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An adaptive neural network topology for degradation compensation of thin film tin oxide gas sensors

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Abstract

A hybrid neural network for gas sensing application is presented, which is based on adaptive resonance theory. The network may use as an input one or more gas sensors. The basic feature of the proposed topology is its ability to learn a new pattern or form a new pattern category at any point of its operation. At the same time it retains knowledge of previously learned patterns or pattern categories. This adaptation ability helps the network to solve many of the problems encountered with tin oxide gas sensors, like instabilities and degradation. The functionality of the network is presented in the two cases of one and four input providing gas sensors. The experimental results show that the effect of sensor degradation maybe compensated by the proposed network topology.

Keywords: Gas sensors; Neural networks

1. Introduction

Human sense of smell is a valuable tool in many areas of industry, such as perfumery, food and drinks production, clinical diagnosis and environmental monitoring. The human sense of smell however, is influenced by many factors such as health and age. An instrument that could perform odour discrimination devoid these influences and it could find application in many of the above areas. Such an instrument is an artificial nose that generally comprises of one or more gas sensors and an appropriate pattern recognition system.

The pattern recognition is usually structured in three distinct steps: feature extraction, classification and identification. Feature extraction performs the important operation that is the transformation of the sensor output to qualitative information. Since this transformation is not a linear one on a sensor output, suitable numerical tricks must be engaged. Classification is a procedure that clusters together the sensor array data as processed by the feature extraction, in order to obtain the classes. This procedure can be an easy one when in the representation space, the subspaces referred to the classes produced by the feature extraction are connected. Then, Bayesian surfaces can be used to separate the classes, but normally this is not the situation in gas sensing applications. Finally, identification is the procedure that assigns a sensor array output to a class.

Neural networks have been applied to a wide variety of applications and they have been considered as the most promising tools for pattern recognition in gas sensing applications. The acute problem, however, of the metal oxide gas sensors degradation in particular has not been tackled so far to the best of our knowledge. Our experience [1–3] with thick and thin film tin and indium oxide gas sensors shows that for applications requiring relatively long term stability and functional reliability as to the selectivity of the sensor, a complex electronic system is necessary for the degradation compensation. In this work, a hybrid neural network is presented, which offers powerful solutions for the compensation of the gas sensor degradation, and subsequently for the excellent improvement of its reliability as shown in the following.

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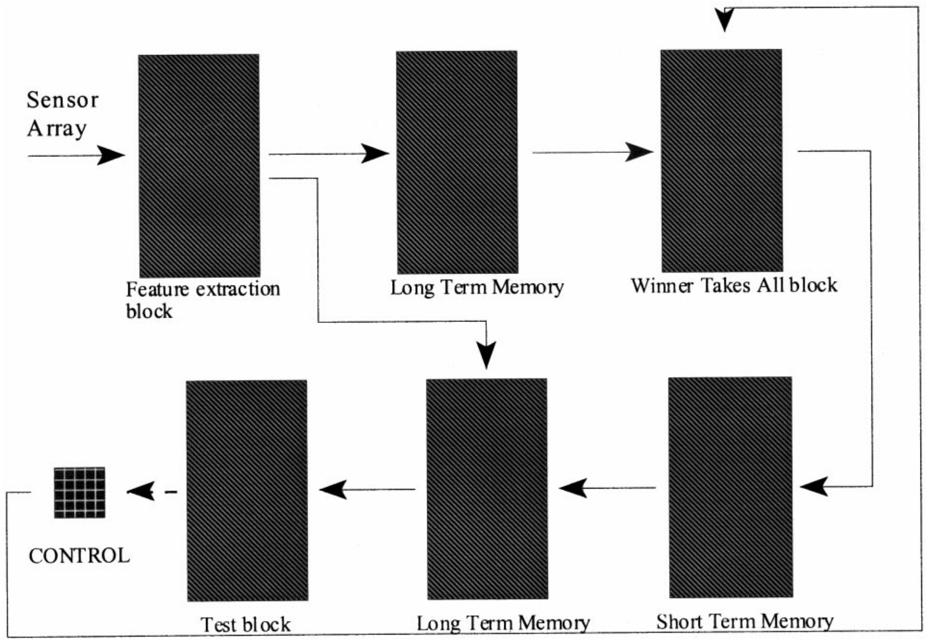

Fig. 1. Network architecture.

2. The proposed topology

2.1. Network architecture

The architecture of the network that has been experimentally studied, is shown in Fig. 1. The network is composed of blocks connected sequentially. Also there is a feedback loop between TEST block and Winner Takes All block. The first block of the network performs feature extraction of the input array. Usually in this block input data normalisation is performed. The next block is a Long Term Memory where the system knowledge is stored. The output of the feature extraction block is transformed through the Long Term Memory to produce a pattern, which corresponds to the activation level of each one of the already ones. The Winner Takes All block that follows, performs classification. In this block the procedure 'Winner Takes All' [4] is applied at the output of the Long Term Memory. Thus, from the patterns stored in Long Term Memory, only the one with the higher activation level is settled as active. Also this block may disable some patterns depending on the signal coming from the TEST block, as it will be explained later. The output of the Winner Takes All block, which is also the output of the system, is normalised at the Short Term Memory. We notice that the existence of the Short Term Memory block is optional. The next block is a Long Term Memory again. At the TEST block that follows, the active pattern is compared with the input pattern. If the two patterns resemble each other, then the active pattern is accepted and the procedure is terminated. If not, the pattern is disabled and a new test is performed again until a pattern is accepted.

The basic characteristics of the proposed topology are:

During operation, compensation of sensor degradation is obtained and thus the system lifetime is increased.

New patterns can be learned without the need of supervisor [5].

The existence of normalisation block increases the signal to noise ratio.

In the feature extraction block at the input of the network, experience can be used in order to promote the network functionality [6].

2.2. Topological description of the blocks

Fig. 2 shows in detail the architecture of the network. At the feature extraction block, normalisation of the input array is performed. So, if (Eq. (1)):

$$a = [a_1, a_2, \ldots, a_n] \tag{1}$$

is the input vector, then the normalised vector b will be (Eq. (2)):

$$b = (1/s) * a \quad \text{where } s = \sum a_i^2 \tag{2}$$

The Long Term Memory block includes a two dimensional array M. In every line of the array an input pattern can be stored. Thus, the transformation of the vector b through the Long Term Memory, which is obtained by the multiplication $c = M*b$, can be consid-

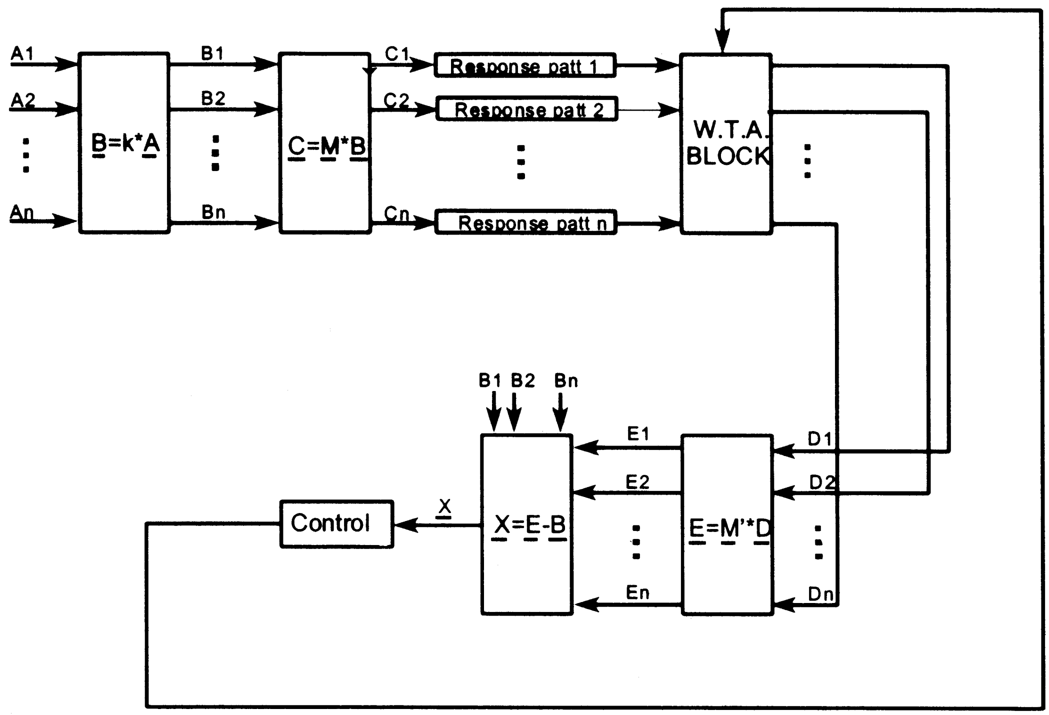

Fig. 2. Functional diagram of the network.

ered as the evaluation of the inner products of vector b with the lines of the array M. The higher value of the calculated vector c corresponds to the stored pattern that is more close to the input.

At Winner Takes All block the following procedure is performed (Eq. (3)):

$$\text{if } c_k = \max_{i=1,2,\ldots n}\{c_i\} \text{ then } d_i = 0$$
$$i = 1,2,\ldots,k-1,k+1,\ldots n \text{ and } d_k = 1 \tag{3}$$

At TEST block the distance between the vectors e and b is calculated. If the distance is smaller than a predetermined level, then the output of the block becomes positive.

2.3. Learning procedure

There are two ways that the network may learn to recognise the input patterns [7]. The first one is in the case when the input pattern is similar to an already one. Subsequently, the learned pattern is slightly modified to the direction of the current input pattern. Therefore, changes in the sensor behaviour with a relatively high time constant do not affect the resolution of the system. The second kind of learning is when a pattern is monitored for the first time. Then the network adjusts the weights in the two Long Term Memory blocks and the input pattern is learned immediately.

2.4. The rejection threshold

As it was mentioned before, in order to accept a pattern, the network compares it with an already learned one. The TEST block calculates the distance between the two patterns and if it is greater than a level the pattern is rejected and a new one is selected, until either all the patterns have been rejected or a pattern is found which matches the input. This level, which is called rejection threshold, can give the network an additional flexibility. If for example, ten patterns have to be learned and classified in four classes, different values of the rejection threshold are examined until the optimum level is found. If the examined value of the rejection threshold is too small, the network will overflow, that is it will classify the patterns in more than four classes. If it is too large, patterns that belong to different classes will be classified in the same class.

3. Experimental results

The sensors used were tin oxide film deposited with a planar magnetron sputtering system [8]. Tin oxide is a wide band gap (3.6 eV) n-type semiconductor, whose conductivity is due to oxygen vacancies [9]. The conductance of SnOx films may be altered by changing the oxygen to tin ratio, i.e. film stoichiometry. In this way the presence of oxidising gases decreases film conductance, whereas the presence of small amounts of reducing gases increases it [10]. The range of applications of this type of gas sensors is limited by the poor selectivity they have (i.e. comparable response to the presence of different reducing gases) [11]. Efforts to enhance the selectivity of these sensors have been focused on the addition catalysis, promoters and filters on the SnOx film [12]. As the principles of catalysis are not yet well understood, the problem has not been solved, although some progress has been made.

The pattern recognition system under investigation was designed in order to distinguish among three gases: zero grade air, carbon monoxide 100 ppm, and ethanol 30 ppm. The effectiveness of the system has been tested for two different groups of measurements.

In the first group only one tin oxide gas sensor was used. In that case, for each one of the aforementioned gases, the corresponding pattern was created by the following procedure: the temperature of the sensor was linearly decreased from 400 to 280°C. During this temperature change, which required 45 min, a samples of the sensor resistance was taken every time the temperature was reduced by 4°C. In this way, a vector of 30 values was created. The graphical representations of the input patterns that correspond to the three aforementioned gases, for three successive measurements, are shown in Fig. 3.

It is worth noting that although the response of the sensor to a specific gas is changing by degradation, the proposed system continue to recognise the gases. This is due to the network adaptive character.

In the second group of measurements, four tin oxide gas sensors were used with initial mean correlation close to 0.2. The mean correlation has been calculated by taking the mean value of the correlation factors of every pair of the sensors. The temperature of the sensors was maintained at 350°C. A pattern for each one of the above gases was created by measuring the resistance of the sensors and forming with the measurement values a four value array. Fig. 4 presents the number of patterns learned by the network as a function of the rejection threshold. Since the input patterns have to be classified in three classes, the value 0.2 for the rejection threshold gives the correct number of patterns. For values of the rejection threshold below 0.15 the network overflowed. Fig. 5 shows the functionality of an adaptive neural network in comparison to a three layer feedforward neural network. The performance of these two different networks and the mean correlation of the sensors is shown as a function of sensor degradation. The performance is measured with a value from zero to one, showing the probability of successful answer of the corresponding network. It is worth noting that the degradation of the sensor array is assigned by calculating the mean change of the sensor resistance in zero

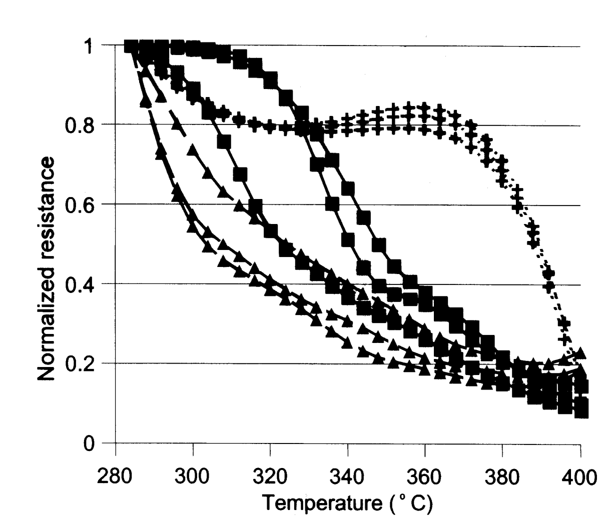

Fig. 3. Experimental results showing the normalised resistance of the sensor as a function of temperature.

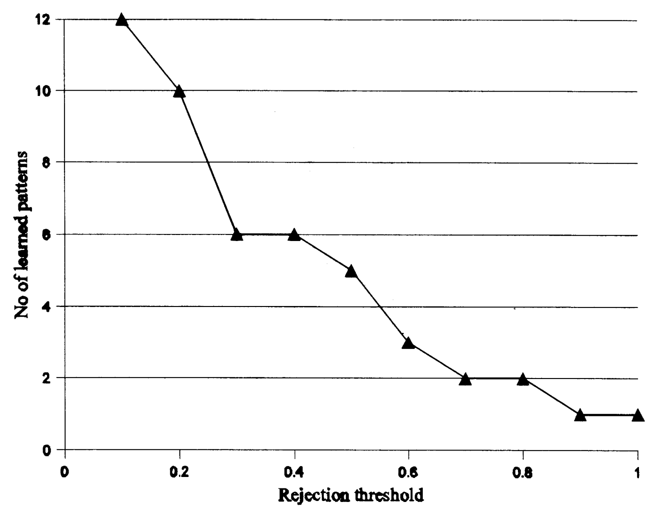

Fig. 4. The effect of the rejection threshold to the resolution of the network.

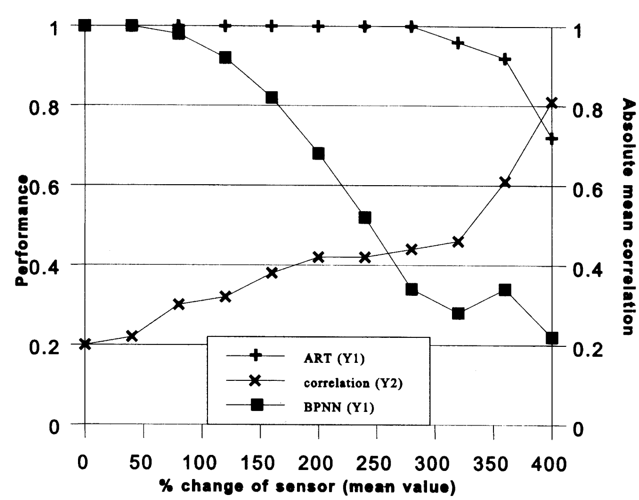

Fig. 5. The effect of sensor degradation to the performance of an ART network and a Back Propagation one, is compared to the mean correlation of the sensors in the sensor array.

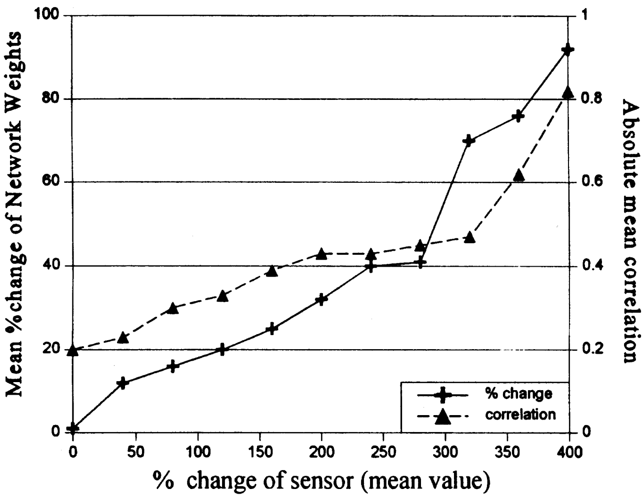

Fig. 6. The effect of sensor degradation to the network weights compared to the mean correlation of sensors in the sensor array.

grade air. It is obvious from the figure that the adaptive network works successfully and it starts to fail only when the four sensors begin to have almost the same response (high values of mean correlation). On the other hand, the feedforward network cannot even follow the small changes in the response of the sensors and fails very soon.

Fig. 6 shows the adaptive character of the proposed network. In this figure, the change of the network parameters is shown as a function of sensor degradation and these results are compared again with the mean correlation of the sensors in the input array. It is apparent that the proposed network dynamically modifies the knowledge representing weights in order to follow the change of the input patterns.

4. Conclusions

The ability of an ART network to create a new pattern classification when a new type of pattern is observed, makes it highly attractive for temporal pattern recognition tasks. The employment of an adaptive hybrid neural network may be used to solve the problem of sensor degradation. The most useful properties of ART type networks are outlined below:

(1). The ART networks undergo unsupervised real-time learning. Their weights change over time as new patterns are presented. There is no distinction between training phase nor is there typically a distinct set of training and test data. Also the number of categories to which these networks associate can increase over time.

(2). The value of the rejection threshold controls the degree to which the ART system insists on goodness of match. The higher the value of the rejection threshold the better the fit has to be. If the degree of match between an input pattern and an already stored pattern is greater or equal to the rejection threshold then a little learning takes place, which refines the values of the connection weights, without the creation of new categories. If the degree of match is less than the rejection threshold, the comparison procedure is repeated for all the already stored patterns that may potentially respond to the input pattern. If all the patterns fail, then a new category is created which corresponds to the input pattern.

(3). The number of categories that are created by the network depends on the value of the rejection threshold. For a gas sensing application the number of the categories has to be equal to the number of gasses under investigation, so that every gas corresponds to one category. We have been experimented with tin oxide sensors that have been constructed in our laboratory. For these sensors the appropriate value of the rejection threshold was found in the interval between 2.7 and 3.3. Therefore the value of 3 was imposed as the rejection threshold of the system.

(4). The use of another sensor (of the same type as these we have been experimented with) necessitates only to reset the network so that all the data in the Long Term Memories is being erased. After that, the system is ready to work immediately.

(5). Before using other type of tin oxide gas sensors, the value of the rejection threshold has to be reallocated. This means that a number of experiments must be performed, in order to find the value of the rejection threshold that allows the system to create the appropriate number of classes.

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Biographies

John Avaritsiotis was born in Greece in 1948. He received his B.Sc. (Hon.) in physics from the Department of Physics of the University of Athens in 1972. His M.Sc. and Ph.D. degrees were obtained from Loughborough University of Technology, UK, in 1974 and 1976, respectively, in the field of thin-film technology and fabrication of thin-film devices.

From 1976 to 1979 he was employed as a research fellow in the Thin Film Group of Loughborough University of Technology. From 1980 to 1986 he was appointed lecturer at the Electronics Laboratory of Athens University, and in 1986 he was elected associate professor in the Department of Electrical Engineering of the National Technical University of Athens. In 1990 he was elected professor of microelectronics in the same department.

He has worked as a technical consultant to various British and Greek industrial firms for the incorporation of new thin-film deposition techniques in their production processes.

He has published over 40 technical articles in various scientific journals, and has presented more than three dozen papers at international conferences.

His research activities have been focused in the field of microelectronic materials and thin film deposition techniques for use in the fabrication of semiconductor devices. His present research interests concern study of the electrical properties of thin insulating and semiconducting films deposited by sputtering, on-chip interconnections and MCMs for high-speed circuits, design of ASICs, development of fabrication processes for the production of solid-state gas sensors and design and prototyping of smart sensors.

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