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A processing architecture for associative short-term memory in electronic noses

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Abstract
Electronic nose (e-nose) architectures usually consist of several modules that process various tasks such as control, data acquisition, data filtering, feature selection and pattern analysis. Heterogeneous techniques derived from chemometrics, neural networks, and fuzzy rules used to implement such tasks may lead to issues concerning module interconnection and cooperation. Moreover, a new learning phase is mandatory once new measurements have been added to the dataset, thus causing changes in the previously derived model. Consequently, if a loss in the previous learning occurs (catastrophic interference), real-time applications of e-noses are limited. To overcome these problems this paper presents an architecture for dynamic and efficient management of multi-transducer data processing techniques and for saving an associative short-term memory of the previously learned model. The architecture implements an artificial model of a hippocampus-based working memory, enabling the system to be ready for real-time applications. Starting from the base models available in the architecture core, dedicated models for neurons, maps and connections were tailored to an artificial olfactory system devoted to analysing olive oil. In order to verify the ability of the processing architecture in associative and short-term memory, a paired-associate learning test was applied. The avoidance of catastrophic interference was observed.

Keywords: electronic noses, multi-transducer data processing, catastrophic interference, associative short-term memory

(Some figures in this article are in colour only in the electronic version)

1. Introduction

The increasing complexity of multi-transducer architectures requires high-efficiency interconnection and cooperation of several control and processing modules. A first step towards a standard design of multi-transducer communication protocols and interfaces was recently defined in IEEE 1451 [1–3]. Enhancing the reliability of high-level processing systems represents the next critical step. Multi-transducer network modules often include tasks such as control, data acquisition, data filtering, feature selection and pattern analysis [4–6]. Heterogeneous techniques derived from chemometrics, neural networks and fuzzy rules, which are all used to implement such tasks, may lead to complications regarding module interconnection and cooperation. According to some authors establishing a multi-channel communication among common artificial neural networks tools, feature extraction and selection processes, and acquisition and control systems may be unreliable [7–9]. Moreover, high-level interfaces often do not allow the architecture and/or the processes topology to be adapted at run time. As a result, complex processing methods have to be designed. In electronic nose (e-nose) applications, the classification task is often performed by working memory models inspired by biology and based on artificial neural networks. Unfortunately, most of these architectures are not able to proceed in new training processes without losing the memory of previous learning (catastrophic interference) [10].

In order to overcome control and process cooperation issues, we present an architecture for a dynamic and efficient management of multi-transducer data processing techniques. The classification task was implemented within the architecture as a hippocampus-based model that is able to gain short-term priming in cooperation with other modules in order to avoid catastrophic interference. From a biological point of view, the hippocampus plays a critical role in the formation of episodic memories as well as the rapid encoding of new information. Moreover, it seems to operate as a sort of content addressable memory system (pattern completion). From a computational point of view the model of the hippocampus architecture proposed by McCloskey and Cohen was recently improved by means of the artificial neuron model proposed by O'Reilly [11, 14]. O'Reilly also showed how existing artificial neural network models are not able to avoid catastrophic interference.

We propose a homogeneous software framework that can simultaneously manage transducer devices and data processing. The framework is realized as a software library in order to exploit the potential of the computational algorithms and to enhance the performance of artificial neural network processing techniques. Synchronization among modules and data flow is managed by the framework and has considerable advantages when heterogeneous complex dynamic processes are being simulated. Specific control processes, pattern recognition algorithms, sensory and actuating interfaces can be created by inheriting base structures from the framework. The framework's base architecture and the implementation of the hippocampus-based working memory processing module are described.

We tested the architecture with an artificial olfactory system for the analysis of olive oil samples. The modules derived from the framework base structures were tailored to the electronic nose for real-time control and processing of multi-sensor signals. The architecture was trained to allow an olive oil sample to be associated both with its geographic origin and with its quality class. A paired-associate learning test (AB-AC test) [12], usually adopted by clinical neuropsychologists to assess human short-term memory, was applied in order to assess the capability of the processing architecture to perform continuous associative short-term memory learning. Results showed that continuous learning of new associations does not interfere with the memory of the previously learned associations.

2. Architecture design

We developed a framework for the management and synchronization of data and processes in which control processes and pattern recognition algorithms are defined as application processes. A block scheme of the framework architecture and of the flow of information is shown in figure 1. Such processes inherit properties and functionalities from the framework base structures, taking advantage of the

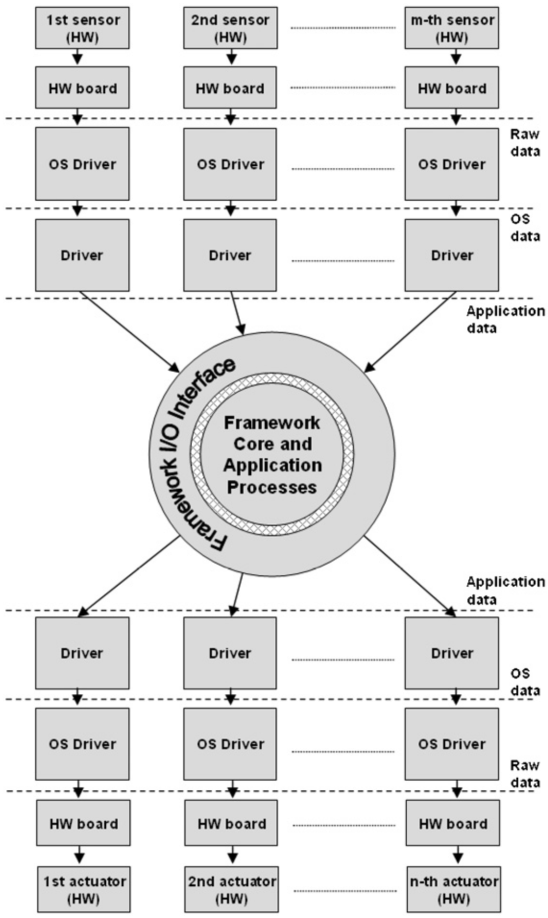

Figure 1. The framework architecture for the parallel management of multiple processes.

process automation provided by the framework core. The framework core and the application processes are interfaced to the outside world through a framework I/O interface. The framework I/O interface was developed in order to act as a buffer for the flow of information coming in from the sensors and out to the actuators. With this strategy, sensory fusion is gained thus enabling an abstraction with respect to the specific transducer technology. Signals coming from the sensors are gathered in parallel and are encoded following a standard protocol. The encoded information is received by a specific filter for each sensor, which then sorts them to a framework I/O interface. For each actuating system a mirror image architecture was reproduced of the one described for the sensors. The information available in the framework I/O interface is encoded by a filter using the same standard protocol. A specific interface for each actuator pilots its specific hardware system. This architecture allows a communication language between the framework core and sensory and actuating devices to be set up. This guarantees increased flexibility thanks to the presence of interfaces that act as interpreters for the specific hardware, and filters which specify the way the framework core 'senses' and 'communicates' the information.

Communication channels are established as connections between application processes. The domain of data flowing through connections and the flow chart of the application

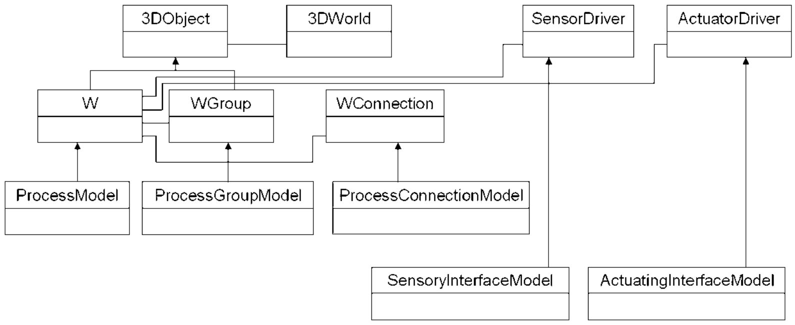

Figure 2. Hierarchical and collaboration chart of the framework base structures.

processes can be designed appropriately according to a specific application. Processes and connections are managed at run time and they can be manipulated under request. The presence of dynamic structures implies configurable resource management, so the framework offers an optimized interface for enumeration and direct access requests. In addition, a spatial definition of the entities involved in the framework can be supplied, making this information available to the control system for subsequent processing. To guarantee the execution of real-time applications, an inner synchronization signal is provided by the framework core to the processes and to the framework I/O interface. This means that a time–space correlation can be achieved. Such dynamic geometric representation can be visualized by a high-efficiency 3D graphic interface, which helps in debugging the system.

2.1. The framework core

The framework architecture was designed as a hierarchical structure whose root is a manager module. It is realized as a high-level container of generic modules representing the environment in which process modules and I/O filtering interfaces are placed. All these modules inherit low-level properties and functionalities from a base module realized as an element that is able to populate the process environment. Virtual and pure-virtual functionality strategies were applied in order to obtain an abstraction with respect to the generic application task. In this way the core can process user-defined functionalities without being reprogrammed. Moreover, modules can be grouped recursively in order to share common properties and functionalities of entity modules belonging to the same type. Communication channels are realized as connections through specific projection types that specify the connection topology. All modules are realized as running processes while their control and synchronization is managed by the framework. A real-time approach for data analysis takes advantage of the framework capability to manage interconnected modules through efficient communication channels. In this way the application can control all the modules of the elaboration chain, including analysis protocol management plus sensory and actuating interfaces.

Connections are delegated to dispatch synchronization information and user-defined data. The filtering interface modules are able to drive the transducer hardware and dispatch information to process modules. All base modules manage dynamic structures and are designed to maintain data consistency if the environment state changes. This behaviour permits the execution of dynamic and real-time parallel distributed processing, while synchronization and data flow are managed by the environment. The framework core contains the processes needed to drive the hydraulic section consisting of the mass flow controller (MFC), the four-way two-state valve and the automatic system for vial selection. The output of each actuator module is a low-level instruction for the actuator hardware, i.e. the control of the hydraulic section. The hierarchical and collaboration chart of the base structures is shown in figure 2. Each block represents a software entity, i.e. an object with methods and attributes, developed within the framework architecture. The arrows between entities indicate inheritance relationships, while the lines indicate collaboration relationships.

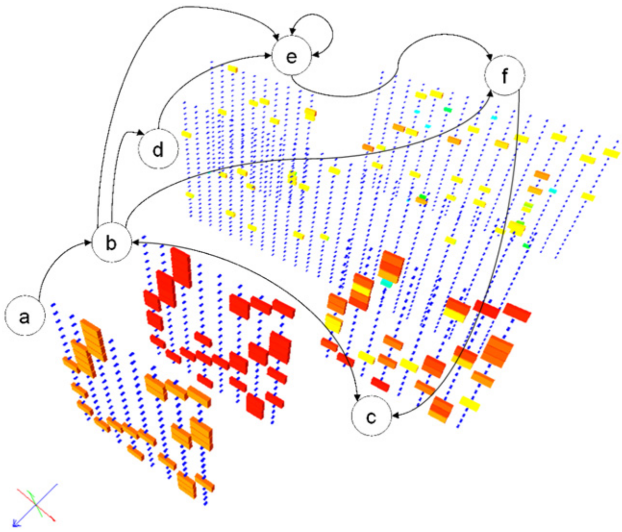

Figure 3. Hippocampus model proposed by McCloskey and Cohen; (*a*) input pattern; (*b*) input entorhinal cortex; (*c*) output entorhinal cortex; (*d*) dentate gyrus; (*e*) CA3; (*f*) CA1.

2.2. The classification module

In this study the classification task was performed by an artificial model of a hippocampus-based working memory processing module. The model operates a pattern separation that avoids catastrophic interference. In accordance with McCloskey and Cohen's architecture [13], input patterns are spread among several interconnected two-dimensional self-organizing maps of artificial neurons (figure 3).

The input entorhinal cortex and the output entorhinal cortex maps represent the input and the output of the net, respectively. Input and output maps have the same dimension in order to evaluate the activation and deactivation error by a one-to-one comparison of neuronal activity. The activation error represents the percentage of neurons that are firing in the output entorhinal cortex and that are under threshold in the input entorhinal cortex. The deactivation error represents the percentage of neurons that are under the threshold in the output entorhinal cortex and that are firing in the input entorhinal cortex. In our application artificial neurons and the learning algorithm were implemented following the model proposed by O'Reilly and Munakata [11, 14]. In particular, their architecture uses a *k*-winners-take-all (*k*WTA) function to achieve inhibitory competition among units within a layer. This architecture was implemented in the framework and was applied to the analysis of multi-sensor data signals coming from an e-nose. The e-nose is used for detecting volatile organic compounds present in the headspace of olive oil samples [15].

2.3. The Leabra neuron model

The Leabra base model is a simplified version of the Hodgkin–Huxley model. The computational model implemented in this paper is taken from O'Reilly and Munakata [11, 14]. Leabra uses a point neuron activation function that models the electrophysiological properties of real neurons, while simplifying their geometry to a single point. This function is nearly as simple computationally as the standard sigmoid activation function, but the more biologically based implementation makes it considerably easier to model inhibitory competition. Furthermore, using this function enables cognitive models to be more easily related to more physiologically detailed simulations, thereby facilitating bridge building between biology and cognition. Leabra uses a *k*WTA function to achieve inhibitory competition among units within a layer. The *k*WTA function computes a uniform level of inhibitory current for all units in the layer, so that the (*k*+1)st most excited unit within a layer is generally below its firing threshold, while the *k*th is typically above threshold. Activation dynamics similar to those produced by the *k*WTA function have been shown to result from simulated inhibitory interneurons that project both feedforward and feedback inhibition. Thus, although the *k*WTA function is somewhat biologically implausible in its implementation (e.g. requiring global information about activation states and using sorting mechanisms), it provides a computationally effective approximation to biologically plausible inhibitory dynamics. For learning, Leabra uses a combination of error-driven and Hebbian learning.

3. Processing of olfactory signals

The e-nose consists of an array of eight chemo-resistive conductive polymer sensors interfaced to an electronic board. Conducting polymers can belong to conjugate or oligomer families polymerized by chemical or electrochemical techniques. In this study poly(3,3′-dipentoxy-2,2′-bithiophenes)-based chemo-resistive layers [16], which change their electrical conductivity in the presence of volatiles, were deposited onto a substrate in correspondence to two metal electrodes. The chemo-resistive layers were obtained by a controlled doping with oxidizing salts in the homogeneous phase. This procedure was previously studied [17] and irreproducibilities are negligible. The controlled doping with different salts and different M/Ox, where M is the number of monomeric unities of the polymer and Ox is the number of inorganic salt molecules, allowed us to obtain sensors with different properties. The responses of these kinds of sensors to organic vapours vary linearly with the compound concentration, and the slope is a function of the compound. In order to evaluate the cross-sensitivity of these kinds of sensors to different volatiles, the sensors were exposed to different volatile compounds present in olive oil in saturation conditions. In table 1 a list of the selected compounds is reported. The data reported in figure 4 are the responses of a poly(3,3′-dipentoxy-2,2′-bithiophenes)-based sensor doped with iron perchlorate at M/Ox = 6. The abscissa shows the steady-state resistance variation. The sensor was exposed to volatiles in a random order. The presence of different flavour components in an olive oil causes the sensor responses to be affected by high cross-sensitivity. For this reason the use of a sensor array joined with an artificial neural network is needed to perform signal processing and classification tasks.

Table 1. List of the main compounds in olive oil, some of which are responsible for flavours and defects.

Aromas		Others	Defects	
Compound	Flavour	Compound	Compound	Defect
2-*trans*-hexenal	Fruity	Ethanol	Hexanol	Musty
Hexanal	Green	Methanol	3-Methyl-1-butanol	Fusty
Nonanal	Fatty	Water	Ethylfuran	Rancid
3-Pentanone	Sweet		Acetic acid	Winey
1-Pentanol	Pungent			

In this work a sensor array composed of eight different sensors was adopted. The sensor array is lodged in an exposure chamber where a gas carries the volatile samples. A chemico-physical interaction occurs between the input volatiles and sensing layers, resulting in an electric resistance variation for each sensor. The response of each sensor is thus an analogue signal versus time. Signals are acquired and digitized by the electronic board and are managed by the framework interfaces.

The e-nose can be divided into a hydraulic and an electronic section. The hydraulic section consists of a sampling system and an exposure chamber. The electronic section was developed using current techniques for noise reduction, and consists of a central processing unit, a digital section and an analogue section. This system allows us to acquire reliable data from conducting polymer sensor arrays and to automatically control the sampling system and the experimental parameters. The sampling system consists of a bottle of ultra-pure nitrogen, an MFC, a four-way two-state valve and a system for automatic vial selection connected to sixteen 125 ml glass vials containing 10 ml solutions (2.5 μl ml^{-1}) of liquid samples. A block scheme of the experimental setup is shown in figure 6. Inert polytetrafluoroethylene tubing and fittings were used for the connections. A thermo-hygrometer inserted into one fitting allows the humidity and temperature of the air flow to be

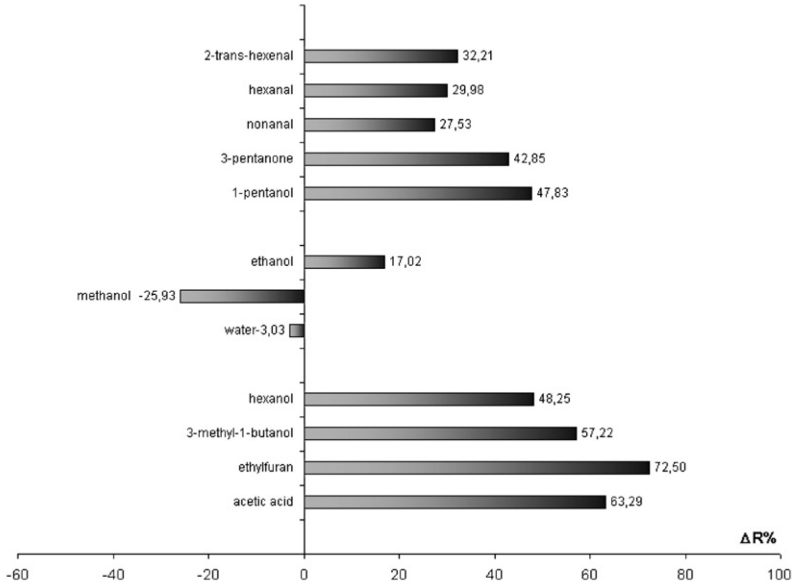

Figure 4. Steady-state resistance variation of a poly(3,3′-dipentoxy-2,2′-bithiophenes)-based sensor doped with iron perchlorate at M/Ox = 6 after the exposure to olive oil volatile compounds reported in table 1 under saturation conditions.

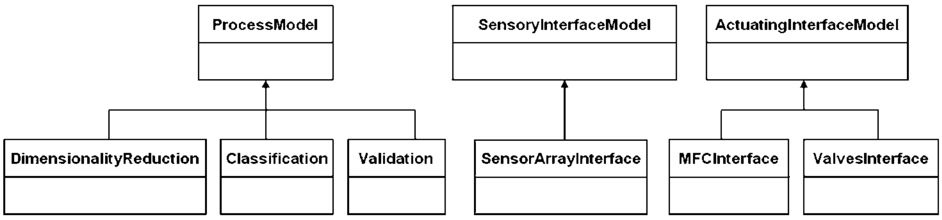

Figure 5. Hierarchical chart of auxiliary modules developed in the framework for an e-nose control system.

measured. Vials were kept at a constant temperature of 25 °C inside a metallic box. Once the vial is selected by the automatic system, the four-way two-state valve is used to switch the system between state 1 (sensors flushed with nitrogen, baseline acquisition and cleaning) and state 2 (exposure of sensors to an odorant). The measurement protocol consists of three phases for each experiment: baseline acquisition (sensors flushed with nitrogen, figure 6(*a*)); exposure (sensors exposed to the sample headspace, figure 6(*b*)); and desorption and cleaning (odours flushed away by nitrogen to restore baseline conditions, figure 6(*a*)).

Starting from the base models available in the framework core, dedicated models for neurons, maps and connections were derived to process signals coming from the e-nose. As mentioned above, in the framework each entity was implemented as a running process. Dedicated modules were also derived in order to dispatch data from the olfactory systems to the core processes. Synchronization is managed by a main process with the support of the framework functionalities. The use of specialized modules derived from the framework base structures, shown in figure 2, led to the development of a stand-alone application that could drive the e-nose hydraulic and electronic sections. Figure 5 shows the processing and interface tailored modules developed for the e-nose control system.

The e-nose was used to assess the headspace of 15 Italian olive oil samples from different regions (Tuscany, Apulia and Sicily) classified by an official panel test as extra virgin, virgin and defective. With the aim of replicating the experiment three

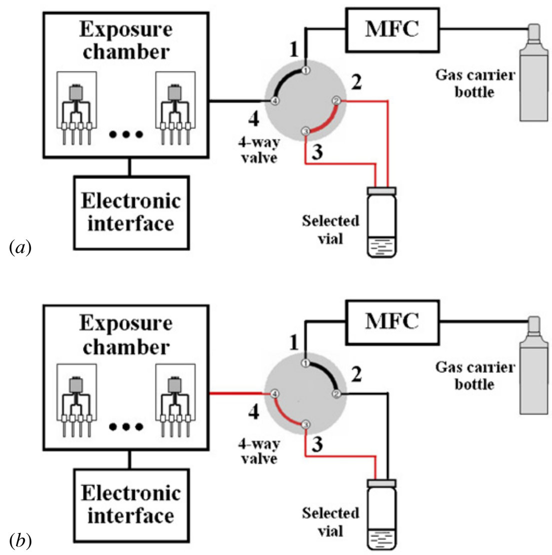

Figure 6. Block scheme of the e-nose experimental setup. (*a*) Baseline acquisition (sensors flushed with nitrogen) and desorption and cleaning (odours flushed away by nitrogen to restore baseline conditions; (*b*) exposure (sensors exposed to the sample headspace).

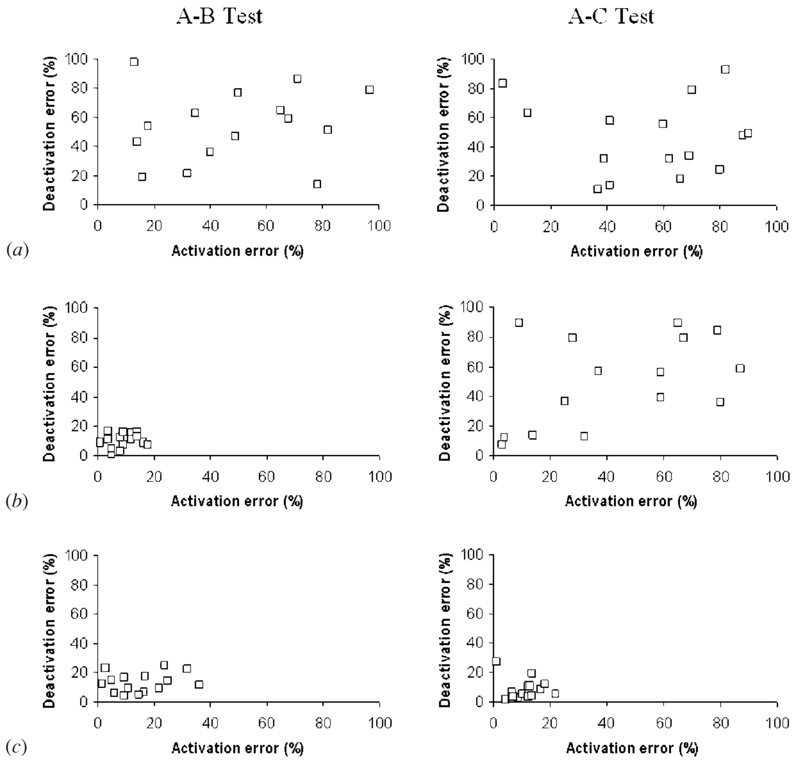

Figure 7. Error mapping during the A-B and A-C tests: (*a*) untrained network; (*b*) after A-B training; (*c*) after A-C training.

Table 2. Standard deviations and mean values of the activation and deactivation errors in the A-B and A-C tests. (a) Untrained architecture; (b) after A-B training; (c) after A-C training.

	A-B test				A-C test			
	Mean		Standard deviation		Mean		Standard deviation	
	Activation error (%)	Deactivation error (%)	Activation error (%)	Deactivation error (%)	Activation error (%)	Deactivation error (%)	Activation error (%)	Deactivation error (%)
(a)	48.5	54.1	27.3	25	56	46.3	26.4	25.7
(b)	9.3	10.1	5	5	43.2	49.9	29.3	29.8
(c)	15.4	13.2	10.5	6.8	10.9	8.3	5.7	7.2

times, 45 vials (volume 125 ml) were prepared by pouring 10 ml of each of the 15 olive oil samples into three vials, sealing and then waiting a few hours for equilibration. The headspace of each vial was conveyed using a gas carrier (nitrogen) with a flow rate of 200 ml min^{-1} into an exposure chamber where the sensor array was lodged. The signals coming from the sensor array were acquired in parallel with a constant scan rate equal to 4 Hz and an acquisition time equal to 17.25 s. For each sensor signal a vector of 69 samplings was obtained. For each sensor signal the baseline phase consisted of 32 samplings (8 s), whereas 5 samplings (1.25 s) were acquired during the exposure phase and 32 samplings (8 s) were acquired during the desorption phase.

The architecture was trained in order to learn the two relations that exist in the association of an olive oil both with its geographical origin and with its quality. This was done with the constraint that the learning of the second relation must not interfere with the memory of the previously learned original one. In order to verify the ability of the processing architecture in such an associative and short-term memory, a paired-associate learning (AB-AC test) was applied [12]. Elements A, representing the output signals of the e-nose for each olive oil, were associated with elements B and C, which represent the geographical origin and the quality class, respectively. The experiment and data processing were controlled at run time by the main process. During the execution of the training processes each paired input pattern was mapped onto the input entorhinal cortex while the association response results were mapped onto the output entorhinal cortex. During the test processes, when the input entorhinal cortex did not include the B or C pattern, the error was obtained by comparing the output entorhinal cortex to the complete original pattern.

The results of the test processes are shown in figure 7. For each sample activation and deactivation, a percentage error is reported in a two-dimensional plane. The first test on the untrained architecture produced, as expected, a high classification error (figure 7(*a*)). Test results after the execution of the A-B training process are shown in figure 7(*b*). As can be seen, a minor misclassification was obtained for the A-B list, while A-C elements were still not recognized.

Test results after the execution of the A-C training process are shown in figure 7(*c*). Correct associations can be observed for the A-C list, while memory for the A-B list is still present with minor misclassifications thus highlighting the avoidance of catastrophic interference. Table 2 shows the mean activation and deactivation percentage errors.

The reproducibility of the model was tested on three repeated experiments. The accuracy was evaluated as the maximum distance from the mean value of the activation and deactivation errors in the three experiments. The precision was evaluated as the standard deviation of the activation and deactivation errors in the three experiments. An accuracy of 4.8% and a precision of 3.6% were obtained.

4. Conclusions

We have presented an architecture for associative short-term memory. Our architecture manages multi-transducer data processing techniques both dynamically and efficiently. The classification task was implemented within the architecture as a hippocampus-based model that can gain short-term priming in cooperation with other modules in order to avoid catastrophic interference. The architecture was tailored to an electronic nose devoted to olive oil analysis. In order to verify the ability of the processing architecture in associative and short-term memory, olive oils belonging to three different qualities and to three different geographic origins were assessed by means of a paired-associate learning test. Our results showed the avoidance of catastrophic interference.

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