NEW APPROACHES TO THE INTERPRETATION OF SIGNALS FROM FIRE SENSORS

by

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New Approaches to the Interpretation of Signals from Fire Sensors

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Abstract

In recent years fire sensors have evolved from threshold devices that sense a single fire signature to multi-mode, multi-criteria sensors that can employ algorithms for decision making. However, these algorithms have so far been based on simple, signal cross-correlation techniques or have employed simple truth tables in an effort to exclude sources of false activations while not rejecting real events. At NIST's Building and Fire Research Laboratory, new research has been initiated to apply our experience with physically based computer models of fire growth and spread in enclosed spaces to the interpretation of signals from fire sensors. Here, data from fire sensors are compared in real time to signals that would be expected from a fire within the protected space. The sensor data is used to adjust the simulation so that it matches reality. Signals that are inconsistent with the physical laws of fire growth can be questioned and when signals track with projections the system can provide detailed information on current conditions within the space as well as an ability to project future conditions. This latter ability is of considerable interest to fire brigades who could be warned of conditions that may threaten their safety or that of occupants. While in its early stages, the research results are promising.

Background and Current Approaches

Automatic fire detectors are about a hundred years old, and are a crucial component in addressing the life safety goals for the built environment. However, most experts agree that the greatest shortcoming of fire detectors is a high rate of nuisance alarms that limit their credibility with the public. Various schemes have evolved to address this problem; methods to discriminate against conditions that mimic the fire signatures upon which the detectors depend. This paper will discuss the most common of these approaches and will present a new approach under development at the National Institute of Standards and Technology (NIST) Building and Fire Research Laboratory (BFRL).

Nuisance Alarms

Like the "Cry Wolf" story, excessive nuisance alarms limit the credibility of fire alarm systems. Ahrens[1] reports that 69% of people surveyed said that a fire alarm does NOT indicate a fire, but rather some other abnormal condition. Of course, this results in people not starting evacuation until some other fire queue appears, increasing the risk of death or injury.

There are several studies in the literature that quantify nuisance alarm rates in (commercial) fire alarm systems. In the early 1970's Fry[2] reported data from the U.K. where most systems were connected to fire brigades and reports on every alarm were made. He found nuisance alarm ratios (the ratio of nuisance alarms to real fires detected) for smoke detectors of 14:1. In a 1980 survey of health care facilities in the U.S., Bukowski and Istvan[3] reported nuisance alarm ratios for smoke detectors also at 14:1. In a paper presented at AUBE '95, an officer with the Swiss fire service, Steck[4] reported data from Bern that 77% of alarms received from smoke detectors were false. This translates into a nuisance alarm ratio of about 14:3.

What is striking about these three studies is that they represent three generations of development of smoke detector technology. Fry's data is for detectors in use in the late 1960's, characterized by incandescent lamps and 90 degree scattering optics within highly restrictive chambers, single chamber ionization detectors, and no signal processing beyond alarm at a fixed threshold. The Bukowski and Istvan data is for detectors of the late 1970's that were likely to use LED's and forward scattering optics in chambers designed for much easier smoke entry or dual chamber ionization sensors that were more stable for variations in ambient conditions. The Steck data was for detectors of the 1990's that utilize drift compensation and possibly even early decision algorithms to make the systems "smart." Yet the evolution of this technology has had little effect on the observed rate of nuisance alarms.

The Search for Intelligence

For much of their history fire detectors have been threshold devices - alarm decisions are made when the signal exceeds some fixed threshold level generally referred to as the device's sensitivity. In the language of modern digital electronics this means that the detector is operating on a single bit of information. Some thermal detectors operate on the rate-of-rise principle (alarm when the rate of temperature rise exceeds a fixed value). Even where the thermal detector has dual elements (fixed temperature and rate-of-rise) they indicate an alarm when either element exceeds its threshold, so they are also one bit devices.

One thermal detector, the rate compensation device, operates such that a rapid increase in temperature causes it to decrease the fixed temperature value at which it activates. This could be considered a two-bit criterion since the conditions interact. One light scattering type smoke detector from the 1970's incorporated a circuit that increased the sensitivity (decreased the alarm threshold) if the rate of rise of the smoke signal exceeded a threshold value. While this was primarily done to compensate for an alarm photocell with an excessively long time constant, it represented a two-bit alarm operation.

Another approach to system intelligence was time of day adjustments. Since most nuisance alarms derive from human activities, some systems in the 1970's were given the ability to increase their sensitivity at times when the facility was unoccupied. This was typically done by building in time of day/day of week calendars by which adjustments were automatically made. However, since adjusting sensitivity can represent a compromise of early warning of fires, this approach is less than satisfying.

Time delays have been used in detectors to eliminate nuisance alarms to transient phenomena. Here, detectors begin the delay period when the alarm threshold is exceeded and will only alarm if the signal persists for the duration of the delay. A variation on this theme is the alarm verification circuit that resets the smoke detector to determine if it will alarm a second time, after some power down/power up delay. Like the time of day adjustment, the introduction of delays can compromise the early warning aspects of the system response to real fires.

Multiple Sensors

Early attempts at real increases in the intelligence used in alarm decisions involved pattern recognition. In theory, if one could determine a unique pattern in the signal from real fire sources it would be possible to differentiate these from nuisance sources. Signal characteristics examined ranged from simple (temporal variations or rate of change)[5] to complex (particle size distribution)[6] but the general conclusion was that none were sufficiently unique to allow systems to reject nuisance signals without significant risk of also rejecting some actual fires.

The first successes in increased intelligence required the combination of different sensors such as thermal and smoke, ionization and scattering, smoke and gas, in detectors sometimes called multi-mode sensors. Early devices simply combined sensors in an AND configuration. Later more sophisticated signal processing techniques such as signal cross-correlation were applied to produce significant improvements in performance. For example, Qualey[7] et al describe the development of a cross correlation algorithm for a thermal/smoke combination intended to reduce nuisance alarms without reducing detection performance.

This success can be explained by the prior analogy to digital electronics. It was now possible to base alarm decisions on multiple bits of information. The more bits available on which to base an alarm decision, the better that decision can be made and the lower is the rate of both false positives (nuisance alarms) and false negatives (unwanted fires not detected).

Fuzzy Logic and Neural Networks
A limitation of these early multi sensor approaches was that they could only be combined in AND or OR configurations through typical digital circuits. Digital electronics is 1's and 0's -- on or off, true or false. The development of fuzzy logic in the 1980's changed that. Fuzzy logic can deal with a range -- bigger, smaller, longer, higher. This allowed multi sensors to utilize multiple criteria for example more smoke required less heat to signal an unwanted fire.

Fuzzy logic was an advance, but as the number of sensor inputs increased it became very difficult to think through the logic of their interaction. Neural networks were the next advance where the system is "trained" in how to categorize various patterns of signals. Neural networks are capable of integrating hundreds of sensors and making decisions on large amounts of data (bits of information. Milke[8] describes work to develop a neural network for residential fire detection.

The underlying problem with signal cross correlation, fuzzy logic, and neural networks is that they represent an empirical fit to data. The correlations, logic tables, or training process are developed by exposing the sensors to fires and nuisance sources and determining the coefficients or settings that alarm to all fires and ignore most nuisance sources. Since it is impossible to include all fires and nuisance sources, and because there is no standard set of nuisance sources, the applicability of this approach is somewhat limited to highly controlled applications.

Neural networks can learn "on the job," so when exposed to a pattern that they have not seen before they might assume a fire to be conservative. Later if this was determined to be a nuisance source the system training could be altered and it would no longer signal fire to this pattern. The fear is that a real fire could look sufficiently like a prior nuisance source that the system would ignore it. What is needed is a system that knows enough about fire itself to decide on signal patterns that it has never encountered before.

The NIST Approach

The field of fire science has made great strides in the past two decades, and the increased understanding of fire has been incorporated into computer fire models of ever increasing sophistication. These model are based on the physics and chemistry of fires and as such are valid over a broad range of conditions. Thus, these models represent a method of assessing the validity of an alarm decision against hundreds or even thousands of bits of data. The technology that is beginning to enable such to be done is the increase in processing power and speed of the modern microprocessor and the simultaneous decrease in cost that allows their incorporation into systems.

As sensors become smaller and less expensive, buildings will incorporate more and more such sensors to regulate many aspects of the building such as comfort levels, energy usage, and security. While many of these sensors' primary function will not be fire protection, their response to a fire is predictable. Using the information from all sensors and an understanding of the physics of fires, the heat release rate and other information on the fire might be deciphered. Further, by examination of data from a series of independent sensors for consistency, a confidence level can be established for the alarm decision.

A simple example will illustrate what we mean. If in a single room, a smoke detector gives a large signal but temperature sensors that might be part of the environmental controls do not record any noticeable rise, it is possible that the smoke detector is faulty or a smoldering condition is present. Similarly, if the energy management system records a large electrical fault just before a smoke detector signal, the chances that the fault has initiated a fire are high..

The difference between this approach and previous methods of alarm discrimination is significant in two ways. First, it incorporates all available information to determine what is happening. The realization is that even in the very early stages of a fire, fire is a global phenomena. It has impact throughout a building and as a fire grows that distant information can be used to establish size, rate of increase and other information that can be helpful in fighting the fire. Second, unlike prior methods of reducing false alarms, this does not simply address the decision to alarm but can also be used to assess level of threat and support a tailored response.

Adaptive Modeling

A major part of the NIST approach is adaptive modeling. In this context, adaptive modeling is using the comparison of sensor data with model predictions to determine model inputs appropriate to better match the sensor data over sometime period. Of particular interest is the heat release rate (HRR) input since it is the driving force for most other phenomena. In general this is a complex optimization problem with a goal to minimize the difference between the building sensor data and model predictions. In general, this requires two techniques: 1) a method to quantify the differences between model predictions and measured data, and 2) techniques to determine appropriate model inputs to minimize these differences.

The first tool needed is a quantification of the error between the building sensor data and the model predictions. This is provided through functional analysis and is discussed in the paper by Peacock et. al[9]. The framework of functional analysis allows us to treat time series as if they were vectors and defines appropriate operations on the vectors. Initially, consider a single experimental measure and a model prediction, say the temperature at time t_i. Let E be the experimentally measured value and m be the value calculated by a model. One measure of the error is the relative difference between the two numbers calculated by

$$\frac{|E-m|}{|E|} \qquad (1)$$

If instead of being two scalar values E and m where two dimensional vectors we can still define a relative difference. Figure 1 shows the difference between E and m. If we call the length of a vector x the norm and write it as $||x||$ then we can define the relative difference between the two vectors as

$$\frac{\|E-m\|}{\|E\|} \qquad (2)$$

The relative difference we will use is directly analogous to the relative difference shown graphically in Figure 1

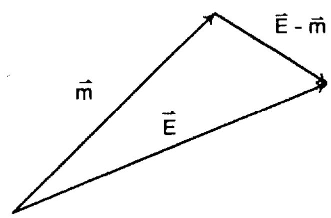

Figure 1

Figure 2 shows the upper layer temperature histories for two CFAST predictions. One is called the experiment the other that has small

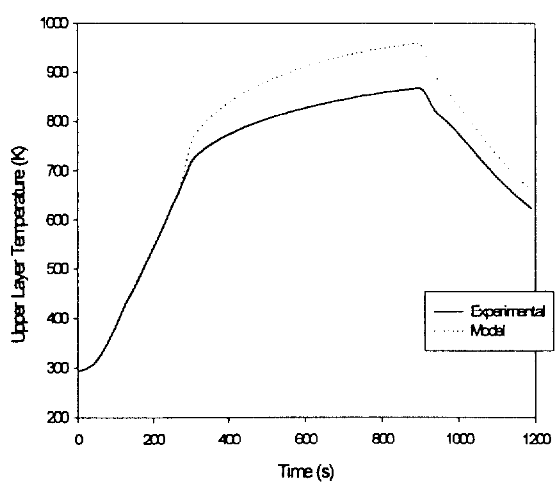

Figure 2

differences in the HRR is the model. In the present framework the two time temperature curves are treated as vectors which allows us to find the relative difference between the two and the lengths of those vectors. The relative difference between the two curves is 0.0857. This means that the length of the difference between the two curves is 8.57% the length of the experimental curve. This metric will allow the determination of the best fit between model and experiment as well as determining which sensor readings are causing the most error.

It is clear that a general method of solving this problem does not meet constraints of reaching a solution in real time. In some cases an enormous number iterations would have to be made before the best fit is established. However if the problem is simplified using knowledge of the physics of a zone fire the problem becomes solvable.

For a simple example consider a single well ventilated room. We can pick a HRR curve that we wish to match using the upper layer temperature of the compartment. A simple procedure gets very close to the actual temperature curve with three model runs is as follows.

Taking a HRR curve of the form

$$at^3 + bt^2 + ct \qquad (3)$$

The values that will be used are 4.6436E-06 for a, 1.2533E-02 for b, and 9.5818E-01 for c. This gives an "experimental" HRR curve to attempt to match. A first guess will be to model the experiment as a medium t-squared fire. Figure 3 shows a comparison of the upper layer temperatures for both the "experiment" and the medium t-squared fire.

To correct the medium t-squared fire HRR to better predictthe upper layer temperature of the

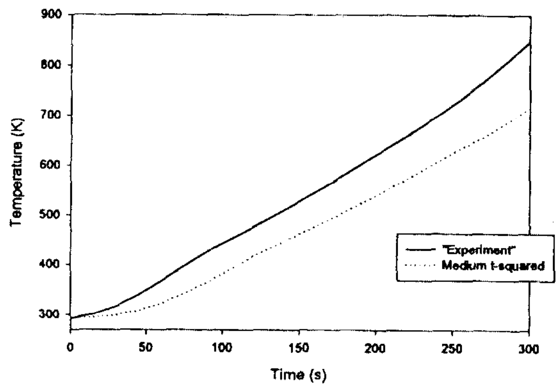

Figure 3

experimental fire, the work of McCaffery, Quintiere, and Harkleroad[10] can be used. They found a correlation between upper layer temperature and HRR using the form.

$$\Delta T_U = c\dot{q}^{2/3} \tag{4}$$

Where ΔT_U is the difference in the upper layer over ambient, $\dot{q}$ is the HRR, and c is the correction due to heat lost to the walls and through the vents. While McCaffery, Quintiere and Harkleroad give the method for calculation of c, for our purposes it is only important that it is independent of HRR and thus constant for a particular building. So using the above correlation gives two equations with four variables.

$$\begin{aligned} \Delta T_{U,E} &= c\dot{q}_E^{2/3} \\ \Delta T_{U,m} &= c\dot{q}_m^{2/3} \end{aligned} \tag{5}$$

Where $\Delta T_{U,E}$ is the upper layer temperature for the "experiment", $\Delta T_{U,m}$ is the upper layer temperature for the model prediction, $\dot{q}_E$ and $\dot{q}_m$ are the HRR for the "experiment" and the model respectively. Since the upper layer temperatures for the "experiment" and the model as well as the HRR for the model are all known,we can solve for the HRR of the "experiment" with the equation

$$\dot{q}_E = \left(\frac{\Delta T_{U,E}}{\Delta T_{U,m}} \dot{q}_m^{2/3} \right)^{3/2} = \left(\frac{\Delta T_{U,E}}{\Delta T_{U,m}} \right)^{3/2} \dot{q}_m \tag{6}$$

Using the above equation we can generate a new HRR curve from the medium t-squared case. Using the new HRR curve we can make a second model run to calculate a new upper layer temperature to compare to the 'measured' upper layer temperature. If the results are not close enough we can continue repeat the process.

Figure 4 shows the "experimental" upper layer temperature with the first three iterations. The relative errors for upper layer temperature for the medium t-squared fire compared to the experiment is approximately 0.134. The first iteration reduces the relative error to 0.029 and the final iteration has a relative error of about 0.009. Figure 5 shows the true HRR used in the "experiment" along with the medium t-squared HRR and the two iterations. Here the relative difference go from 0.338 for the medium t-squared fire to 0.043 for the first iteration to

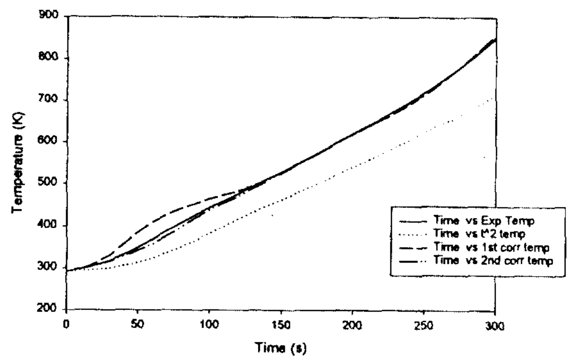

Figure 4

finally 0.01 for the last iteration.

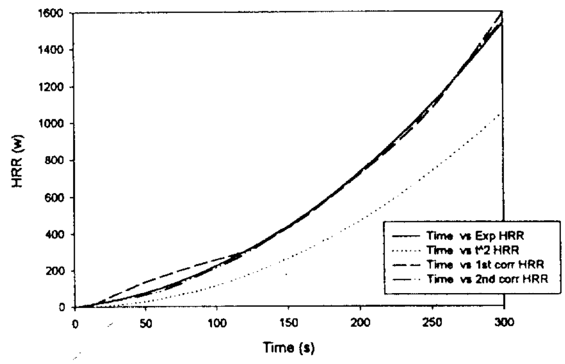

Figure 5

Threat Assessment

The purpose of the adaptive model is to obtain the key characteristics of the fire, primarily the heat release rate (HRR). HRR is widely recognized as the key indicator of the level of threat represented by a fire to occupants, contents, and structure[11]. If the threat posed by a fire can be assessed, it is possible to determine the most appropriate response to that threat.

Fire brigades in the U.S. report ever increasing budgetary pressures. Resources are becoming scarce and more efficient use of these scarce resources are becoming crucial. If a system can report to the fire brigade at dispatch, that the fire has a HRR that is relatively low and is growing slowly, a limited response might be mounted. Alternatively, if the HRR is high and rapidly growing toward flashover, additional units might be dispatched earlier. Such a system could provide a significant improvement in the efficiency of fire brigade operations and improve safety of fire fighters by assuring sufficient people to address the specific situation.

Decision Algorithms

Another important purpose of incorporating the model with sensor information is to provide an underlying knowledge of fire that can be used to make better alarm decisions. Here the sensor signals can be evaluated as to whether they are consistent with the physical laws of fire phenomena so that alarm decisions do not require prior experience as do the correlational approaches discussed previously.

Work on multi-mode sensors by Milke [8] and by Gottuk and Williams[12] have shown that simple consistency criteria such as looking for a simultaneous rise in both smoke and CO or CO_2 can substantially improve nuisance alarm discrimination, but does not completely eliminate the problem. The embedded model can provide opportunities for far more detailed consistency tests.

For example, soot yield fractions for specific fuels are relatively constant under fully ventilated conditions. Thus there should be a constant relation between the soot production rate and the HRR while the oxygen concentrations are above about 12% or while the CO/CO_2 ratio is low. Where smoke, gas, and thermal sensor signals are processed through the adaptive model these criteria can be applied to discriminate against non-fire sources that do not demonstrate this phenomenological consistency.

In more sensor rich environments it should be possible to use information from a range of building systems to make decisions. The classical fire signatures of heat, particulates, and gas species could be augmented by pressures, flows, and other conditions produced in spaces containing fire. The more parameters observed that are consistent with the occurrence of fire, the higher the confidence that a fire condition exists. The assignment of a confidence level (low, moderate, or high) to an alarm could be useful information where uncertainties are of concern.

Concluding Remarks

Clearly, the reliability and accuracy of alarm decisions can be improved by increasing the information basis for these decisions. Current correlational methods provide improvements in system performance but may not be able to discriminate against nuisance signals not previously encountered. Modern predictive fire models may be able to impart to systems a sufficient understanding of fire phenomenology that they will be able to make correct interpretation of conditions not previously encountered. Several, major steps will need to be taken for the embedding of an adaptive model into a fire alarm system can be accomplished. NIST is working with a consortium of industry and users toward a proof of concept demonstration within the next year. If this is successful, it should open up an entire new line of research in signal processing and interpretation.

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