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Artificial Nose and data analysis using Multi Layer Perceptron

M. S. Santos, T. B. Ludermir, F. L. Santos, C. Pinto de Melo & J. E. Gomes
Department of Informatic, Physics and Chemical, University Federal of Pernambuco and University Catolica of Pernambuco, Recife, Brasil
EMail: mss@di.ufpe.br, tbl@di.ufpe.br, chico@df.ufpe.br

Abstract

An Artificial Nose is being made to detect the smell of some substances and the results of prototype phase 0 and phase 1 are displayed. In phase 0 and phase 1 we utilize conducting polymer sensors.

A pattern recognition technique based on Multi Layer Perceptron (MLP) model of Artificial neural network (ANN) is adopted. In this paper we present a study that was done with the recognition of the whisky, wine, ethanol, carbon thetracloride and methanol.

The NeuroSoluction software is used in this study.

1 Introduction

To survive and communicate men need to acquire information about their environment. And it is through the organs of sense that they get the necessary information to survive. Among these organs the nose is the one that has played very important role in human behavior.

Besides its importance among the other organs of sense, smell can be considered the most complex to be studied in spite of being the most primitive. There are still many mysterious to be unveiled and artificial noses have been developed because they look like simple than biological olfactory system.

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Researchers have been interested on artificial noses or electronic noses for 30 years and there is still a kind of mystery around this matter because it is really necessary to understand well the biological olfactory system.

Despite of those difficulties, research in the area have conduct significative advance and specialized artificial nose can have several practical and useful application to comunity, as follows: drugs recognition; applications that involve security in the work with handling some type of lethal vapor; detection of sickness and utilization in telemedicine [1,2,3,6,7].

Usually the artificial nose is composed by two parts: one sensitive part and one of smell classification and characterization, where quimiomectrics technical of pattern recognition can be utilized [4,8,9]. In the second part, it can be utilized quimiomectrics technical of patter recognition or Neural Network. In the first part we used conducting polymers and in the second part Networks Neural[5].

In this context, the aim of this paper is to show some results obtained with the first prototype of an artificial nose: phase 0 and phase 1 that we have been developing . It is able to detect several substances. This nose is composed of several sensors that have polymers as its basis, which signal will be treated through neural networks.

First of all an artificial nose prototype is presented; then a section about artificial neural networks is apresented. The next section has a description on the experiments and a discussion about results afterward. At last we present a conclusion and thankfulness.

2 Artificial Nose Prototype

The artificial nose prototype we are developing is composed by an array of sensors, which are constructed based on conductors polymers [10]. Conductors Polymers are able of conducting electrical current and can be used in several kinds of sensors. The advantage of using polymers as sensors is that the direct conversion of the detection effect in the material leaves as an electrical signal. This signal can be treated by an electronic equipment.

The response standard of each array of sensors depends on some parameters, like the smell source (type and intensity); sensitive material source (physical structure); amphiphilic nature and environmen-

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2.1 Phase 0

In this phase, two electrods were used to prepare each sensor, and they were separated in a way that distance let the film growing. The measurement of resistence variation taking in account time and the acquisition of datas was made with a digital multimeter and a computer in intervals of 30s with the sample under movement.
Figure 1 shows this system.

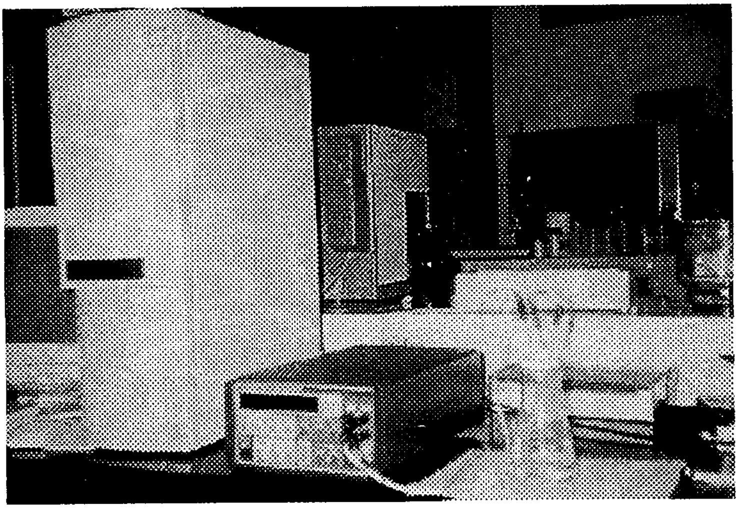

Figure 1: Test System Phase 0

Each sensor has presented a different sensibility for each type of substance. Nevertheless, the electrical behaviour of the polymers has been the same in all cases, showing that the resistance increased when the sensor was exposed to different samples of ethanol, carbon thetracloride and methanol. In this phase we used 3 sensors [11].

2.2 Phase 1

In phase 1 we made a system were sensors are built with eletrodos disposal at store. These sensors doped with different substance are based on resistive behavior, common to the polymers that are present in the smell sensors. For this purpose we used the four point method where the electrical tension is measured in the two more internal eletrodos while a constant current is injected in the two more external electrode [12].

Although we have used just 4 and 5 sensors, the system is ready to work using 8 sensors. The system was tested with four sensors for to detect the smell of red and rose wines. To distinguish between the smell of whisky and white wine we used 5 sensors. The data acquisition was done automatically using a Data Acquisition Protoboard with 0.5 seconds intervals. Figure 2 shows this system.

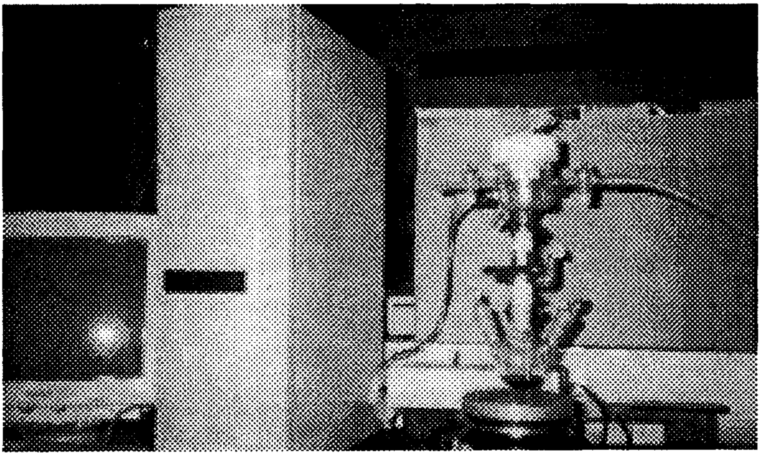

Figure 2: Test System Phase 1

We have used artificial neural network as a technique to recognise the response of the sensors.

3 Artificial Neural Network

In this work, we use the MLP model, which has been used to deal with smell recognition.

The MLP learning algorithm, developed by Rumelhart, Hinton e Williams, has been considered a very popular one to supervisioned trainning. It is an dependent gradient method to minimize the total error square of the output computed by the net.

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The results provided by the output layer are used to compute the total error which will be applied by the delta rule to do the connection weight adjustment of all previous layers. The algorithm's aim is to train the net to find a balance between the capacity to reply correctly to input standards used to trainning and the capacity to provide a response considered good to the input.

4 Experiments descriptions

Initially, data acquisition is done in an environment without substances. In the following, sensors are exposed to test substances and finally the sensors are cleaned up using nitrogen. Although having a lot of data acquisitions, we have used just those which are relevant to recognition.

4.1 Formation of the Data Base

As we used two methods to acquire dates, we decided to make two different data base: Base 0 and Base 1. All the signals of these two bases were transmitted by sensors. Although we had got many acquisitions, we used only those we thought to be relevant to recognition.

After data collection, we have formatted them according to NeuroSolution, the simulator we are using to train the networks. In the following, we have pre-processed the data, normalizing them between 0 and 1. Data were then mixed and classified into 3 groups: 50% to trainnig, 25% to verification and 25% to test. The standards to those 3 subsets are exclude, i.e., each pattern can be just in one of the sets.

4.1.1 Base 0

Here the aim is to make the network distinguist among ethanol, carbon thetracloride and methanol. Having three input informations related to the three used sensors as its base. The expected answers are related to the three substances mentionado before. This base of dates consists on a set composed by 267 from which 89 refers to ethanol, 89 to carbon thetracloridesamples and 89 to methanol. A small set of that base is represented in Table 1.

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Table 1: Representation Data Base 0- Problem 1

S1	S2	S3	ETHA	TETRA	METHA
2,50	3,86	480	1	0	0
19,95	2,64	310,23	0	1	0
2,11	2,11	527,420	0	0	1

4.1.2 Base 1

There are two problems we have to solve: first to see if the artificial nose can distinguish between the smell of the red and rose wines. We used four input information which we got through the signals of four sensors and two output informations corresponding two the smell of the red and rose wine.

All the information about the smell of the red wine and the rose wine have altogether a total of 249 patterns. From this total 122 dates refere to the smell of red wine and 127 to the smell of rose wine. A small table of this base is shown as follow.

Table 2: Representation Data Base 1- Problem 2

S1	S2	S3	S4	RED	ROSE
87	444	319	86	1	0
0,02	10	11	24	0	1

The second problem is to see if the network can distinguish between the smell of whisky and white wine. We used five input information which correspond to the emitted signals of five sensors and two output informations corresponding two the smell of the whisky and white wine.

All the information about the smell of the whisky and the white wine have altogether a total of 279 patterns. From this total 156 dates refere to the smell of whisky and 123 to the smell of white wine. A small table of this base is shown as follow.

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Table 3: Representation Data Base 1 - Problem 3

S1	S2	S3	S4	S5	WHISKY	WINE
90	71	63	332	80	1	0
58	175	2	324	80	0	1

4.2 Networks Trainning

We have used the MLP model and the backpropagation algorithm to train the nets. Since we are dealing with the same type of dates we decided to adopt a single configuration to all the sets, but during the developments we concluded that the methodology was not appropriate.

We have tested distinct architectures. We have done variantions on quantity of epoches of trainning; on learning function; on quantity of hidden layers; and on quantity of neurons per hidden layer.

In Table 4, we show the configuration of those networks with presented the best performance to each problem.

Table 4: ANN training parameters

PARAMETERS	PROB 1	PROB 2	PROB 3
Architecture	3-5-3	4-5-2	5-8-2
Activation	Sigmoid	Tangent	Tangent
Ste size	1	1	1
Momentum	0,7	0,7	0,7
No of epochs	100	50	50

In Figure 3, we show the configuration of one of the used architectures.

In Figure 4, we show the graphical declination of the network error. The network considered was the one which presented the best trainning, validation and test performance.

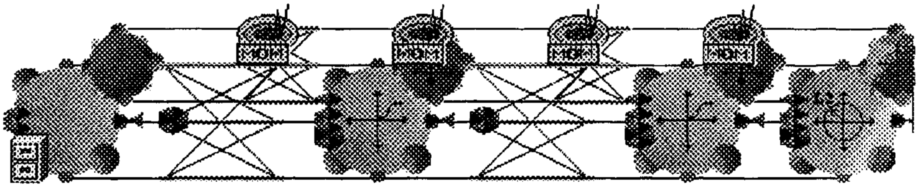

Figure 3: One example of architecture

4.3 Results and Discussion

This discussion were based on the results of the neural network and in the graphs. These graphs, (Figures 5, 6, 7) show the pattern of the fractional changing of resistence to three sensors that were submitted to the smell of a single substance.

After all the trainning we noticed that tetra, amonia and ethanol substances showed good results. The Table 5 show results of the network performance.

Table 5: Percentage of output - Problem 1

PERFORMANCE	ETH	TETRA	METH
Percent Correct	96.4912	98.3871	98.2759

Referring to the smell of whisky and white wine good results were obtained as well, Table 6. We used five sensors.

Table 6: Percentage of output - Problem 2

PERFORMANCE	WHISKY	WINE
Percentage Correct	100	95.2381

Excelents results we obtained referring to rose wine versus red wine, with 100 percentage of output classified correctly.

Look at the graphs we can notice that the 3 substance pattern are completely different and that confirm the results presents by the

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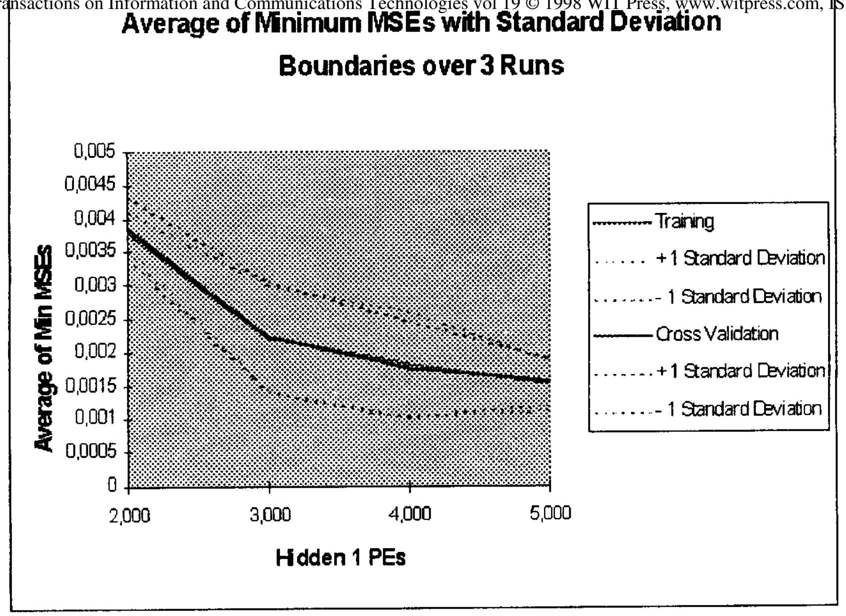

Figure 4: Trainning performance

networks.

If we go on analysing the same graph we can observ that a bigger variation in sensor one, took place when exposed to the smel of ethanol, carbon thetracloride and methanol. Visually we can distinguish the three substances.

Observing the ansewer of sensor 2 we can detect a small variation to ethanol. To carbon thetracloride and methanol the sensor 2 almost did not show any variation.

The variation of the sensor 3 to ethanol and carbon thetracloride is pratically in the same range. The variation of the same sensor to methanol is a little different from that two the outher substances.

Sometimes the same sensors can show the same signal to different substances. That makes differences among smell seem more difficult to be observed and it is necessary the use of more sensor. That way easier to detect substance. To exemplify this affirmation we can take a look at the graphs and see that the sensor three resistence variation is almost the same to ethanol and carbon thetracloride. As you can note the scales of the graphs are differents. In this case, if we

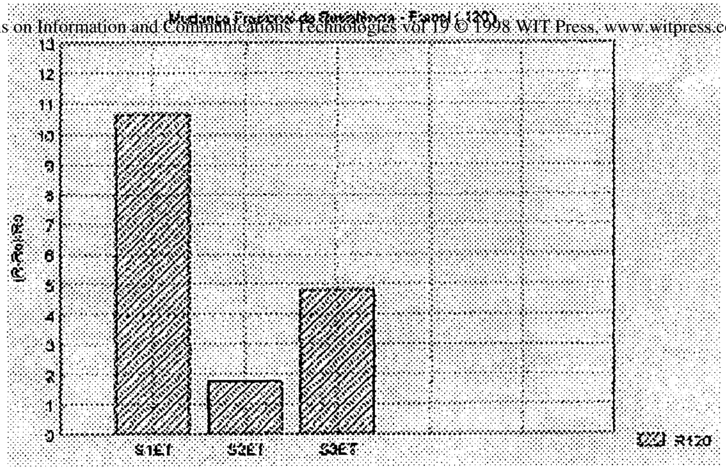

Figure 5: Fractional difference - Ethanol

used only this sensor, it would be impossible to an artificial nose to distinguish between the two substances. A greater number of sensor increased the capacity of recognising a bigger quantity of differents smell. That also makes the systems become powerful to the present of noise in some of the sensors.

With these results we believe that the date of the substance can be very different and the quantity of used sensors can also interfere in them. Using more sensors perhaps we will obtained more specific information to distinguish between substances with similar smell.

5 Conclusions and Future Work

In this paper, we have presented the prototype of an artificial nose, which is able to distinguish the smell of whisky versus white wine; red and rose wines; ethanol, carbon thetracloride and methanol, when exposed to the environment.

In the next phase will not used commercialized eletrods but eletrods made at the physical Departament of this University. We intend to use a bigger quantity of sensors in the next tests and to distinguish equal kinds of wines that belong to differents crops.

With the prototype of phase 1 we are making new tests with

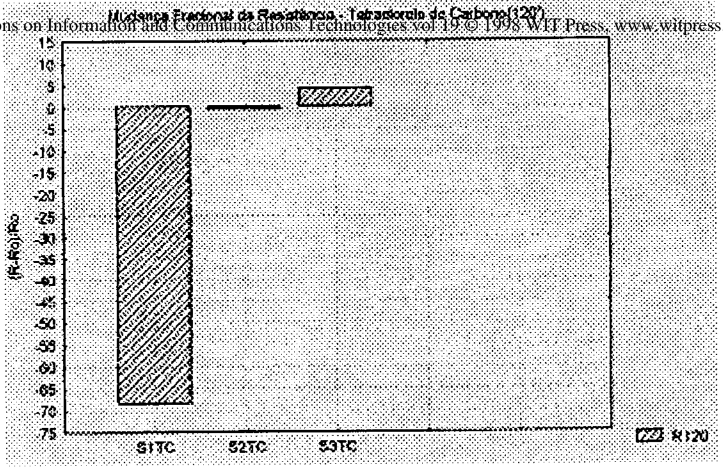

Figure 6: Fractional difference - Ethanol

those used substances, to check if there is an improvement in the performance of the networks.

We are now working on the refinement of the artificial nose improving the data acquisition. We are also doing tests increasing the quantity of sensors and substances.

As future work, we are planning to use others neural network models to compare to MLP and to verify if there is another model[13]more suitable to smell recognition and to allow to do real-time recognition.

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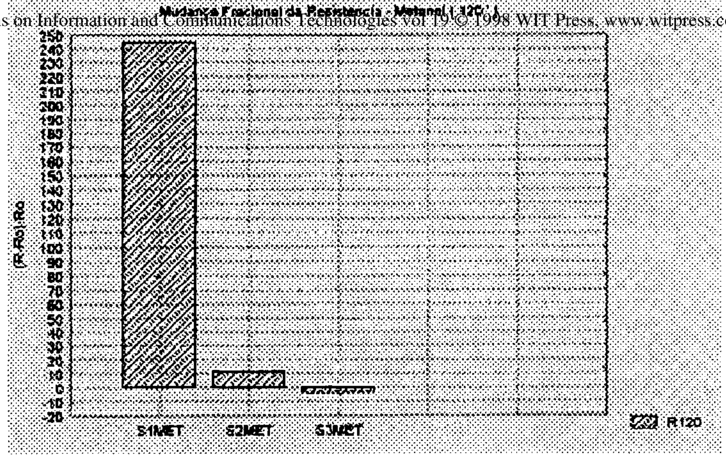

Figure 7: Fractional difference - Ethanol

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