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Sensors and Actuators B 85 (2002) 137–144

SENSORS AND ACTUATORS B CHEMICAL

www.elsevier.com/locate/sensorb

A comparative analysis of basic pattern recognition techniques for the development of small size electronic nose

Manuele Bicego[a,*], Gino Tessari[b], Giampietro Tecchiolli[a,1], Marco Bettinelli[b]

[a]*Dipartimento di Informatica, Università di Verona, Ca' Vignal 2, Strada Le Grazie 15, I-37134 Verona, Italy*
[b]*Dipartimento Scientifico e Tecnologico, Università di Verona, Ca' Vignal 1, Strada Le Grazie 15, I-37134 Verona, Italy*

Accepted 5 March 2002

Dedicated to the memory of the late Professor Gino Tessari

Abstract

In this paper, we propose the investigation and the realization of an artificial sensor system and an analysis system able to extract analytical information from odors, under the constraint of being suitable for miniaturization and portability. A sensor array was realized with a series of carbon black–polymer detectors. The lack of reproducibility of those sensors was compensated using a very flexible calibration and recognition tool based on neural networks. The training strategy used in this work, that performs better than derivative-based optimization techniques like standard back-propagation, permits a very low cost VLSI realization, necessary condition for deep miniaturization of the system. A comparative analysis of different pattern recognition approaches was performed in order to evaluate the suitability of this kind of neural networks, which allow deep computing circuit miniaturization. Moreover, we used dimensionality reduction techniques to decrease the computational complexity of the classification technique. The analyses carried out in this study could allow the development of a compact and self-contained electronic nose, in which the analysis system is directly embedded in the sensor device. This should permit to minimize the costs and to obtain better portability and performances. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Electronic nose; Reactive Tabu search; Neural networks; Chemical sensors array; Odor classification; Dimensionality reduction techniques; *K*-nearest neighbor

1. Introduction

Odor detection by chemical sensors is a very interesting task from both a fundamental [1,2] and an applied point of view [3,4]. In a first approach, sensors were built using a lock and key technique, which made them very selective, i.e. designed for only one type of analyte. Recent approaches are directed to the detection of a wide variety of volatile compounds, by combining chemically different sensors in an array. Many solutions have been investigated for the hardware component of the sensor system. A non-exhaustive list consists of surface acoustic wave (SAW) [5–7], quartz crystal microbalance (QCM) [8], optical sensors [9], thin oxide detectors [10,11] and conducting organic polymer sensors [12,13]. However, the chemical composition of those devices is only one aspect of the electronic nose topic: signal processing and pattern recognition are also decisive factors in order to obtain a versatile instrument able to reliably recognize a wide variety of odors.

In this paper, we present a research project focused on the study and the realization of an artificial sensor system and a set of techniques able to extract analytical information from odors (i.e. mixture of analytes), under the constraint of being suitable for miniaturization and portability. The project strategy is well defined: instead of creating a set of sensors able to provide precise and specific information, we opted for a solution based on the methods of collective analysis of the data gathered by a less specific sensor array. Therefore, our attention was focused on the improvement of the analysis and recognition techniques rather than on the sensor hardware, keeping clear in mind the objectives of miniaturization and portability. To the best of our knowledge, the majority literature works on electronic nose is focused on chemical aspects rather than signal processing and pattern recognition, although some excellent papers on this subject have appeared (e.g. [14,15]).

The sensor array was realized with a series of carbon black–polymer detectors [16,17] (a subclass of conducting polymer sensors), which were chosen for their low cost.

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[*] Corresponding author. Tel.: +39-45-8027072; fax: +39-45-8027928.
E-mail address: bicego@sci.univr.it (M. Bicego).

[1] Present address: Neuricam S.p.A. Via S. Maria Maddalena 12, 38100 Trento, Italy. Tel.: +39-461-260-552; fax: +39-461-260-617.

PII: S0925-4005(02)00065-5

Briefly, the individual sensor elements were constructed from films consisting of carbon black particles dispersed into insulating organic polymers. The carbon black endows electrical conductivity to the films (chemical diversity among elements in the array was obtained using different organic polymers for each sensor). Swelling of polymer during solvent exposure increases film resistance; by this way, we could simply and efficiently monitor the presence of vapor of interest. The lack of reproducibility of those sensors was compensated using a very flexible calibration and recognition tool based on neural networks [18,19]. This technique, with different variants [20–24], was successfully applied in various odor detection systems. In this work, we used a multilayer perceptron [25], trained with the reactive Tabu search (RTS) [26]. This optimization strategy, unlike standard back-propagation technique, is more effective in finding a global optima of the training function. Moreover, and most important, this technique is very suitable for deep circuit miniaturization, an example is given by the TOTEM chip [27,28].

The main innovative aspect of the present study relies on the investigation and improvement of the signal analysis and recognition techniques, in view of a device miniaturization. In particular, a comparative analysis of different pattern recognition approaches was performed in order to authorize and validate the use of the RTS multilayer perceptron, which allows deep computing circuit miniaturization.

Another important aspect is the analysis of the impact of the dimensionality reduction techniques on the classification performances of the system. In this paper, we used the dimensionality reduction techniques to diminish the curse of dimensionality [29] impact on the classification techniques. As shown in this paper, the dimensionality reduction, decreasing the computational complexity, can eliminate part of data redundancy, with consequent noise reduction. Methods analyzed in this study are based on simple linear transformation of data; these transformations, if calculated off-line, can be implemented with neural network having linear activation functions, therefore, suitable for our project goal.

Finally, we wanted to better exploit the information obtained from each experiment considering the time evolution of the sensor responses as well. To achieve this aim, we used additional features, that can better characterize the sensor and analysis system.

2. Experimental

2.1. Materials

Carbon black–polymer sensors were prepared using Black Pearls 2000 (BP 2000), a furnace black material. Polymers adopted in order to obtain the active material are listed in Table 1. These polymers were purchased from Sigma–Aldrich and were used as received. The following solvents were employed: acetone (J.T. Baker, 99.5%), 2-propanol (J.T. Baker, 99.7%), ethanol (Merck, 99.8%) and tetrahydrofuran (THF) (Merck, 99.5%). These solvents were used as received.

2.2. Instrumentation and apparatus

The experimental apparatus was composed by a gas line and a signal acquisition system, connected to a personal computer via a LabPC+ card. The gas line was an automated flow system used for producing and delivering to sensors a predetermined analyte concentration: a stream of carrier gas was passed through a bubbler filled with the solvent of choice. The bubbler was a standard glassware tube (30 cm long with a 3 cm diameter) equipped with exit sidearms. A glass tube terminating with a coarse filter frit was inserted in this tube. The carrier gas was introduced into the solvent through the porous ceramic frit, and the solvent saturated gas mixtures exited the bubbler via the sidearms of the glass tube. This flow was then diluted with pure carrier gas to obtain a well-determined analyte–carrier ratio. Gas flow rates were controlled with valves driven by an electrical signal (connected to a personal computer via parallel port) and flowmeters. Bubblers were equipped with a thermostatic system, realized with a cavity where a well-known temperature water flowed. The carrier gas for all experiments was compressed oil-free laboratory air (80% nitrogen, 20% oxygen), containing less than 2 parts per million (ppm) of water vapor; it was introduced in the gas line at 0.5 bar pressure, and was neither filtered nor dehumidified. The

Table 1
Elements of the sensor array

Sensor	Polymer	Polymer quantity (mg)	Carbon black quantity (mg)	Solvent (THF) quantity (ml)
0	Poly(4-vinylphenol)	10	90	35
1	Poly(styrene)	10	90	25
2	Poly(vinylpyrrolidone)	10	90	35
3	Poly(4-vinylphenol)	10	90	35
4	Poly(sulfone)	10	90	65
5	Poly(vinyl acetate)	10	90	100
6	Poly(styrene)	10	90	25
7	Poly(vinyl acetate)	10	90	100

vapor mixture was then introduced in the sensors chamber, a glass tube 32 cm long and 5 cm large, containing the sensors circuits. One side of this tube was for gas entering, the other was sealed with a ground-glass stopper through which electrical lead wires had been sealed. Two lateral outlets allow the downflow of the mixture from the chamber.

The datasets used for testing classification methods were obtained performing 102 experiments with these experimental conditions: carrier flowed at 0.9 l/min at 0.5 bar pressure, while analyte flowed at 0.1 l/min. Analyte temperature was $6.7 \pm 0.5\,^{\circ}\mathrm{C}$; concentrations of three analytes were 5.8 ± 0.1 parts per thousand (ppth) for 2-propanol, 22.62 ± 0.02 ppth for acetone and 5.7 ± 0.1 ppth for ethanol. Mass loss of solvent in bubblering was used to determine analyte concentration (analyte/carrier ratio) for each experiment series.

2.3. Fabrication of carbon black–polymer composite detectors

Each sensor was based on ceramic capacitors (22 nF, approximately 2 mm × 4 mm × 4 mm). The top of the capacitor was removed by using progressively finer grades of SiC sandpaper and diamonds paste of 6 μm. After this polishing step, the capacitors were sonicated in acetone for 10 min to remove any residual alumina. All capacitors used for sensors had an initial resistance higher than 10 MΩ (the upper measurement limit of our multimeter).

To prepare the carbon black–polymer composites, 10 mg of carbon black and 90 mg of one of insulating polymers were added to a well-determined quantity of solvent (shown in Table 1), which was for all cases THF. Solutions were then sonicated for 10 min to suspend the carbon black. The polished capacitor was dipped into solution one or more times until a good resistance film was obtained (from 80 to 200 kΩ). Before use, sensors were dried in open air for 24 h and placed in air flowing at 0.5 l/min for 5 h.

The film resistance stability, in absence of any volatile organic compound (VOC) was verified to guarantee sensor quality. To reach this aim, the sensor circuit was solicited with a progressively higher frequency sinusoidal signal; amplitude and phase of the circuit gain function were gathered via a lock-in amplifier (SR830 DSP—Stanford Research System). The goodness of the fit of these experimental points with the theoretical curve was used as measure of the sensor quality. This goodness was estimated using χ^2 method [30]. All sensors employed in this work were very high quality sensors, as they showed the behavior of a pure RC circuit, without any frequency non-linearity, at least in the precision range characteristic of the equipment employed.

2.4. Measurements

The dc resistance of each sensor was determined as a function of time: each sensor was placed in an array cell, with an operational amplifier containing the sensor in its feedback circuitry, in series with a well-known resistance R_0. The stimulus was a dc voltage V_{in}; the resistance sampling rate was approximately 38 times for seconds. For each experiment, R_0 and V_{in} were chosen to maximize signal to noise ratio, reducing impact of the digitizing error due to analogic–digital conversion. A typical experiment consisted of a three-step process that began with 5 min of air flow to determine the baseline resistance, followed by 10 min of vapor exposure and by 10 min of air flow, to restore baseline resistance values.

2.5. Feature extraction

The feature used for data analysis was extracted from the temporal series $R_j(t_i)$, one for each sensor j of the array. These series were obtained by periodically sampling sensors resistance. To resolve a vapor task, the maximum relative variation of each sensor resistance was used:

$$R_{j,\Delta\max[a,b]} = \frac{R_{j,\Delta\max[a,b]} - R_{j,\min[a,b]}}{R_{j,\mathrm{base}}} \qquad (1)$$

where $R_{j,\mathrm{base}}$ represents the baseline value of resistance obtained averaging 5–10 s of gathering, after a suitable washing interval (typically, 10 min). $R_{j,\Delta\max[a,b]}$ and $R_{j,\min[a,b]}$ represent respectively the maximum and the minimum value of jth sensor resistance in the gathering interval $[a, b]$:

$$R_{j,\min[a,b]} = \max_{t_i \in [a,b]} R_j(t_i)$$

$$R_{j,\min[a,b]} = \min_{t_i \in [a,b]} R_j(t_i)$$

Typically [16,17] $[a, b]$ represents the whole vapor exposure interval. In most situations, nevertheless, exposition time cannot be so long; reaction and analysis should be faster. Therefore, analyzing evolution of value (1) is very interesting: we can also investigate the minimum time needed by the sensor system to resolve a particular vapor sensing task. To achieve this, we calculated (1) in progressively growing intervals [0, 1 s], [0, 2 s] and so on. Then we grouped all data collected from same interval $[a, b]$, generating several dataset, used to test various analysis techniques. These sets were nicknamed ‘‘photo sets’’, name that recalls the way they are obtained.

3. Basic pattern recognition theory

3.1. Dimensionality reduction

In this paper, we have adopted the dimensionality reduction techniques belonging to linear transformation family:

$$Y = A^{\mathrm{T}} X$$

where X and Y are the original and the reduced data matrix, respectively. Aim of these techniques is to determine matrix A, maximizing (or minimizing) a given criterion.

Principal component analysis (PCA) [31] chooses the matrix A that minimizes mean squared distance between original data and those reconstructed from reduced data. In [32], it is shown that such A is determined considering the eigenvectors of the covariance matrix corresponding to m first dominant eigenvalues, where m is the resulting dimensionality. With discriminant analysis (DA) projection directions are those that maintain maximum class separability in resulting space. In this work, Fisher's criterion [33] was used to estimate class separability and projection directions are chosen solving an eigenvalue–eigenvector problem [32]. Discriminant component analysis (DCA) is a relatively new technique [34] which transforms original space into orthonormal space such that for each direction there is an eigenvalue representing discriminatory power of projection in that direction: this is obtained with an iterative procedure.

3.2. Classification

K-nearest neighbor (KNN) [32,35] is a classical classification technique widely used in pattern recognition problems. To determine item class this method investigates its neighborhood class. Given a point to classify x_0, KNN determines set U formed by Kx_0 nearest neighbors, calculated using a metric Σ (usually Euclidean metric). The most frequently class C_k in U is assigned to x_0. In this work, we also employed two variants of this scheme: Local KNN [36] and discriminant adaptive nearest neighbor (DANN) [37]. KNN, Local KNN and DANN parameters were determined with a cross-validation technique, called leave one out [38].

Neural network [18,19] is a semi-parametric classification technique inspired on animal neural system; it is a complex structure formed by many simple processing units, called neurons. Multiple neural network types are obtained varying neuron type and network topology. In this paper, we used a standard perceptron-based feed forward neural network [18,25], with two hidden layers, each containing 10 units. The activation function used was the logistic one, and the output layer was composed by one unit for each class of the classification task. Each networks training was stopped before over-training situation (detected using a cross-validated set) or when the training error was adequately low. All neural networks used in this work were trained using an optimization strategy called reactive Tabu search (RTS) [26]. Unlike standard derivative-based optimization methods, as back-propagation, this technique escapes rapidly from local optima, discourages cycles in the searching trajectory and is very robust with respect to the choice of initial configuration, leading to a more effective training. With respect to our project guidelines, the most important aspect is that the RTS scheme is very suitable for special-purpose hardware realization, with simple, but fast electronic components. In particular, the TOTEM chip, a commercial chip implementing an artificial neural network [39], is trained with RTS [27,28].

3.3. Classification accuracy

The mean classification accuracy is calculated as

$$A(f) = 1 - E(f) = 1 - \sum_{i=1}^{c} P_i \left(\sum_{j \neq i} C_{ij}(f) \right)$$

where f is the discriminant function of the classifier, P_i the ith estimated class prior probability, and $C(f)$ is the f confusion matrix [39].

Each element of this matrix can be estimated with

$$\tilde{C}_{ij}(f) = \frac{100}{N_i} \sum_{k=1}^{N_i} f_j(x_k)$$

where x_k is the kth element of the ith class.

Usually, only one dataset is available from the problem: several techniques able to obtain training and testing set from dataset are explained in [38]. In this study, we used the ‘‘averaged holdout’’ one, which randomly split dataset into two mutually exclusive subsets, one for learning and one for testing. In order to make the result less dependent on the partition, we generated 30 different partitions, calculated accuracy for each of them and then averaged the results.

4. Results and discussion

4.1. Classification performances

A first analysis was made on the whole dataset, and results are shown in Table 2. We can note that accuracy values are very high: the nose discriminated well from these solvents at these concentrations. The second analysis was made on reduced datasets, using different classification methods, varying data dimensionality reduction technique and dimensionality of resulting set. For DA, the maximum resulting dimensionality is $c-1$, where c is the number of classes of the problem [40]. Results of this analysis are shown in Table 3. We can infer some considerations from this table. First, excluding DCA, on two-dimensional reduced sets the performances of classifiers were comparable with those on not reduced dataset: there was a lot of redundancy on data. Second, in many situations dimensionality reduction implies error reduction. Probably data redundancy was source of noise, and its reduction causes a partial noise decreasing. Final, DA seems to be the most suitable technique for classification, even if its application is limited by number of classes.

Table 2
Classification accuracy of various classifiers on whole set

Classifier	Accuracy (%)
KNN	99 ± 1
Local KNN	99 ± 1
DANN	99 ± 1
Neural nets	100 ± 0

Table 3
Classification accuracy on the set reduced with principal component analysis (PCA), discriminant component analysis (DCA) and discriminant analysis (DA), varying resulting dimensionality

Resulting dimensionality	Method	KNN accuracy (%)	Local KNN accuracy (%)	DANN accuracy (%)	Neural nets accuracy (%)
1	PCA	92 ± 3	93 ± 3	92 ± 3	94 ± 2
1	DCA	69 ± 5	69 ± 4	69 ± 5	71 ± 4
1	DA	69 ± 5	69 ± 4	69 ± 4	71 ± 5
2	PCA	99 ± 1	98 ± 1	100 ± 0	99 ± 1
2	DCA	70 ± 4	69 ± 5	71 ± 5	77 ± 4
2	DA	100 ± 0	100 ± 0	99 ± 1	100 ± 0
3	PCA	100 ± 0	99 ± 1	100 ± 0	100 ± 0
3	DCA	89 ± 4	89 ± 3	82 ± 4	90 ± 2
4	PCA	99 ± 1	99 ± 1	99 ± 1	99 ± 1
4	DCA	90 ± 3	90 ± 3	92 ± 4	92 ± 3
5	PCA	99 ± 1	98 ± 1	99 ± 1	99 ± 1
5	DCA	100 ± 0	100 ± 0	99 ± 1	100 ± 0
6	PCA	99 ± 1	99 ± 1	99 ± 1	99 ± 1
6	DCA	100 ± 0	100 ± 0	99 ± 1	100 ± 0
7	PCA	99 ± 1	99 ± 1	99 ± 1	99 ± 1
7	DCA	100 ± 0	100 ± 0	99 ± 1	100 ± 0

4.1.1. Photo sets

Another analysis was made evaluating classifiers performance on photo sets, obtained with eight intervals [0–1] [0–2] . . . [0–8] seconds. Results are given in Table 4: accuracy values increased when increasing interval dimension; the accuracy on the last interval photo set is appreciably high.

We then used these sets to determine ratio of total responses that each sensor showed after *n* seconds of solvent exposure. In order to obtain this aim, for each sensor, we calculated the averaged ratio between *n* second and total response (after the whole exposure interval). These ratios are shown in Table 5 (percentage values): ratios after 8 s were still low. Moreover, same sensor showed different ratios for different analytes. From these considerations, we can suggest the hypothesis that the speed of the sensor response is a factor useful in solvent discrimination.

4.1.2. Final considerations on performance analysis

About classification performances, we have shown that KNN, Local KNN, DANN and neural network showed same performance level on examined datasets. Regarding computational aspects, nevertheless, these techniques are very different.

For neural networks, the training was the most onerous part: some preliminary tests showed that the use of the RTS training algorithm replacing the standard back-propagation results in a great improvement in the speed of the convergence of the training error. KNN showed pattern storage problem, which can be very important on wider context: nevertheless, it was a good classifier, fast and sufficiently accurate. Using Local KNN quantity of information maintained in memory increased; moreover, system initialization took much time. DANN needed very long execution time (one or two magnitude order greater), due to metric estimation.

4.2. Sensor analysis

In this section, we propose an analysis of sensor responses. We tried to evaluate sensor response reproducibility, comparing responses of the same sensor in different experiments (with the same experimental conditions). Then

Table 4
Classification accuracy on photo sets varying interval dimension

Dim of interval (s)	KNN accuracy (%)	Local KNN accuracy (%)	DANN accuracy (%)	Neural nets accuracy (%)
1	82 ± 5	81 ± 4	75 ± 6	84 ± 3
2	91 ± 2	90 ± 3	92 ± 3	94 ± 2
3	90 ± 3	91 ± 4	93 ± 3	96 ± 2
4	93 ± 3	93 ± 3	93 ± 3	96 ± 2
5	95 ± 3	94 ± 3	94 ± 3	97 ± 2
6	95 ± 2	94 ± 2	94 ± 3	97 ± 2
7	96 ± 2	95 ± 2	96 ± 2	97 ± 2
8	96 ± 2	96 ± 2	96 ± 3	97 ± 2

Table 5
Fraction of total responses, in percentage value, showed by each sensor in a photo interval, varying interval dimension[a]

Dimension of interval (s)	Analyte (I/A/E)	Sensor 0 (%)	Sensor 1 (%)	Sensor 2 (%)	Sensor 3 (%)	Sensor 4 (%)	Sensor 5 (%)	Sensor 6 (%)	Sensor 7 (%)
1	I	2.37	13.04	4.95	5.37	14.71	6.44	9.37	8.07
	A	0.36	1.34	1.50	0.26	4.81	3.93	2.42	3.37
	E	2.38	13.69	0.83	1.42	17.64	27.42	20.78	6.96
2	I	2.87	13.51	5.21	5.86	15.66	11.97	11.54	11.09
	A	1.01	2.02	1.66	0.27	5.06	8.41	3.90	5.33
	E	6.24	35.13	0.89	1.47	18.75	54.14	39.00	10.36
3	I	3.32	14.55	5.35	6.38	16.35	17.03	13.21	15.60
	A	2.07	2.90	1.96	0.29	5.27	14.43	5.92	8.55
	E	10.81	51.38	1.02	1.78	18.92	76.60	53.93	17.07
4	I	3.65	15.20	5.58	6.70	17.08	22.55	16.37	20.16
	A	3.45	4.03	4.03	0.33	5.50	20.77	7.86	13.15
	E	15.64	66.25	66.25	2.54	19.76	89.77	66.15	24.52
5	I	4.28	16.58	5.94	6.79	17.54	27.7	19.17	24.96
	A	4.90	4.98	4.70	0.44	5.79	25.77	9.65	18.72
	E	21.16	80.42	1.52	3.70	20.62	94.86	78.47	35.53
6	I	4.80	18.07	6.64	6.85	18.68	32.02	22.29	29.13
	A	6.37	5.99	7.23	0.65	6.36	30.20	11.28	23.62
	E	26.80	93.92	1.84	5.33	22.80	97.92	90.08	45.46
7	I	5.46	20.09	7.02	7.03	19.29	36.74	25.34	33.05
	A	12.27	17.64	4.66	1.66	10.70	59.65	25.25	31.22
	E	20.96	39.88	5.15	3.64	19.45	66.20	48.64	52.11
8	I	6.15	21.89	7.41	7.62	21.97	40.47	27.86	37.34
	A	9.10	7.17	13.12	1.12	8.32	35.92	13.10	32.02
	E	39.76	97.51	2.62	9.19	30.85	97.19	98.10	64.59

[a] I, A and E stay for 2-propanol, acetone and ethanol, respectively.

we tried to evaluate interchangeability of sensors made with same active material, comparing responses of analogue sensors in the same experiment.

4.2.1. Response reproducibility

To measure response reproducibility we calculated mean and standard deviation of each sensor response for each experimental series, reported in Table 6. Reproducibility was acceptable. In this sense, the worst sensor was 2 (poly(vinylpyrrolidone)), which was very unstable during the whole work. We tried to stabilize its response, e.g. putting it in a furnace at 40 °C for 24 h, without any success. Another consideration: worst responses were those that presented lower entities, where data acquisition noise is more influent.

Table 6
Mean responses and standard deviations of array sensors

Sensor	2-Propanol		Acetone		Ethanol	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
0	0.013	0.002	0.053	0.004	0.031	0.004
1	0.007	0.001	0.024	0.002	0.008	0.001
2	0.014	0.008	0.033	0.009	0.060	0.020
3	0.009	0.003	0.046	0.009	0.028	0.005
4	0.008	0.002	0.011	0.001	0.008	0.002
5	0.008	0.002	0.024	0.002	0.009	0.002
6	0.011	0.002	0.024	0.001	0.012	0.002
7	0.007	0.002	0.015	0.001	0.008	0.002

4.2.2. Sensor reproducibility

During the production of sensors, the reproducibility was poor: seldom we obtained two sensors, made with the same active material, showing the same baseline resistance value. Nevertheless, responses of sensor were baseline value independent, because they were differential measures. To have an idea about the sensor reproducibility, we duplicate some sensors in the array: in the same experiment, we hoped to find analogue responses for analogue detectors. With photo sets analysis, we could obtain information about response speed. From Table 5, we can see that the response speed were not the same in analogue sensors. Speed depends on film thickness, and with fabrication technique used in this work this factor cannot be controlled.

4.2.3. Alternative support analysis

We tried to test reproducibility of sensor response when varying sensor support: we build an alternative support, based on thick standard glass strips, of 3 mm × 3 mm. Electrical contacts were obtained sealing copper wires on strips ends. Sealing process was performed using silver paste (CW2400 Circuit Works Conductive Epoxy Kit, made by Chemtronics Inc.). A 2 mm gap was guaranteed between two electrical contacts. To obtain sensor, we dipped support in carbon black–polymer solution one or more times, until a good film resistance was obtained. Each solution was composed by 80 mg of polymer, 20 mg of carbon black and 30 ml of THF and was prepared following procedure mentioned earlier. After recreating array shown in Table 1, we repeated experiments in condition explained in Section 2. We then tested the compatibility using the analysis of variance (ANOVA) test [30]: the null hypothesis that the data obtained from the two kinds of sensors are equivalent was rejected for all the carbon black–polymer composites. The level of significance of this rejection was 0.05 for the second sensor (made with poly(vinylpyrrolidone), the very unstable one), 0.01 for the others. Thus, the compatibility was not present; we could reasonably deduce it also from the analysis reported in Section 4.2.2.

5. Conclusions

In this work, we showed that the RTS neural network approach represents an adequate classification technique for odor detection, with performances that are equivalent to KNN and other methods: this method is moreover very suitable for miniaturized device. Moreover, we demonstrated that in this problem dimensionality reduction techniques, principally DA, could reduce the computational complexity of classification techniques, without substantial information loss. Moreover, their application reduces noise level on redundant sets, resulting in performances that are sometimes better than those on not reduced sets. Finally, we could better characterize sensor and analysis systems creating a new features set. In fact, using photo sets, we could determine, e.g. the reproducibility of the speed of response of a sensor built with the same active material. We could obtain more than one dataset from one experimental session, useful for testing classification techniques. Photo sets analysis clearly shown that the speed of the sensor response can be used as discriminant factor to resolve a wide range of vapor sensing tasks.

We believe that the analyses carried out in this investigation should allow the development of a compact and self-contained electronic nose, in which the analysis system is directly embedded in the sensor device. This should permit to minimize the costs and to obtain better portability and performances.

Acknowledgements

We want to acknowledge the Cabot Europe G.I.E. for the generous donation of the Black Pearls 2000 (BP 2000). We also would like to thank Erica Viviani and Gianluca Righetti (Università di Verona) for their skilful assistance in the fabrication of the system hardware.

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Biographies

Manuele Bicego received his degree in computer science from University of Verona in 1999, with a graduation thesis concerning the analysis of chemical sensor array signals. Since 2000, he is a PhD student in computer science in the Computer Science Department of University of Verona. Since 2000, he is working in Vision, Image Processing and Sound (VIPS) Laboratory of the same department. His research interests include statistical pattern recognition, artificial vision, electronic noses, neural networks and graphical models. Manuele Bicego is member of the IAPR-IC Society and student member of the IEEE Systems, Man, and Cybernetics Society.

Gino Tessari received his degree in chemistry from the University of Padova in 1959. From 1964 to 1966, he was visiting researcher at Louisiana University and at New York University, with professor Paul Delahay. From 1980 to 1986, he was professor of analytical chemistry at University of Bari. From 1986 to his death (1999), he was professor of chemistry in the University of Verona. His recent research interests included electronic noses, chemical sensors and synthesis and characterization of nanocrystalline materials.

Giampietro Tecchiolli received his degree in physics from the University of Trento in 1986. Since 1987, he is associated with the Italian Institute of Nuclear Physics (INFN) working in the area of parallel and distributed computing for computational theoretical physics. He was a participant of the Special INFN initiative for realizing RTS-specific VLSI chips and co-designer of the TOTEM chip. From 1988 to 1998, he was with the Institute for Scientific and Technologic Research (IRST) of Trento. Since 1993, he has been with the Computer Science Department at the University of Verona, where he is adjunct professor. He is currently with NeuriCam S.p.A., Italy in charge of the research and development activities. His research interests include discrete, continuous and functional optimization, parallel and distributed computing, computer architectures and algorithms complexity. Giampietro Tecchiolli is member of the IEEE Computer Society.

Marco Bettinelli received his degree in chemistry from the University of Parma in 1981. In the years 1983–1992, he has been assistant professor of inorganic chemistry at the University of Padova, and in 1992, he was appointed associate professor of inorganic chemistry at the University of Salerno. Since 1993, he is associate professor of inorganic chemistry at the University of Verona. He is a member of the Board of Directors of INSTM (Consortium on Materials Science and Technology among 38 Italian Universities). He is a Fellow of the Royal Society of Chemistry (FRSC CChem) and a reviewer for numerous international journals. His scientific interests deal with many aspects of Solid State and Materials Chemistry.