mu L), H_2O(0.15ml), etanol(3.0ml)$
$\gamma = C_4H_{12}O_3Si(0.5g)$, 30%$HNO_3(10\mu L), H_2O(0.3ml), etanol(3.2ml)$

Sensor number	Materials of mebrane
sensor1	α
sensor2	β
sensor3	γ
sensor4	α
sensor5	γ
sensor6	α
sensor7	β

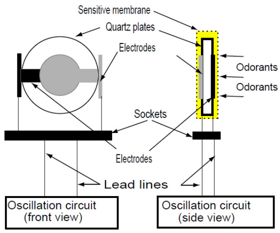

Fig. 4. Principle of QCM sensor

The QCM sensor is integrated into a resonance circuit. If the membrane of the sensor absorbs odorant, the weight of quartz plate will be modified. Oscillation frequency is also reduced when the membrane absorbs odorants. Thus, the original frequency of the crystal oscillation will become smaller according to the density of odorants

2.4 Odor Sensing Hardware System

Generally, this type of system, for example an air purifier, a breathalyzer, etc., is designed to detect some specific odor. Each of the QCM membranes has its own characteristics in response to different odors. When combining many QCM sensors together, the ability to detect the odor is increased. Odor sensing systems (called electronic nose (EN) systems), shown in Fig. 5, were developed based on the concept of the human olfactory system. Odor generating machines are using Permeater, as shown in Fig. 6.

Permeater can continuously generate standard gas of many kinds (inorganic and organic gas) for a long time. The process takes place in the standard gas generator, which generates a continuous standard of trace gas concentration. The combination of QCM sensors, listed in Table 1, is used as the olfactory receptors in the human nose. The odors used here are shown in Table 2.

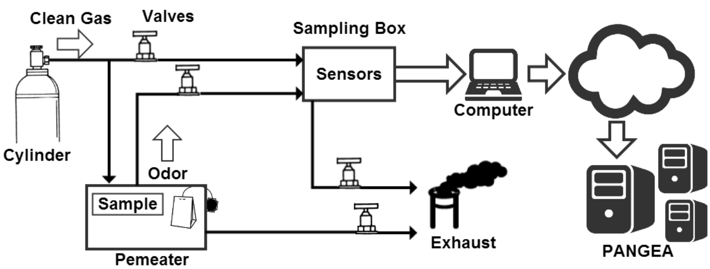

Fig. 5. Odor sensing systems

First, allow the dry air to flow so the odor coming from the Permeater get to the sampling box. Then, the reaction of the QCM sensor is accumulated into frequency counter as data. In addition, the gas is exhausted from the sampling box. The PC converts the data stored in the frequency counter into a text file.

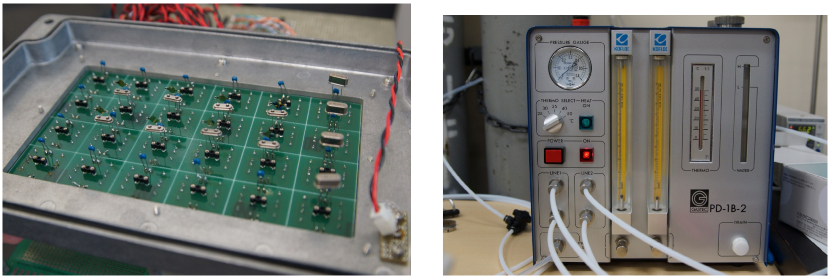

Fig. 6. Permeater and QCM sensors

Table 2. Kinds of odors measured in this experimet

Symbols	Kind of odors
A	ethanol
B	toluen
C	ethly acetatate

2.5 Measurement of Odor Data

We have measured four types of odors as shown in Table 2. The sampling frequencies are 1[Hz]. Diffusion tubes are used to control the density of gases. This is because it is possible to generate the gas at various concentrations by using a diffusion tube through Permeater. Odor data are measured for 900 [s]. They may include impulsive noises due to the typical phenomena of QCM sensors. To remove these impulsive noises we adopt a median filter which replaces a value at a specific time by a median value among neighboring data around the specific time. In Fig. 7 we show the measurement data for the symbol A where the horizontal axis is the measurement time and the vertical axis is the frequency deviation from the standard value (20M[Hz]) after passing through a three-point median filter.

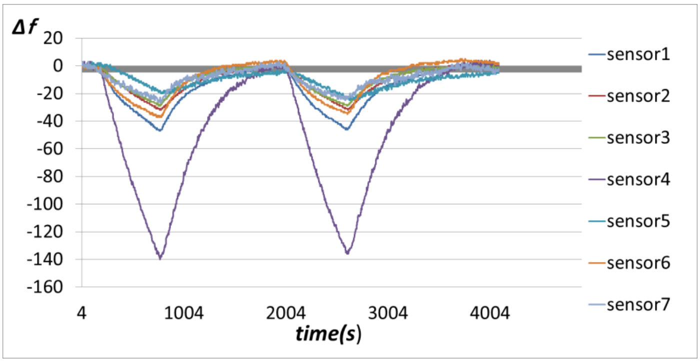

Fig. 7. Measurement of odor data

Here, seven sensors are used. The maximum value for each sensor among seven sensors is selected as a feature value for the sensor. Therefore, for one odor, there are seven sensor values, which will be used for classification.

3 Conclusions and Results

In order to classify the feature vector by using error-back propagation, we allocate the desired output for the input feature vector, which is a seven-dimensional vector, as shown in Table 3. By adding the coefficient of variation to the usual feature vector, the variations for odors are reduced. The training was performed until the total error was less than or equal to $1\times10-2$ where $\eta=0.8$.

Table 3. Training data set for ethanol (A), toluene (B), and ethyl acetate (C)

Symbols	Output A	Output B	Output C
A	1	0	0
B	0	1	0
C	0	0	1

We have examined two algorithms, a learning vector quantization, and error back propagation. In learning vector quantization and error back propagation, the training sample number P'= 8 and test sample number is three.

The total number of classification of 100 test samples is checked. The results are summarized in Table 4 and Table 5.

Table 4. Classification results for learning vector classification (LVQ)

Odor data	Classification results (97%)			
	A	B	C	Correct
A	100	0	0	100
B	1	97	2	97
C	4	1	95	95

Table 5. Classification results for layered neural networks

Odor data	Classification results (88%)			
	A	B	C	Correct
A	86	14	0	86
B	14	84	2	84
C	2	3	95	95

We have presented the reliability of a new EN system designed from various kinds of QCM sensors. We have shown that after training the neural network for each odor, we were able to classify the original odor from the mixed odors in the case of two odors.

In addition, we have proposed and developed a multi-agent system which is able to increment the percentage of correct outputs and reduce the training time by sharing all the data between other similar odor detecting systems, and correcting the error between their sensors. The multi-agent system implemented in PANGEA performs communication, control and data management services in a distributed and flexible way. In the case study presented, a classification method is implemented. However the use of PANGEA makes it possible to extend the system by using new methods for the classification of odors and making the system scalable in terms of functionality.

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