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Application of Neural Networks for Discriminating Fire Detectors

Abstract

Research is being conducted to describe the characteristics of an improved fire detector which promptly reacts to smoke while discriminating between smoke and odors from fire and non-fire sources. This study is investigating signature patterns associated with fire and environmental sources via small- and large-scale tests toward the development of an improved fire detector. On the tests, smoke and odors are produced from a variety of conditions: flaming, pyrolyzing and heated samples, and nuisance sources, such as aerosols, household products and cooked food. Measurements include light obscuration, temperature, mass loss, CO, CO_2, O_2 and oxidizable gas concentrations. The feasibility of an elementary expert system to classify the source of the signatures from small-scale experiments was demonstrated in the first phase. In the recently completed second phase, a similar expert system correctly classified the source of the signatures in large-scale experiments in 85% of the cases. Neural networks have been applied to both sets of data from the small- and large-scale tests providing an even greater successful classification rate.

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 to discriminate between sources is a significant limitation. Data from U.S. fire incidents during the 1980's indicates that 95% of all alarms from smoke detectors were unnecessary [1].

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 [2,3]. However, these contemporary detectors are still not capable of adjusting even to commonly encountered temporary 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 sensors, to provide the capability to discriminate between conditions from fire and non-fire sources, without sacrificing response time [4].

An appreciable amount of effort is being expended by industry to develop odor detection based on an analysis of the response from an array of sensors [5]. Applications for such a detector have been developed for the food industry, *e.g.* process control for products such as coffee and beer, and quality control evaluations of coffee beans and tobacco blends for cigarettes. Implementation of odor detectors for these industrial applications indicates that an accurate assessment of environmental odors is possible as a result of recent developments in sensor technology and analysis techniques. The feasibility of applying odor detection using metal oxide sensors for fire detection has been demonstrated by Okayama [6,7].

Successful development of a smart fire detector is based on the premise that the response of each sensor contained in a detector can be related to the yield of selected species from the source. The response of any one sensor, S_i, is proportional to the concentration of a gas specie or odor, C_i, transported to the location of the sensor:

$$S_i \propto C_i \tag{1}$$

The concentration of the transported specie, C_i, is related to the yield, Y_i, mass loss rate of the source, $\dot{m}_f$, and mass flow rate, $\dot{m}_o$, past the sensor:

$$C_i \propto \left(\frac{\dot{m}_f}{\dot{m}_o}\right) Y_i \tag{2}$$

According to Tewarson [8], Y_{CO2} and Y_{CO} are appreciably different for flaming and non-flaming combustion, *e.g.* Y_{CO2} is on the order of 1.0 to 2.0 g/g for most flaming fire sources and 0.05 to 0.2 g/g for most non-flaming fire sources. Consequently, a physical basis for a discriminating detector exists in the form of the proportionality relations expressed as equations (1) and (2), where the sensor response, S_i, can be related to the type of the source.

An experimental effort is being conducted at the University of Maryland to determine if a sufficient distinction in signatures can be observed to support development of a smart fire detector. The research is being conducted by teams in the Departments of Fire Protection Engineering and Chemical Engineering. The fire protection engineering team is concentrating on identifying signatures from fire and non-fire sources. The chemical engineering team is applying neural networks to investigate the sensor response patterns and provide the discrimination capability between fire and non-fire sources. The emphasis of this paper is to describe the experimental effort led by the fire protection engineering team.

Small-scale Experimental Program

Initially, small-scale tests were conducted to characterize the signatures from fire and non-fire sources [9]. The experiments were designed to be conceptually similar to those by Okayama [6], with modifications incorporated to provide a greater range of measurements for describing the signature.

The small-scale experimental apparatus was a simplified tunnel which included measurement equipment and a means for generating odors. Measurements of light obscuration, temperature, gas species concentrations (CO, CO_2 and O_2) and presence of any oxidizable gas are provided. The presence of oxidizable gases was measured by a Taguchi metal oxide sensor. Sources of the smoke or odor were placed under a hood at the inlet end of the apparatus. A variety of fuels and environmental sources selected to be representative of a residential environment. Smoke and odors were produced from a wide range of conditions: samples with flaming and pyrolyzing combustion, heated samples and aerosols.

An elementary expert system successfully classified 28 of 31 sources. The rules of the expert system are:

- CO_2 concentration exceeds 1500 ppm only for flaming fires
- Peak CO concentration exceeds 28 ppm and Taguchi detector response less than 6V is acquired only for pyrolyzing solids.
- All other combinations are acquired from nuisance sources.

An ellipsoidal neural network was applied to the small-scale data, using two-thirds of the data for training and the remainder for testing [10]. An improved classification rate was obtained, accurately classifying all sources except one smoldering source (which was classified as a flaming source).

The level of success attained from the small-scale experimental program confirmed the feasibility of the concept presented by Okayama. However, the success of the expert system and neural network only related to the limited range of fuel sources investigated and the small-scale test apparatus.

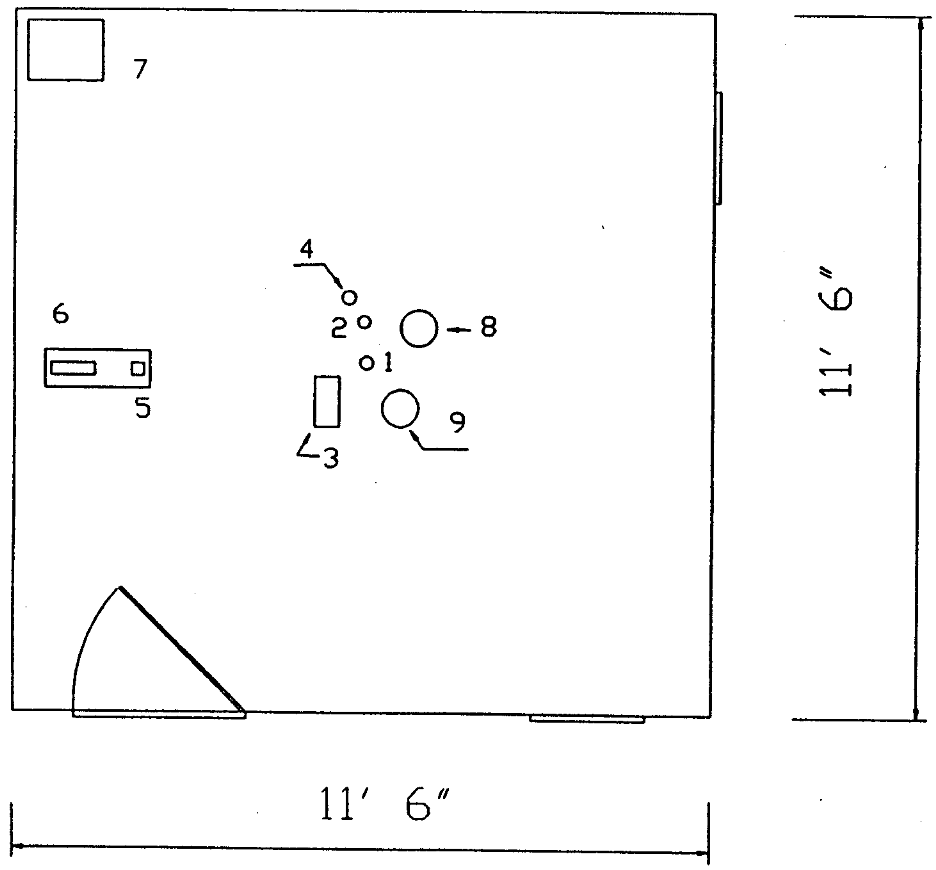
Large-scale Experimental Program

Recently, a large-scale experimental program was conducted to determine whether the trends identified in the small-scale experimental effort were also applicable in large-scale environments. The large-scale experiments were conceptually similar to the small-scale experiments where signatures from a wide variety of fires and environmental sources were monitored and sensor response patterns were explored.

The large-scale experiments were conducted in a 3.6 x 3.6 m room with a height of 2.4 m [11]. Measurements included temperature, mass loss of the fire sources, CO, CO_2 and O_2 concentrations, light obscuration and the voltage output from two metal oxide sensors (Taguchi model 822 and 880). In addition, two commercial smoke detectors (one photoelectric and one ionization) were located on the ceiling, at the center of the room. A diagram of the room, including the relative locations of the sensors is provided as Figure 1. The metal oxide sensors responded to the presence of oxidizable gases and environmental odors respectively. Mass loss measurements were used to estimate the yield fractions of the signatures from the fire sources. Because the tests were conducted in an unconditioned space, data was collected for at least two minutes prior to introducing any source in order to document ambient conditions.

The variety of sources used to generate conditions within the room are summarized in Table 1. Again, the sources were intended to be representative of residential fire and nuisance sources.

Flaming liquid tests were conducted by placing 50 ml of the sample in a pre-cooled metal container ignited by a match. The container was cooled prior to the tests to limit evaporation of the liquid prior to the initiation of flaming. Tests with



1. Thermocouple tree
2. Taguchi 822
3. Taguchi 880
4. 4.75 mm copper sampling tube
5. Photocell
6. Helium-neon laser
7. Load cell
8. Ionization smoke detector
9. Photoelectric smoke detector

Figure 1. Diagram of Test Room

Table 1. Test Sources

Heated Fuels: Liquid	Heated Fuels: Solid	Heated Fuels: Gas	Environmental Sources
heptane, 1-propanol, methanol, toluene, vegetable oil[1]	paper, cotton, polystyrene, pine, cardboard, cheesecloth, toast[2]	propane	propane, aerosols (disinfectant, furniture polish, cooking spray, hair spray), nail polish remover, ammonia-based window cleaner, bleach, water mist, boiling water, toast, cigarette smoke, coffee

[1] Boiling only
[2] Pyrolyzing only

flaming solids involved placing the fuel in an aluminum pan, then igniting the fuel with a match. Tests with pyrolyzing solids were conducted by placing the fuel in an aluminum pan on a preheated hotplate.

The group of tests involving the environmental sources were conducted by several approaches, depending on the typical usage of the product in a residence. One approach consisted of dispersing the product throughout the room, including water mist, cigarette smoke and household aerosol products. Alternatively, solid and liquid products such as bleach, nail polish remover (without acetone), boiling liquids, coffee and toast were located at floor level in the center of the room. The test with toast was conducted by placing the bread in a toaster that was kept "on" throughout the test. Tests with coffee included fresh coffee grounds as well as brewed coffee.

Data from the sensors was reviewed for the purpose of identifying patterns associated with the categories of sources. Concentrating on the maxima for each sensor, an expert system was formulated similar to that developed for the small-scale test data. As an initial step, this analysis was conducted manually. Work is ongoing using a principal components analysis (PCA) to define an expert system which is less complex and uses fewer sensors.

The elementary expert system developed for the large-scale tests is presented in Figure 2. The success rates of the system are summarized in Table 2. All of the flaming sources are properly classified, with smoldering sources classified properly in 62% of the tests and nuisance and ambient sources classified properly in 87% of

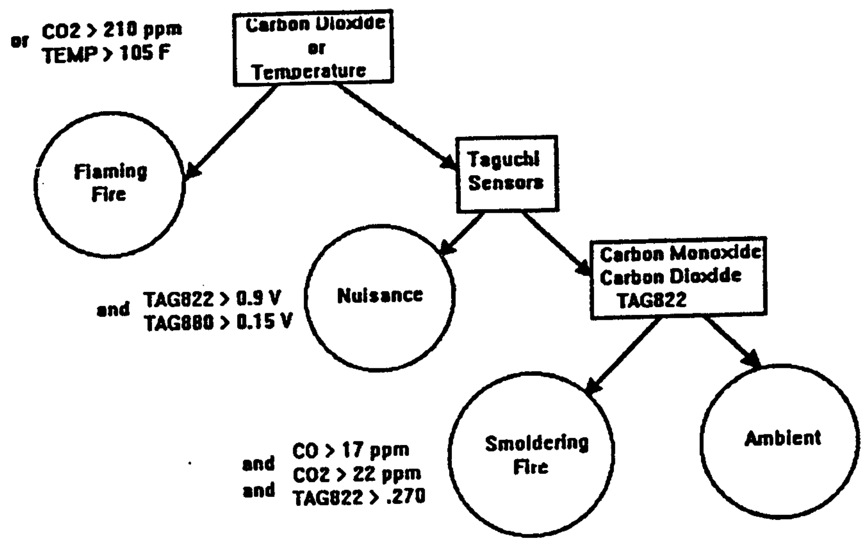


Figure 2 Expert System for Large-Scale Experiments

the tests. As indicated in the table, the greatest challenge is in distinguishing between smoldering and nuisance/ambient sources. In some tests, the distinction was debated by the research team where the difference is vague, for example the burned toast is labeled as a smoldering source.

Table 2. Classification of Test Sources

	Classification			Summary	
	Flaming	Smoldering	Nuisance /Ambient	Total	% Correct
Flaming Fire	34			34	100
Smoldering Fire		10	6	16	63
Nuisance/ Ambient		5	32	37	87
Total				87	87

An improvement in the success rate for characterizing the nature of the source can be achieved using a PCA. Preliminary results from the application of the PCA for smoldering sources using data from all of the sensors provides a 88% correct classification rate. In contrast, only 50% of the smoldering fires were detected by commercial smoke detectors.

In addition to the improved classification rate, the time for detection of the sensors with the PCA-based intelligence (the "prototype detector") was significantly less than that for the commercial detector. The time required for detection was reduced an average of 109 s, with the detection time for the prototype detector being 18 to 259 s less than that for the first responding commercial detector.

Summary

As a result of the experimental effort, an early fire detector consisting of an array of gas sensors appears feasible, with discrimination provided by a neural network analysis of the sensor responses. However, many questions still remain prior to the application of this technology as a means of early fire detection. Additional research is required to optimize the number and types of sensors to be included in the array, while still providing the desired level of sensitivity and discrimination ability. Continuing PCA applications on the large-scale data will assist in the optimization process. In addition, the data acquired has been from experiments conducted with one type of source, *e.g.* a flaming source without a nuisance source being present. Additional experiments are needed to assess the potential for a nuisance source to mask a flaming or smoldering source.

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