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EMBEDDED SYSTEM TO CLASSIFICATE HEAT POWER OF A FUEL GAS AND THE QUALITY OF ALCOHOL

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Introduction

Recently in academic and industrial fields there was a considerable increase in interest on electronic noses, because the possibility to make direct measures with few refinements and because its facility of implementation [1]. An electronic nose has many applications, for example: liquid and solid smell recognizers, perfumes and chemical reagents [2-4], illness detection [5], breath alcohol measurement [1], quality of potable water monitoring [6], among others.

An electronic nose in almost all cases is implemented with Artificial Neural Networks, because its noise robustness that can exist in analyzed samples [7-8], moreover it has a great capability of generalization, that lead to new samples inferences, corrects in most of cases, outside the training samples set. The application implemented in this work is the classification of heat power of a fuel gas.

When there are many variables to be analyzed, a principal component analysis is in general applied to minimize the dimensionality of the input space, keeping as most information as possible in data [9-10].

The six gas sensors measures in our apparatus were analyzed into two approaches: the use of raw data, and the use of data processed by a principal component analysis with fewer sensors.

Traditional methodologies to measure the heat power of a fuel gas can be divided in three categories [11]: combustion of a gaseous sample inside a calorimetric bomb, combustion of a gas in an open flame of a gas burner, and combustion without a flame on a catalyst. Those methods require in general expensive machinery. An embedded system of classification can be a low cost alternative in classification of the heat power of a given fuel gas.

This work is in its initial phase. The proposed objective is to develop an embedded system to recognize the heat power of a fuel gas. A matrix of six sensors will be used to measure the concentration of different gases. However, as the measure is in its initial stage, synthetic data have been generated to simulate the sensors behavior. These data was applied in some artificial neural network topologies and an fuzzy inference system, and they are being implemented in hardware, using DSP’s and micro controllers.

Methodology and Experimental Results

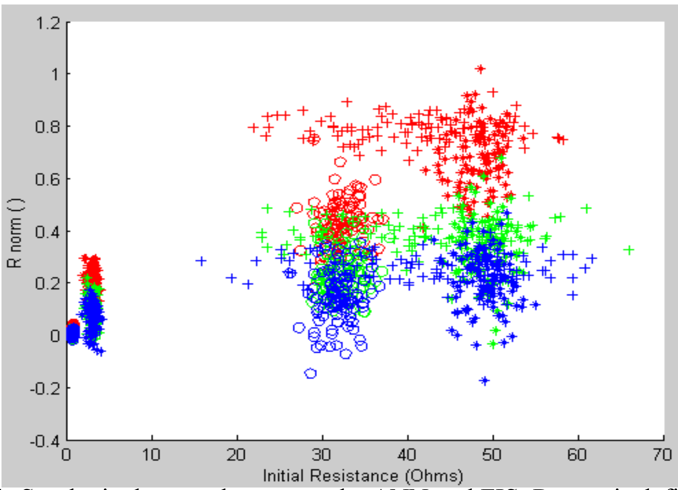

Fig. 1. Synthetic data used to create the ANN and FIS. Rnorm is defined in equation (1)

A Heat Power Recognition Using Artificial Neural Networks

A system that consists of a chamber with six SnO_2, was used to recognize the heat power of a given fuel gas pattern. They detect concentrations of different gases (CO, CH_3, CH_4, etc.). The gas fuel was injected in this chamber with N_2 gas. The concentration ratio of this mixture was adjusted with flow meters. Given a fixed fuel gas flow (3ml/min), the N_2 gas flow was fixed by two flow meters. This gas mixture was applied in the sensor's chamber by the adjustment of another flow meter R7. Because the measurements are in its initial state, few experimental data of only one pattern of gas was acquired with concentration of 5.155ppm of gas fuel. The variation of the N_2 gas flow will simulate the others patterns of gas fuel.

Some measures were taken with sensors steady state values of resistances before and after each injection of the fuel. With these data, a database of data was mounted with six features, corresponding to the sensors values. This database was subdivided in two subsets, a training and a test data sets with equal size.

Synthetic data was used because only few experimental data existed in the moment this paper was made. Three hundred data points was created following gaussian distributions, which corresponds to a hundred for each fuel pattern. Synthetic data of six sensors for a given temperature and pressure values are shown in Fig. 1. Standard deviation and mean of the normalized resistance for the first pattern was obtained with the current available measures. As a first approach, the different patterns were obtained with the same standard deviations of the first class for each sensor, but the second pattern mean was set to a 1/3 ratio of the first pattern, and the mean of the third pattern as a ratio of 1/2.

The data in red are the first fuel pattern with higher heat power value. The second pattern in blue has the least heat power value. The third pattern in green is a fuel pattern with an intermediate heat power value. Fig. 2 shows a scattered plot of a given sensor normalized resistance versus its initial value. The normalized resistance value is defined in equation (1):

$$R_{NORM} = (R_{INITIAL} - R_{FINAL}) / R_{INITIAL} \tag{1}$$

Two topologies of ANN was tested to recognize the gas fuel patterns: backpropagation and LVQ. To the backpropagation ANN, two train functions was used, traingdx (descendent gradient with adaptive momentum) and trainlm (Levenberg-Marquardt train function), with or without the principal component analysis.

Backpropagation ANN's without PCA had six neurons for the input and hidden layers, and three neurons for the output layer. Backpropagation ANN's with PCA had four neurons for the input and hidden layers, and three neurons for the output layer.

Each ANN was trained 100 times. Stop criterion was mean square error less than 0.01 or error gradient less than 0.001. Data were divided in two subsets, which 150 data points was used to train and 150 data points was used to test the ANN, both with 50 different data points of each fuel gas pattern.

Counts of correct inferences of ANN were made with the test data set. The backpropagation ANN using the training function 'trainlm' was the network that had more corrects inferences, but many times it had some anomalies in the training step. The training of LVQ network was limited to 200 epochs, because it was observed that the mean square error had oscillations after the epoch of number 50.

NeuralWorks was another software used to train the ANN's. The same train and test data sets were used in this program. It had six neurons for the input and hidden neurons, and three neurons for the output layer.

A backpropagation ANN with Delta training rule were used. The network was trained ten times without the "MinMax" table, and more ten times with this table. According to the "MinMax" table records maximums and minimums values of each input data of each network layer. It's used to perform a data pre-processing that applies a scale in layer's input data. Thus it prevents the saturation of the activation function that stops the learning process of the neurons. Training stop criterions were maximum iteration of 50000 epochs, or the root mean square error less than 0.001. The maximum epochs were fixed to ensure that the ANN doesn't suffer "overfitting".

A LVQ neural network was also trained. The learning rule for the firsts 4500 iterations used a conscience factor of 1.0, which encouraged all the neurons in the learning step. For the others 2250 iterations, the training rule did a refinement between patterns. Generalization results of NeuralWorks' ANN's were better than the others networks. Thus, the chosen network to obtain the C code for the neural network implementation in hardware was the backpropagation ANN with "MinMax" table.

Alcohol quality recognition using Artificial Neural Networks

The same system of Taguchi sensors was used to classify the quality of vapor of alcohol fuel. Two patterns of alcohol were considered: good quality (with concentrations between 93% and 98.3%) and the bad quality (others concentrations). The alcohol fuel was injected in the sensors chamber by a syringe. Flow meters devices were replaced by a tube system. A ventilator and an air filter containing a humidity absorber substance were used to clean the chamber. The data acquisition system was the same.

Two ANN's topologies were tested to recognize gas fuel patterns, backpropagation and LVQ, with or without PCA. ANN's without PCA had six neurons for the input and hidden layers, and two neurons for the output layer. ANN's with PCA had four neurons for the input and hidden layers, and two neurons for the output layer.

Fig. 2 shows a scattered plot with the experimental data of alcohol fuel. Dark blue points represents good alcohol pattern, and pink points represents bad alcohol pattern. Dark blue poins inside pink points region can explain why ANN's had some problems of generalization.

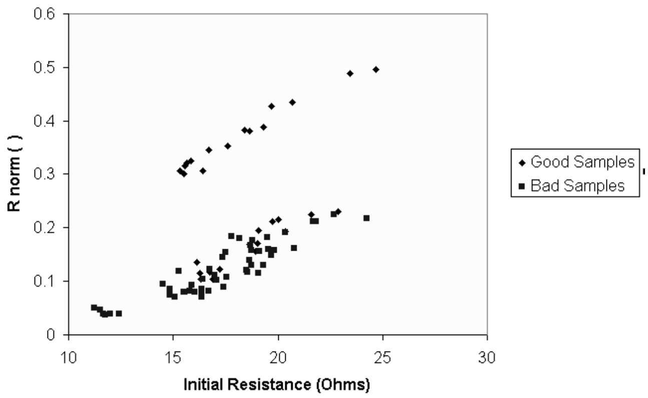

Fig. 2. Scattered plot of normalized resistance variance versus initial resistance obtained by experimental data in sensor 6

Simulations of injection of Alcohol, has lead to creation of a synthetic database. These data was helpful to analyze the effects of pre-processing of data in the training performance of a ANN backpropagation.

Stop criterion of the ANN were root mean square error less than 0.01. DataSculptor software was used to automatically pre-process the data. With the "brief" pre-processing data method, DataSculptor applied a scale in data, and divided the database in test and train subsets. The use of pre-processed data accelerated the ANN training step in a ratio of 0.15.

Hardware implementation of ANN

An ANN trained with NeuralWorks software was implemented in an Analog Devices DSP kit. The NeuralWorks software transformed the trained ANN in a C language program code. No further hardware self-learning steps were considered. Thus, the code generated by NeuralWorks only had mathematical operations, representing the trained neural network.

The initially implemented system was the quality of alcohol fuel recognizer. As a first approach, the test data set was included in the DSP kit program. With a button of the kit, all test data was read, and the results of the trained ANN was shown in two LED's of the kit. The simulation of the trained ANN had the same results of the implemented in the DSP kit.

A dedicated hardware to recognize the quality of alcohol fuel was designed in our laboratory. It has a micro controller, an EEPROM and a FLASH chips. The ANN program was stored in the EEPROM chip, and the synaptic weights were stored in the FLASH chip. As the amount of chip memories was small, the ANN program had to be optimized. This system only process the final and initial response sensor values in steady state. With these values, it calculates and shows the response of the ANN in its LED's.

Fuzzy Inference System

A FIS were used to solve the problem of classification of gas heat power patterns. FIS's rules were extracted from the synthetic data. According to [12], rules are extracted from estimative of data clusters, and each data cluster represents a rule which relates an input region with an output pattern.

Subtractive clustering made the Fuzzy rules extraction. And were obtained a center point for each cluster of each pattern. The features analyzed were the sensor initial resistance and its normalized variation shown in Fig. 3.

Results of FIS without optimizations were not satisfactory. The first 150 samples were applied to FIS sequentially, one by one, during one second for each sample. Among them the first 50 samples were from the first pattern, the next 50 were from second pattern, and the last 50 were from the third pattern. FIS output values ranging from 0 to 0.25 recognizes the first pattern. Output values ranging from 0.25 to 0.75 recognizes the second pattern. And finally, output values ranging from 0.75 to 1.00 recognizes the third pattern..

The behaviors of the ANN's and FIS couldn't have been compared, because the FIS are still in its initial step of design. More accurate differentiation of these two systems would be obtained when more experimental gas fuel data patterns is acquired, and when the FIS is more developed.

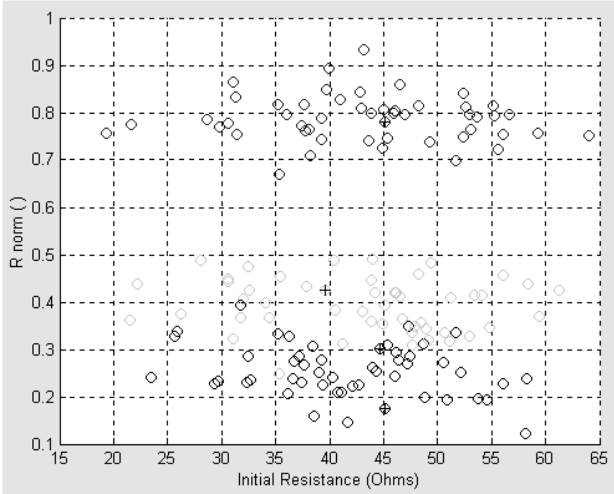

Fig. 3. Scattered plot of normalized resistance variation versus initial resistance of sensor 2 with synthetic data

Conclusions

It has been shown that implementation of an embedded system for classification of heat power of a fuel gas or classification of alcohol fuel is possible. It can be done with an ANN or a FIS. The ANN had a high rate of accurate responses, which shows its capability of generalization.

Principal Component Analysis is an important tool to reduce the input space dimensionality of a system. It can accelerate the training step of a ANN. However, it can prejudice the capability of generalization of the network. Sensors that apparently don't have sufficient sensibility can help the correct classification of a pattern. Also it can be shown that data pre-processing accelerate the training step of an ANN.

FIS can be an alternative solution to the problem. An important advantage is that its model is accessible. ANN's models are difficult to obtain, because each time it is trained, different models are obtained. And the user can't access these models. ANN's behavior is like an non-linear black box.

It was observed that implementation of an ANN in hardware is easier than the implementation a FIS in hardware. It's because the architecture of an ANN is easier than the required architecture to implement a FIS. The most difficult function in a backpropagation ANN is the non linear activate function. FIS requires several mathematical calculi in fuzzification, inference and defuzzification steps.

This work requires the acquisition of more experimental data of different fuel gas patterns, and new ANN training with these new data. With more experimental data, detailed analysis of the sensor's signal in time can be done. Analysis of sensor's several time responses will be possible. Thus, a gas fuel pattern can be faster recognized, improving the performance of the acquisition data system.

The FIS can still be enhanced with a method of automatic optimization of its membership functions. An option is to use a correction function based on gradient descendent.

Hardware implementation of the fuel gas is still in its initial stage. It will be necessary to implement input analogical signal circuits from the sensors, an operator's interface indicating the time in which the embedded system will initiate or terminate a treatment of the electric signals of the sensors, and finally, it will need command software for all this hardware.

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