01 Feb 2008

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Recommended Citation

S. Bashyal et al., "Embedded Neural Network for Fire Classification Using an Array of Gas Sensors," *Proceedings of the IEEE Sensors Applications Symposium, 2008. SAS 2008*, Institute of Electrical and Electronics Engineers (IEEE), Feb 2008.

SAS 2008 – IEEE Sensors Applications Symposium
Atlanta, GA, February 12-14, 2008

Embedded Neural Network for Fire Classification Using an Array of Gas Sensors

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Abstract— **Fire is one of the most common hazards in US households. In 2006 alone, 2705 people were killed due to fire in building structures. 74% of the deaths result from fires in homes with no smoke alarms or no working smoke alarms while surveys report that 96% of all homes have at least one smoke alarm. This study discusses the development of a fire sensing system that is not only capable of detecting fire in its early stage but also of classifying the fire based on the smell of the smoke in the environment. By using an array of sensors along with a neural network for sensor pattern recognition, an impressive result is obtained. Instead of confining the ANN to a PC based application, this work extends the implementation of the neural network fire classifier in a general purpose microcontroller. The result is a low cost intelligent embedded fire classifier that can be used in real life situations for fire hazards minimization, for example this intelligent fire classifier can be used for the development of a smart extinguisher that detects the fire, classifies it and then uses appropriate extinguishing material required for extinguishing the particular class of fire.**

I. Introduction

FIRE is one of the most common hazard in US households and laboratories killing 2705 people in 2006 [1]. Extinguishing fire in its primitive stage is utmost important for minimizing fire-hazards. One approach to prevent fire from spreading is to devise a mechanism that can automatically detect fire in an early stage, inform the occupants / rescue workers of the fire and possibly take necessary measures to extinguish it. National Fire Protection Association (NFPA) of the United States of America classifies fire into four primary classes and suggests the use of compatible extinguishing material for each class of fire. Commercial automatic fire extinguishers that are presently available in the market are not capable of identifying the type of fire and often fail to use appropriate extinguishing material as per NFPA directives. Fully automatic fire extinguishers therefore need an ability to sense the fire in its early stage, classify it and then select appropriate extinguishing material(s) to be used.

In this work, an Artificial Neural Network (ANN) is used for fire-classification based on the odor signals detected by an array of gas and temperature sensors. This work differs from previous works in fire detection-classification in three major aspects:

i. The ANN fire classifier is proposed to be used for selection of appropriate fire extinguishing materials in real time unlike other similar works that use ANN fire classifier for forensic investigation.
ii. The proposition in (i.) requires that the ANN be implemented in an Embedded System instead of previous PC based implementations.
iii. The NFPA recommendation is the basis for classification

Works involving the processing of aroma signals often use an array of gas sensors along with a neural network [2], [3], [4]. Electronic noses, as the arrangement is commonly called, have been used in numerous fields to achieve good results. Readers are referred to [5] for a review of different applications of electronic noses. Most of the electronic noses developed are implemented in a Personal Computer (PC) based platform which, due to cost, size and power requirements, limits their use in day to day life. Recently, some works have reported the implementation of neural networks in embedded platforms. In [6], the authors detail some of the features of embedded implementation of an electronic nose.

This study discusses the development of an 8051 family microcontroller based embedded system and implementation of ANN in the embedded system for fire classification. The embedded system consists of an 8 bit Analog to Digital Converter (ADC) used to convert analog signal from the sensor array to digital samples. Taking the sampled sensor signals as inputs, the ANN implemented in the embedded system classifies the fire and displays the result in an alphanumeric display.

Part of this work was completed at the Undergraduate Research Division (URD), Nepal Engineering College as a senior design project by Bandana Paudel and Binny Maskey. The gas sensors used in this project were made available to Nepal Engineering College by Figaro Engineering Inc for research purposes.

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978-1-4244-1963-0/08/$25.00 ©2008 IEEE

II. EMBEDDED PLATFORM

The embedded platform is built around an 89c55 microcontroller. 89c55 is an MCS51 family general purpose microcontroller and has 512 Bytes of RAM and 20 KB of reprogrammable flash memory.

An array of sensors, comprising of six gas sensors and a temperature sensor, is used for detection of the olfactory signals in the environment. All of the sensors used are tin oxide gas sensors from Figaro Engineering Inc and the different sensors in the array are sensitive to different gases. The analog signal from the sensor array is converted to its digital equivalent using ADC0808, an 8 bit Analog to Digital Converter (ADC). The ADC0808 has an in-built multiplexer and the analog signals from seven different sensors in the array is read by the microcontroller one at a time using the multiplexing feature of the ADC. An alphanumeric display is used to display the signal readings from the sensor during the training phase and to display the classification result during the testing phase.

TABLE I
SENSORS USED IN THE SENSOR ARRAY AND THEIR RESPECTIVE TARGET GASES

S.N.	Sensor ID	Detectable gases
1	TGS 880	Volatile gases from food, Alcohol
2	TGS 822	Xylene, Toluene, alcohol, volatile organic vapors
3	TGS 2600	Air contaminants, CO_2, CO
4	TGS 2611	Natural gas, methane
5	TGS 2610	General combustible gas, LP gas, propane
6	TGS 2602	Air contaminants, hydrogen sulfide, ammonia
7.	Thermistor	Temperature Sensor

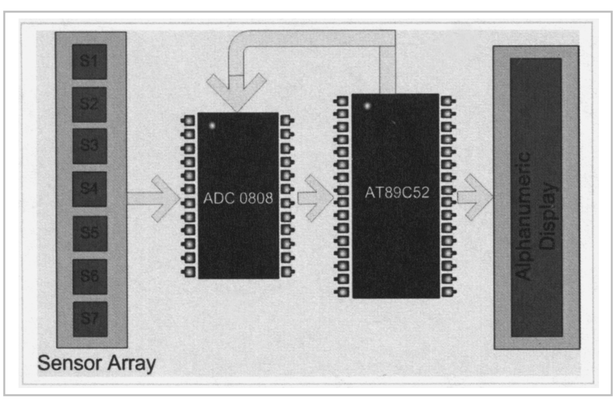

Figure 1: Block Diagram of the embedded system

III. ANN IMPLEMENTATION

The embedded fire classifier needs an ability to identify specific input patterns from the array of sensors. ANNs have been frequently used for such sensor pattern recognition tasks. In this work, the possibility of training a neural network for fire classification on the basis of gas concentrations in the environment is explored.

When in normal condition, the system displays "Normal" indicating that no fire has been detected. Once the system detects smoke, the system classifies the fire as either Class A or Class B fire as per NFPA directives. Though this work does not incorporate automatic fire extinguishing, the classification result can be easily used for extinguishing purposes.

A multi-layered feed-forward neural network with a single hidden layer is used. The number of nodes in the input layer is equal to the number of sensors in the sensor array (i.e. 7). The hidden layer has 12 nodes and the output layer has 3 nodes (for three different output cases: No Fire Detected, Class A Fire Detected and Class B Fire Detected).

The sigmoid activation function is used for modeling the perceptrons in the neural network. The weights in the network are initialized with random values in the beginning and then the network is trained using the supervised back-propagation learning algorithm.

TABLE II
SUMMARY OF THE ANN IMPLEMENTATION

S.N.	Parameters	Values	Remarks
1.	Average Time for Converging	3.2 Minutes	PIII 550MHZ, Windows98
2.	Hidden Layer	12	
3.	Input Layer	7	No. of Sensors = 7
4.	Output Layer	3	Class A, B; Normal
5.	Program Size	7.3 KB	Hex file
6.	RAM Required	255 Bytes	
7.	Activation Function	Sigmoid Function	

The reading of the seven different sensors in the sensor array is scanned by the embedded system discussed above and displayed in the alphanumeric display as a value between 0 and 255. These values are then normalized and manually entered to the PC based ANN application for training. After the training is complete, the weights are saved to a text file and then ported to the embedded neural network application.

The embedded neural network is developed using C. Two different C compilers are used during the development of the embedded neural network; the PC based ANN learning algorithm is implemented in Turbo C 3.0 whereas the embedded neural network application is developed using the Small Device C Compiler (sdcc).

IV. OBSERVATIONS AND FINDINGS

Initially, the sensor array, along with sampling routine in the embedded system, is subjected to different types of fire and subsequent readings in the range of 0-255 is noted manually from the alphanumeric display. The readings are then normalized manually. Table III presents the normalized readings from the sensor array when subjected to different fire conditions.

Of the different types of fire used for training and testing of the embedded ANN; the fire occurring due to the burning of paper, plastic and wood belongs to Class A according to the NFPA classification. Similarly, fires that occur due to the burning of Petrol, Kerosene and LPG fall in Class B.

TABLE III
NORMALIZED INPUT READINGS USED FOR ENN TRAINING

Sample	Temp	TGS	TGS	TGS	TGS	TGS	TGS
Paper	0.72	0.14	0.72	0.63	0.52	0.20	0.12
Paper	0.67	0.06	0.66	0.60	0.55	0.20	0.30
Petrol	0.69	0.10	0.69	0.52	0.69	0.18	0.09
Petrol	0.56	0.24	0.85	0.72	0.74	0.40	0.07
Plastic	0.67	0.09	0.38	0.39	0.35	0.09	0.13
Plastic	0.67	0.01	0.43	0.56	0.50	0.13	0.16
Kerosene	0.60	0.13	0.74	0.67	0.70	0.13	0.09
Kerosene	0.63	0.19	0.78	0.66	0.63	0.14	0.08
Normal	0.58	0.02	0.10	0.12	0.09	0.05	0.08
Wood	0.73	0.13	0.60	0.60	0.66	0.23	0.29
Wood	0.69	0.13	0.55	0.70	0.73	0.28	0.39

The normalized input values from the array are then manually ported to the ANN source code for training of the network in the PC environment. The training is continued as long as the maximum error in the network was greater than 0.5. Once the error is minimized to a value lower than 0.5, the trained network is subjected to a set of test cases. Table IV summarizes the result of the test cases. After verifying the accurate classification of the trained network, the weights of the network is saved in a text file which is then used for developing the embedded neural network. To verify the proper functioning of the neural network after being ported to the embedded platform, the final embedded neural network and the PC based ANN were both subjected to the same sets of input and the output of both network matched in all test cases.

The final embedded system automatically reads the sensor input from the array, normalizes them and computes the neural network output for the set of sensor values. The system then displays the result in the alphanumeric display. The result of the test clearly reveals the fact that the embedded neural network can accurately classify the fire as per NFPA classification system.

TABLE IV
PERFORMANCE OF THE TRAINED NETWORK IN DIFFERENT TEST CASES

Test Case	No. of Tests	Correct Results	Incorrect Results	Remarks
Paper	2	2	0	100%
Wood	2	2	0	100%
Kerosene	2	1	1	50%
Petrol	2	2	0	100%
LPG	2	2	0	100%
Plastic	2	2	0	100%

V. LIMITATIONS AND FURTHER WORK

The present work only focuses on implementation of back-propagation training algorithm for training the MLP. Other training algorithms and neural network architectures can be experimented in future works. The signals from the sensors are read directly using a simple potential divider circuit. Preprocessing operations (like amplification and filtering) can be added in hardware to improve the sensitivity of the system.

The major limitation of this work, similar to that of other embedded implementation of ANN, is the manual intervention of the source code during the conversion of the ANN from the PC based application to the embedded application. Further work is to explore the minimization of the intervention during conversion from PC based application to the embedded implementation.

VI. CONCLUSION

This study clearly shows that fire classification can be achieved by using artificial neural network along with an array of general purpose gas sensors. Moreover, the memory foot-print of the neural network can be minimized enough to fit in a limited memory space of a low cost microcontroller. The approach results a versatile intelligent fire classification system at a much lower price and thus can be used in real life situations to minimize fire hazards.

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