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Multivariate Methods for Fire Detection

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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. Discrimination is accomplished by comparing signature response patterns from fire and environmental sources collected in small- and large-scale tests. Smoke and odors are produced in the tests 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 second and third phases, an expert system was developed by Multivariate statistical methods to distinguish between fire and non-fire sources. In addition, the presence of a fire could be identified despite the interjection of signatures from nuisance sources which could mask the fire signatures.

Introduction

Prompt fire detection is the primary objective of automatic fire detection. The time to detection can be increase by increasing the sensitivity of the detector. However, a highly sensitive detector may be prone to provide unnecessary alarms because contemporary smoke detectors cannot discriminate between smoke and odor sources. 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 combinations of current sensor technology.

Research is being conducted via an interdisciplinary team at the University of Maryland to determine the characteristics of a sensitive, discriminating 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 Multivariate statistical methods to investigate the sensor response patterns and provide the discrimination capability between fire and non-fire sources. This effort has been conducted in three one-year phases.

Small-scale Experimental Program

Initially, small-scale tests were conducted to characterize the signatures from fire and non-fire sources [2]. The experiments were designed to be conceptually similar to those by Okayama

[3], 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 (light obscuration, temperature, gas species concentrations (CO, CO_2 and O_2) and presence of any oxidizable gas) and a means for generating odors. 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 were 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 were:

- 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 [4]. 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.

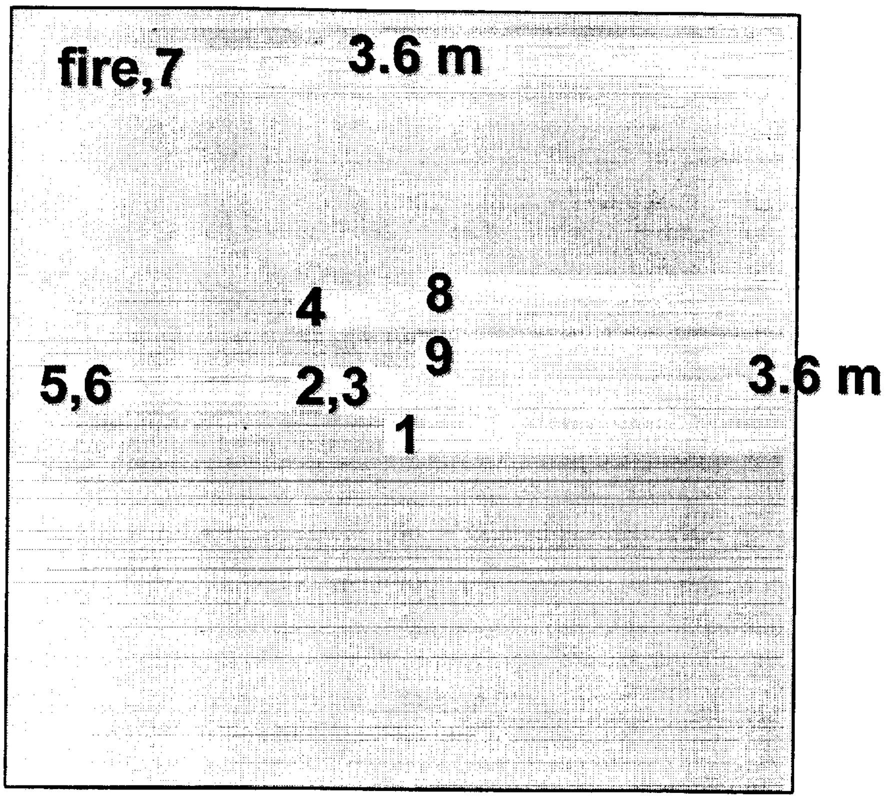
Large-Scale Experimental Program

In the second and third phases, large-scale experiments were 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. In the second phase, either fire or non-fire sources were introduced alone. In contrast, in the third phase mixed sources including both fire and non-fire sources were provided simultaneously.

The large-scale experiments were conducted in a 3.6 x 3.6 m room with a height of 2.4 m [5]. 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.



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

Single Source Experiments

The variety of sources used in the second phase to generate conditions within the room are summarized in Table 1. The sources were intended to be representative of fire and nuisance sources in residences. The 87 tests involved introducing 34 flaming sources, 16 smoldering sources and 37 nuisance sources.

Table 1. Test Sources

Heated Fuels			Environmental Sources
Liquid	Solid	Gas	
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			

Data from the sensors is reviewed for the purpose of identifying patterns associated with the categories of sources. General trends are noted from a manual review of the maximum values recorded for each sensor. An expert system similar to that developed for the data from the small-scale tests is developed. In addition, a Multivariate statistical analysis is applied to the maximum values recorded for each sensor during each test to identify the nature of the source. The type of statistical analysis, a principal component analysis (PCA) makes use of the experimental maxima, arranged in a data matrix, **X** [6-8]. Each row of **X** consists of one set of readings for all *m* sensors of the x_i variables under consideration. The number of rows in **X** equals the number of experiments. PCA determines the linear combinations of the maxima that are capable of explaining most of the variations in the measurements. The linear combination are called scores, t_i, and the number of t_i's used is typically much smaller than the number of sensors. These scores are used to reconstruct the raw sensor measurements. The squared difference between the raw sensor values and the reconstructed values is called the squared prediction error (SPE). The SPE is used to detect abnormal situations [7]. Both the scores and the SPE reflect all of the sensor measurements because both the scores and the SPE involve data compression as well as synthesis.

Measurements from the following six sensors used in the tests are applied to develop the PCA model: CO, CO_2, two Taguchi sensors (T880 and T822), temperature and smoke obscuration. The data for each sensor is scaled to zero mean and unit variance. The data collected from each sensor prior to the introduction of the source is used to establish normal, background conditions for that test. Three PCA components explain approximately 76% of the variability in the normal data. Consequently, three components are used to classify the sources.

The SPE is used to flag abnormal situations, with its confidence limit set at 99.5%. The SPE is successful in identifying all 87 tests as differing from normal conditions. The scores (t_i) are used to distinguish the type of source, using the following rules:

- if $t_3 > 5$, then the source is a flaming fire
- if $-8 < t_2 < 0$, then the source is a smoldering fire
- otherwise the source is a nuisance source.

The results of applying the above rules are summarized in Table 2. All of the flaming sources are properly classified, with smoldering sources classified properly in 88% of the tests and nuisance and ambient sources classified properly in 73% of the tests. 27% of the nuisance source cases are misidentified as smoldering sources and hence represent false alarms. Improved classification is expected by increasing the number of sensors to respond to additional attributes of the signatures.

Table 2. Classification of Test Sources

	Classification			Summary	
	Flaming	Smoldering	Nuisance/ Ambient	Total	% Correct
Flaming Fire	34			34	100
Smoldering Fire		14	2	16	88
Nuisance/ Ambient		10	27	37	73
Total				87	86

In addition to the improved classification rate, the time for detection of the sensors with the PCA-based intelligence (the "prototype detector") is significantly less than that for the commercial detector. The time required for detection is 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.

Mixed Source Experiments

The variety of sources used in the third phase to generate conditions from combinations of sources within the room are summarized in Table 3. A set of baseline tests are conducted using each of the sources alone.

Table 3. Combinations of Fire and Non-Fire Sources

	Non-fire Sources				
Fire Sources	None	Aerosol Disinfectant	Window Cleaner	Aerosol Hairspray	Boiling Water
None	-	x	x	x	x
Heptane	x	x	x	x	x
Paper	x	x	x	x	x
Cloth	x	x	x	x	x
Hamburger	x	x	x	x	x

A manual review of the data from the mixed sources indicates that the expert system from the previous phase can be amended to properly classify many of the sources. Application of the PCA approach to the data from the mixed sources is in progress.

Summary

As a result of the experimental effort, an early fire detector consisting of an array of sensors appears feasible, with discrimination provided by a Multivariate statistical analysis of the sensor responses. Additional research is necessary to compare the performance and cost of a detector using a limited number of sensors, including sensor types currently used in commercial detectors with a detector containing an array of sensors such as incorporated in this experimental investigation..

Acknowledgments

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Discussion

Walter Jones: In your early tables on what you could attempt either correctly or incorrectly, there were a total of twelve at 80 cm. Either you detected fire where there was not fire, or you did not detect a fire where there was one. Which is about a 15% false alarm rate. It appears to me it is considerably better than what exists now. However, the only downside to this would appear to be that you need multiple detectors. Given the earlier point by Mr. Mengel that price is the driving factor, is there any hope for multiple detectors again on this improvement?

James Milke: I agree that I think we showed the key advantages to multisensors being incorporated into the detectors. We have not been involved in any multiple sensors, however, and I would suspect at this point in time, such would be fairly expensive. However, there is an economy of scale that it is well recognized, so it may become economically more feasible later.

Question: I have to comment on your including toast as both a fire source and a false alarm. This raises a very interesting issue. In our testing, we also had toast as both a fire source and a false alarm source. The issue really is when the toast is burning in the toaster, when it's charcoaling in the toaster, you would probably consider it a nuisance, but when it transitions to flaming, which ours did in several tests, now it's a real fire source. Where's the line? And I think toast is not the only case where that happens. Another example that we saw is a pilot lamp. If you're just heating it up, it creates aerosols that are a nuisance, but if it heats too long it turns into a fire. I think this raises a very interesting point about nuisance alarms sources versus real alarm sources.

James Milke: I'd like to respond to your comment in two ways. One, is that our own classification of what's a nuisance, what's a non-fire source can be ambiguous by itself so that some of the false alarm rates we get are high. The other point that you make is that there is a possibility for the nuisance source to transition to something else and that is very difficult balance to try and obtain.