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Survey of Automatic Fire Classification and Extinguish Techniques using Embedded Based Neural Network

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Abstract

Automatic fire detection is important for early detection and promptly extinguishing fire. Using of embedded Neural Network in automatic fire detection is one of the most important applications of Neural Network. There are many studies investigating the best sensor combinations and appropriate techniques for early fire detection. In the previous studies fire detection has either been considered as an application of a certain field (e.g., event detection for wireless sensor networks) or the main concern for which techniques have been specifically designed (e.g., fire detection using remote sensing techniques). These different approaches stem from different backgrounds of researchers dealing with fire, such as computer science, geography and earth observation, and fire safety. In this report we survey previous studies from point view of facilities of the system, ability of application in real life and performance parameters like training time and convergence time. This work also proposes a solution for implementing neural networks on microcontrollers for many embedded applications.

Keywords: *Artificial Neural Networks, Embedded System, Fire Classification, Microcontroller and Network Training.*

1. Introduction

Fire detectors are intended to be sufficiently sensitive to detect fires promptly without reacting to false sources. Contemporary smoke detectors have the ability to respond quickly, but generally cannot discriminate between smoke or odor sources. The inability m discriminate between sources is a significant limitation. Data from U.S. fire incidents during the 1980Is indicates that 95% of all alarms from smoke detectors were unnecessary [11].

One solution proposed for minimizing unnecessary alarms without sacrificing prompt activation involves using intelligence along with current detector technology. Some recently developed intelligent detectors provide a step in this direction where a correction can be made for background noise, ambient conditions or changes in detector sensitivity [14]. However, these contemporary detectors are still not capable of adjusting even to commonly encountered temperature conditions from tobacco smoke, cooking odors or aerosol sprays. The next step in the evolution of a smart detector involves incorporation of intelligence, possibly with additional senso and to provide the capability to discriminate between conditions from fire and non-fire sources, without sacrificing response time [15].

Fires may take place in various environments, such as residential places, forests or open spaces. The easiest way to detect a fire at residential places is using the smoke detectors or any other similar sensors, which are usually sensitive to ionization or obscuration [11]. The problem with such detectors is that they are prone to false alarms. This means that in noisy conditions, such as smoking a cigarette or toasting a bread, a fire alarm may be generated wrongly.

Fires are classified by the types of fuel they burn. As shown in the tables below[11]

Table 1: Fire Classifications

ISO Standard 3941	NFPA 10
Class A: Fires involving solid materials, usually of an organic nature, in which combustion normally takes place with the formation of glowing embers.	Class A: Fires in ordinary combustible materials, such as wood, cloth, paper, rubber and many plastics.
Class B: Fires involving liquids or liquefiable solids.	Class B: Fires in flammable liquids, oils, greases, tars, oil-based paints, lacquers and flammable gases.
Class C: Fires involving gases.	Class C: Fires which involve energized electrical equipment where the electrical Non-conductivity of the extinguishing medium is of importance.
Class D: Fires involving metals.	Class D: Fires in combustible metals, such as magnesium, titanium, zirconium, sodium, lithium and potassium.

2. Review of Embedded Neural Networks

Neural networks have become a promising area of research over the last few decades and have affected many branches of industry [9]. In the field of industrial electronics alone there are several applications for neural networks, some include motor drives and power distribution problems dealing with harmonic distortion. Due to the nonlinear nature of neural networks, they have become an integral part of the field of controls [13]. On a parallel note, embedded applications are also becoming exponentially more prevalent [7].

Many people have a predisposition about neural networks, one being that they require significant computing power. One researcher stated, "most embedded microprocessor cores lack the performance for running neural networks" [12]. Many researchers have implemented neural networks on sophisticated hardware; for example, creating dedicated Application-Specific Integrated Circuits (ASICS) as in [12]. Others have used Field Programmable Gate Arrays (FPGAs) to perform the neural network calculations for embedded tasks [10].

There have been several papers published on microcontroller-based neural networks. These papers will be discussed in the following section. However, they are lacking in several categories. These categories are neural network architectures, activation function, and training algorithms. Neural networks are great for approximating systems with limited training points but are exposed to a large variety of input patterns. Neural networks do a great job of predicting the outputs between the data points. In a large portion of the research, neural networks are used to solve digital type problems with a limited number of inputs and outputs. These problems are not well suited for neural networks but could be solved simply using logic gates. In these applications all possible scenarios are specifically trained. This situation does not utilize the full power of the neural network.

2.1 Embedded Neural Network for Fire Classification using an Array of Gas Sensors Related Works

Bashyal *et al.* at Missouri University of Science and Technology created an embedded neural network for fire classification [8]. This application does not require the system to be able to continuously process data in real time since once a fire is detected and classified, its work is finished. Even if the calculations required several seconds, this is acceptable for this application. This network is very large relative to the simplicity of the problem to be solved. It has seven inputs and three outputs. Each of the seven inputs is one individual sensor and the three outputs represent the three types of fires to be classified: No Fire, Class A, and Class B. This work appears to questionable due to the data used for training the network. The table containing the training data displays the seven sensor readings for different types of materials burning. Of the seven sensors, however, only one sensor is needed to classify the difference between Class A and Class B fires. The other six inputs become irrelevant. Based on this data, a neural network of this size is not needed to analyze the data. The sensor in the far right column accurately distinguishes the differences between the items burnt once the temperature level is elevated.

The network configuration is inefficient for this dataset because a neural network will train to the simplest distinguishing characteristic; in this case it was the last sensor and the temperature sensor and the other data need not be used.

Bashyal *et al*. also only used integers and not fractional math which is a limiting factor of the work. The authors used Error Back Propagation (EBP) for training, which they admit is another limitation of the system. The authors also mention that the embedded network was manually converted from the computer based network to an embedded network and that it would be optimal to have an automated system for this implementation.

In 2013, Sunny *et al*. [3] came up with a new method for classification of gases/odors called average slope multiplication (ASM) using dynamic characteristics of thick film gas sensor array.

In 2013, W. Khalaf [4] pointed out in Sensor array gases identification and quantification that a practical electronic nose for simultaneously estimating many kinds of odor classes and concentrations. The multi-input/multi-output function is decomposed into multiple many to one task.

Dae- Silk Lee *et al*. designed a sensor array with nine discrete sensors integrated on a substrate to recognize the species and quantify the amount of explosive gases. A review of the pattern analysis of machine olfaction was laid before by Ricardo Gutierrez-Osuna a member of IEEE.

In 2014, Sunny *et al.* [2] proposed a new feature technique called average slope multiplication to quantify individual gases/odors using dynamic responses of sensor array.

In 2011, Ravi Kumar *et al.* [5] laid before a new soft computational approach using multi scale principle component analysis/ (MSPCA) for discrimination of gases. The network was found to identify the gases with a high success rate.

Ali Gulbag and Fevzullah Temurtas [1] put forward an adaptive neuro-fuzzy inference system (ANFIS) for quantitative identification of individual gas concentrations in their gas mixtures.

S. Capone *et al.* [6] proposed an array of highly sensitive and mechanically stable gas sensors based on different sol–gel fabricated Pd-doped SnO_2 nanocrystalline thick films which were used to detect concentrations of the range 0–100 ppm CO and 0–4000 ppm CH_4 at 50% relative humidity.

Table 2: Comparative Analysis of Some Existing ANN-based Fire Classification Models

PAPER	OBJECTIVE	MODEL	FINDINGS
S. Bashyal, G. K. Venayagamoorthy, and B. Paudel, "Embedded neural network for fire classification using an array of gas sensors,"	To design embedded neural network for fire classification.	A trained multi-layer feed-forward neural network was used for classification purposes.	This application does not require the system to be able to continuously process data in real-time since once a fire is detected and classified, its work is finished. Even if the calculations required several seconds, this is acceptable for this application. This network is very large relative to the simplicity of the problem to be solved.
S. Sharma, V.N. Mishra, R. Dwivedi, R.R. Das, "Classification of gases/odors using dynamic responses of thick film gas sensor array",	To design new method for classification of gases.	Average slope multiplication (ASM) using dynamic characteristics of thick film gas sensor array.	The model indicated better results compared to that of a previous model. The average classification error recorded was small.

W. Khalaf, "Sensor array system for gas identification and quantification", in: M.A Strangio (Ed.), Recent Advances in Technologies, InTech, Rijeka, Croatia, 2013.	To implement Sensor array gases identification and quantification that a practical electronic nose for simultaneously estimating many kinds of odor classes and concentrations.	A supervised artificial neural network model has been used.	The multi-input/multi-output function is decomposed into multiple many to one task.
R. Kumar, R.R. Das, V.N. Mishra, R. Dwivedi, "Wavelet coefficient trained neural network classifier for improvement in qualitative classification performance of oxygenplasma treated thick film tin oxide sensor array exposed to different odors/gases"	To develop a new technique for gas classification.	a new soft computational approach using multi scale principle component analysis/ (MSPCA) for discrimination of gases.	The network was found to identify the gases with a high success rate.
A. Gulbag, F. Temurtas, "A study on quantitative classification of binary gas mixture using neural networks and adaptive neurofuzzy inference systems"	To develop an array of highly sensitive and mechanically stable gas sensors based on different sol–gel fabricated Pd-doped SnO2 nanocrystalline thick films.	The system is based on different sol–gel fabricated Pd-doped SnO2 nanocrystalline thick films.	The system was used to detect concentrations of the range 0–100 ppm CO and 0–4000 ppm CH4 at 50% relative humidity.
S. Capone, P. Siciliano, N. Bârsan, U.Weimar, L. Vasanelli, "Analysis of CO and CH4 gas mixtures by using a micromachined sensor array"	To combines gas sensor array and artificial neural network recognition.	Electronic nose principle.	They applied the principle of electronic nose system in artificial olfactory system which combines gas sensor array and artificial neural network recognition.

3. Current Research Summary

The current research on embedded neural networks in low end microcontrollers does not fully utilize the neural networks to their potential. Most of the work modifies the neural networks to simplify calculations to make them easier to implement, or simplifies the data to make their training work easier. The networks are all converted manually from a PC based network to the embedded network. None of the current work uses arbitrarily connected neural networks but instead only MLP networks. All of the previously published networks that are trained are trained using EBP which greatly limits the ability to train the networks. These neural network implementations used integer math or single digit fixed point math to achieve their results. This work addresses most of these shortcomings of the listed work. It first offers a capability of implementation of ANN in Arduino directly without need of implement it firstly in PC, by using equations found in the literature a simple system is established including first and second order algorithms. An automated system was created to convert the newly trained network to an embedded network. The embedded networks are all configured using any feed-forward architecture. The embedded neural network also uses a pseudo floating point algorithm for exceptional accuracy on a limited system. In addition to the pseudo floating point mathematics is a second order approximation of tanh. This is a very accurate and nonlinear approximation to maintain the integrity of the nonlinear neural network.

4. Conclusions

This paper presents a survey for embedded neural networks across many types of hardware and for many applications, and a solutions for many drawbacks of the previous works. The software package presented here allows the user to develop a neural network for a desired application, train the network, embedded it in any platform, and verifies its functionality. This software package is a complete embedded neural network solution.

The Present work cannot stress enough that the proof of concept shown here opens the door for neural networks to be used on any platform for problems of virtually any kind. The complexity of the problems can range from a simple one neuron one input one output system to dozens of neurons and many inputs and outputs. This solution has endless problems it is capable of solving.

The next step in this research is to extend the C version to other microcontrollers and compare calculation times. The final step would be to train the network on data collected for a physical system. This would demonstrate and verify the speed of the neural network in a hardware application.

5. Benefits of Current Survey

The current survey reviews the most papers presented in the field of application of embedded Neural Network in firefighting technique, which is becoming very important field as the world is interested in Safety. The current research is important tool for researchers who want to proceed in this field, as he will find a summary of presented papers.

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