Design of a Programmable, Portable and Low-Cost Electronic Nose

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Abstract

In this work we present a programmable, portable and low cost system for sensor signal processing. A specific application developed to detect several gases is described based on a thermally-modulated SnO_2 gas sensor and a 16-bit microcontroller. A Wavelet transform method is applied to extract the most important features of the signal produced by the sensor. Wavelet coefficients are the inputs to a support vector machine (SVM) that can either be used to classify the gas or be used to estimate the gas concentrations. In this work we have trained the system to detect CO, NO_2 and a mixture of both gases in air. This system could be adapted to work with other gases or odours in industrial applications.

1. Introduction

Traditional methods for gas analysis involve the use of various techniques and technologies, that tend to produce relatively expensive sensors and analysers. Often these solid-state gas sensors lack fast response times and suffer from poor selectivity in the field.

Research in the field of electronic noses during the last twenty years may hold a solution to the problems presented by classical methods. Electronic noses are described as an array of electronic chemical sensors and an appropriate pattern recognition system. Much of the published work is collected in [1],[2]. The outcome of most studies indicate that may seem to work well in a controlled environment but the implementation in real conditions is problematic. However, there are enough techniques described to build a system able to work in a practical environment.

The design of an e-nose can follow two strategies: specific and flexible. Specific means that the architecture is only valid for one application. Flexible means that the system architecture is thought to serve for different applications, being possible to be adapted for applications defined by an end user.

The principles of the designed system are to be flexible, portable that means that the system must work in different environments. The principle of portability also necessitates a design to be of low power consumption. These assumptions have an important role in the design.

The system developed can work in two modes: training and testing. Figures 1.1 and 1.2 show the functionality block diagram of each of these modes.

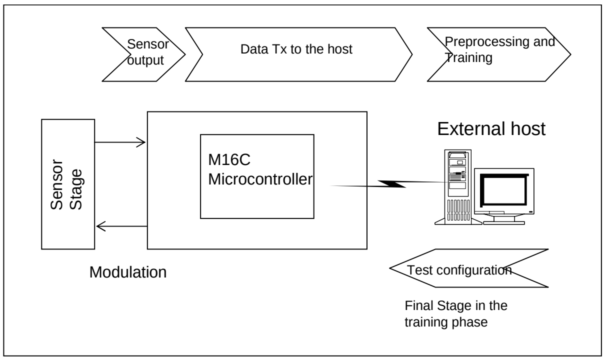

Figure 1.1 Training mode scheme.

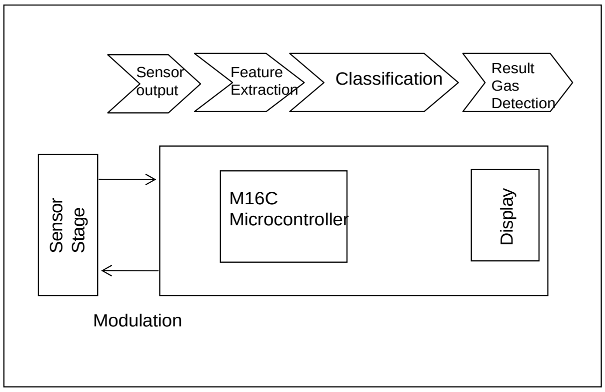

Figure 1.2 Testing mode scheme.

In the training mode, the system sends the signal, captured in the sensor stage and digitalized by the microcontroller, to an external host that is responsible for extracting the most relevant features to classify or to estimate the concentration. The target of this mode is to produce a configuration file that will be loaded in to the system to be ready for the test stage.

In the testing mode, the system has been updated with the necessary information to know what features of the signal are needed to be extracted and the coefficients of the support vector machines to identify the gas or the mixture. So, the result is sent to a display that informs the final user.

2. Sensor Stage

Keeping a low-cost strategy is necessary that every sensor used has to be cheap and sensitive enough to detect a broad spectrum of gases.

SnO_2 sensors have been widely used due to their advantages in the needs of low-manufacturing cost and high sensitivity. Their main disadvantages are drift and their low selectivity. Thermomodulation has been used to overcome these disadvantages, giving dynamic at responses that will follow a periodic pattern in the time domain, depending on the presence of a concrete gas or a mixture. In this sense, with just, one sensor, we can detect a wide area of gases and mixtures. The fact of adding a new sensor will only be justified if it can detect target gases or mixtures for our application.

To produce the thermomodulation, a signal from the microcontroller is sent to a heater resistor. In our case, this modulation has sinusoidal form and a frequency of 50 mHz has been selected. Higher frequencies will not result in variations of the heater.

In the application described we have chosen to detect CO, NO_2 and the mixture of both. Although this is a simple application and gases can be discerned (CO has no odour and no colour and NO_2 is brown and has very sharp odour) it is a good starting point to test the system performance.

3. Wavelet Transform

As has been mentioned, in the presence of a gas or mixture the sensor produces a dynamic signal that acts as a “fingerprint” of the gas (or mixture) and its concentration.

The aim of this stage is to extract the information from the dynamic response to serve as an input to the pattern recognition system. A classical approach for this stage is the use of FFT. The Discrete Wavelet Transform (DWT) is an alternative technique to Fourier analysis that allows a non-linear multi-resolution analysis. Wavelet transform can be calculated as the decimated output of a filter bank composed by two filters.

In our design the wavelet transform is applied as follows: one temperature period of the signal is taken as input signal to a wavelet filter bank where it is filtered and decimated by a low-pass filter h[n] and a high-pass filter g[n]. In figure 2.1 is shown the original signal and in Figure 2.2 is shown the lowpass filtered output of the first stage. The signal obtained from the low-pass filter and decimated is the new input for the filter bank, shown in Figure 2.3, and so the scheme is reiterated. Signal lengths are given by L+P-1 where L is the length of the input signal and P the length of impulse response filters. We can repeat this scheme several times obtaining a parameter called the depth of the decomposition.

This scheme is considered as a multi-resolution analysis and we can describe it as obtaining an approximation signal, that is the output of the low-pass filter and a signal containing the details that will be the output of the high pass filter. Due to noble identities it is not necessary to have completed every decomposition begin before a new one, but all coefficients can be calculated from the entry signal.

In the training mode, the external host tries different wavelet transforms based on different wavelets that lead to different coefficients of the filters. Once the host finds the best family of filters for the training set, then the coefficients are sent to the microcontroller as part of the information necessary to work in testing mode.

A single vector will be formed with the union of the different outputs of the filter bank.

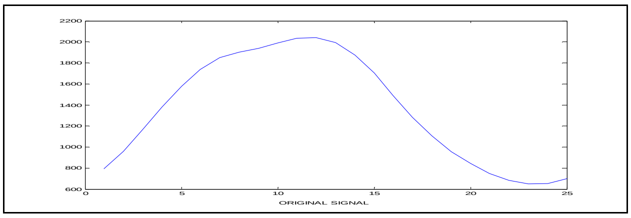

Figure 2.1. Original Signal

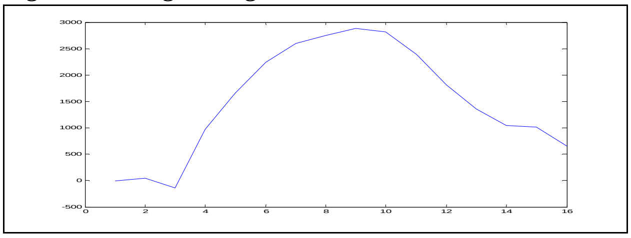

Figure 2.2. 1st Low Pass Filter Decomposition Signal.

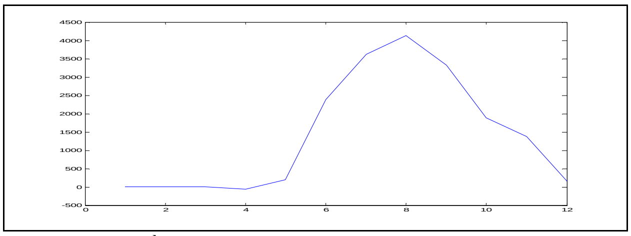

Figure 2.3. 2nd Low Pass Filter Decomposition Signal.

4. Support Vector Machines

The use of SVM in the pattern recognition area is extensive due to the ability in the design to make a generalization of the problem. In the supervised training phase the SVM creates the optimal hyperplane for the linear case, or the optimal hypersurface in the non-linear one, with the largest margin between the hyperplane or hypersurface and any training data. Those training samples that are near of the hyperplane become the support vectors.

Thus, the decision function can be written as:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{Ns} \alpha_i y_i K(\boldsymbol{s}_i, \boldsymbol{x}) + Bias\right)$$

Where Si is the i_{th} support vector and Ns is the number of support vectors. The optimal hyperplane can be founded in the linear case and will be defined by the support vectors as:

$$\boldsymbol{w} = \sum_{i=1}^{Ns} \alpha_i y_i \boldsymbol{s}_i$$

A non-linear case can be performed by the transformation of $x \rightarrow \phi(x) \in H$ where the inner product in *H* is performed by a kernel function K(*x*,*y*). This kernel allows to find the optimal hypersurface without an explicitness knowledge on the transformation $\phi(x)$.

In our application the linear case appears to show good enough results to be applied to the classification problem. The using of a linear transformation allow us an added advantage because we know that all the components of the separation hyperplane low enough will mean that the vector component is not relevant for classification proposes as are orthogonal to the separation hyperplane. The term "low enough" will lead us to keep the n higher components of the vector that describes the hyperplane. We can consider this technique as selected extracted feature, since only those wavelet coefficients resulting meaningful will be the entries of the support vector machine. Developing this idea in our system, the host has to send to the microcontroller what wavelet coefficients have to be extracted to be the input of the SVM.

If the problem under study cannot be solved with a linear Kernel, better results may be achieved using non-linear kernels. As the transformation is not necessary known it is not trivial to apply the same principle to this in the linear case. In such a case, we can also eliminate components of the training vectors, make a feature selection by means of genetic algorithms, or make another pre-processing transformation before training the SVM. This last case will be only justified when the operations number that can be saved in the pattern recognition is greater than the operations number used for the pre-processing stage.

SVM can also be used to estimate the concentration. In this case the function is quite similar to the classification problem

$$f(x) = \sum_{i=1}^{Ns} \alpha_i y_i K(\mathbf{s}_i, \mathbf{x}) + Bias$$

5. Results

As mentioned in this work we have trained the system with different parameters to classify and estimate the concentrations of CO, NO_2 and a mixture of both gases in air.

In the training mode, the external host has been programmed to train with different wavelet transforms. Once that the external host obtains the necessary information, it is sent to the system. This information includes the wavelet filter coefficients and the information required to build the SVM.

Table 1 shows the confusion matrices obtained in the test mode with different types of wavelets for our classification problems. Different elements of the table are $P(D_i/H_j)$.

Wavelet Daubechies Length = 8	CO	NO_2	$CO+NO_2$
CO	1	0	0
NO_2	0	1	0
$CO+NO_2$	0	0,0625	0,9375

Table 1.1 Confusion matrixes using 8-tap Daubechies.

Wavelet Coiflets Length=1 8	CO	NO_2	$CO+NO_2$
CO	1	0	0
NO_2	0	1	0
$CO+NO_2$	0	0,0625	0,9375

Table 1.2 Confusion matrixes using 18-tap Coiflets.

Wavelet Biorthogonal Length=9/7	CO	NO_2	$CO+NO_2$
CO	1	0	0
NO_2	0	1	0
$CO+NO_2$	0	0,03125	0,96875

Table 1.3 Confusion matrix using 9/7-tap Biorthog.

In order to reduce the computational cost of the system it is shown the results using the feature selection technique described. Figure 3 shows for each gas the probability of success, being the diagonal elements of the confusion matrix, with the number of features considered. For this example, the wavelet transformation used was the Daubechies 8-tap filter. This idea confirms the using of the hyperplane information for feature selection in the case of linear kernels.

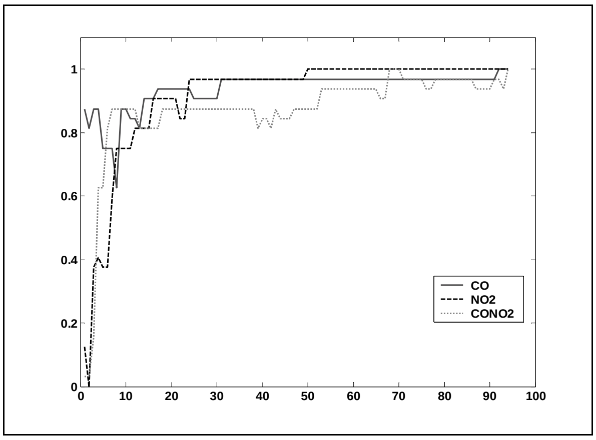

Figure 3. Vector dimension vs probability of success.

The designed system is not only able to classify but to estimate the gas concentration. The normalized error is measured as:

$$\varepsilon = \frac{1}{N}\sqrt{\sum_i \left(\frac{|y_i - f_i|}{y_i}\right)^2}$$

Where y_i is the target value, *fi* is the regression value calculated by the SVM and N is the number of samples to be tested.

	Kernel = RBF Wavelet = Daub Length 8	*Kernel = RBF Wavelet = Biorthog. Length 9/7*	*Kernel = Linear Wavelet = Daub Length 8*
CO	0,2867	0,3622	5,6124
NO_2	0,1659	0,2108	2,0152

Table 2. Normalized error in concentration estimation

In table 2 we can see the normalized error obtained for the estimation of the concentration. This shows that a linear kernel does not provide satisfactory results and so a radial basis function (RBF) kernel was employed. The kernel is given by:

$$K(x, y) = e^{-\gamma |x-y|^2}$$

The gamma parameter manages the spread of the RBF and plays and important roll in results. Figure 4 shows the evolution of the normalized error as the gamma parameter is changed, in this case for the CO concentration estimation.

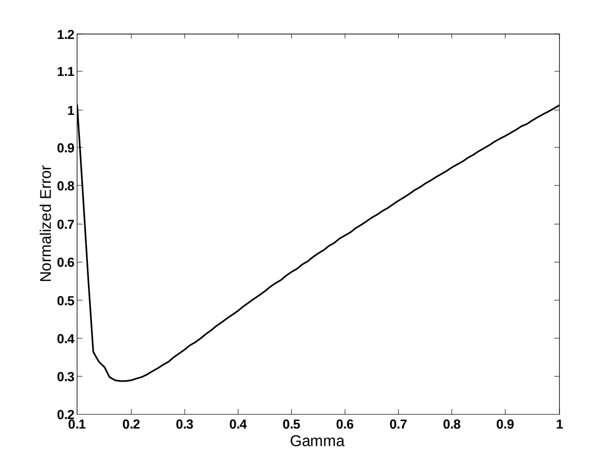

Figure 4. Gamma value vs normalized error

6. Conclusions

We have presented in this paper a flexible, portable and low cost system. The employment of efficient pattern recognition algorithms allow us to classify gases with low cost requirements.

The system is flexible enough to be programmed by an external host where the heavy training processes run and only the necessary information is sent to the system. The application presented, although simple, validates the process and the ideas exposed. Future work will be the research of the most efficient preprocessing and pattern recognition techniques, and address the recognition of complex odours.

Acknowledgments

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