

## **DISCRIMINATION OF IN-ORDINAL STATE IN ROOM TEMPERATURE BASED ON STATISTICAL ANALYSIS**

Ken-ichi Takanashi, Daisuke Kozeki, Yoshiyuki Matsubara

National Research Institute of Fire and Disaster, JP

### **ABSTRACT**

In this paper, an approach to determine the in-ordinal condition of a room, which is based on multi variable analysis, is proposed. According to this approach, the distance of a state from the ordinal condition is thought to be evaluated by the Mahalanobis' distance. The temperature changes of a room were measured and their statistical characteristics such as distribution type, the mean value and the standard deviation are studied. The applicability of the method for the fire detection is also investigated.

### **INTRODUCTION**

In the research works to improve fire detection systems, two antithetical aims are required. That is, to raise the sensitivity and to reduce the false alarm. If we could develop an odor sensor which can detect a burnt smell, it may enable us to dramatically improve the fire detection systems. The availability of such sensors, however, is quite low for the present. Hence, we offer an improvement in the algorithm of fire detecting system based on existing types of sensors.

Almost all of the fire detecting devices currently in practical use, such as the rate of rise detectors, the fixed-temperature type detectors and the smoke detectors, use a simple logic that they respond when the detection element reaches a predetermined value. In the case of these type of fire detector, some threshold values should be determined and set prior to their installation. Although there exist some newly developed so called smart fire detectors[1][2][3], which utilize the Artificial Intelligence (AI) technology, their logic should be determined and installed in advance, and so, these are also classified into a predetermined logic base system.

In anyway, all of fire detection systems now in use are such systems that respond not to the anomalous situation for a room where the system is installed, but to predetermined anomalous situations. As is easily guess, low threshold gives high sensitivity and frequent false alarms. On the contrary, high threshold value can reduce the number of false alarms, but it delays the time for detection and sometimes causes the missing of fire. The algorithm to determine the appropriate threshold value is an essential issue for the improvement of the fire detector.

We concluded that one of the fundamental defects of existing fire detection algorithm is that they use threshold values which are adoptable for many conditions of rooms. As is illustrated in Fig. 1, the boundary of the normal situation for both room A and room B becomes wider than that only for room A. The condition, with which no false alarms will not experienced for variety of rooms, have to be loose one and can not be specialized to the particular room where the detector is installed. On the other hand, in the case of the rooms where the temperature and/or smoke density tend to be higher than ordinarily assumed environment, the fire detector tuned for standard rooms gives frequent false alarms.

If we adopt a system in which each fire detector has a threshold suitable for the room where it is installed, such system is of great advantage to the existing fire detectors.

In the first part of this paper, we would like to propose an algorithm by which a fire detector learns its environment and determines its threshold after it is installed.

According to this algorithm, the detector stores the past data for some period, and will determine a suitable

threshold for the environment based on the statistical theory. This algorithm also enables us to give enough flexibility to the fire detection system to adapt themselves to the change in environmental condition such as seasonal one.

In the latter part, we would like to present the result of our continuous observation of room temperature for maximum of 3 weeks, and of a statistic analysis of data to ensure the adaptability of the algorithm.

### DISCRIMINATION OF ABNORMAL AND NORMAL

It is quite a challengeable issue to distinguish Abnormal states from normal ones. It is reasonable if one decides a state as anomalous when the probability of the occurrence is very small. Even when the state is not caused by a real fire, in most cases it is worth being reported for the manager of the room. Hence, we offer an algorithm for the decision of anomalous state after statistical theory.

Statistical theory says that the probability  $P(x_0)$  when the valuable  $x$  exceeds  $x_0$  is estimated by the following formula, when the distribution obeys the Normal distribution[4].

$$P(x_0) = \frac{1}{\sqrt{2\pi}\sigma} \int_{x_0}^{\infty} \exp\left(-\frac{(x-m)^2}{2\sigma^2}\right) dx \quad \dots\dots (1)$$

Where,  $m$  is the mean value and  $\sigma$  is the standard deviation of the distribution.

Table 1 gives some figures calculated by this formula, and this table says that the probability when the deviation of  $x$  from the mean exceeds  $3\sigma$  is as small as 0.18%. If the distribution can be assumed the Normal one, when one knows the mean value and the standard deviation, the probability of the state when the valuable  $x$  exceed the threshold  $x_0$  can be obtained by the same calculation. In another word, if one define the abnormal state by the measure of the probability

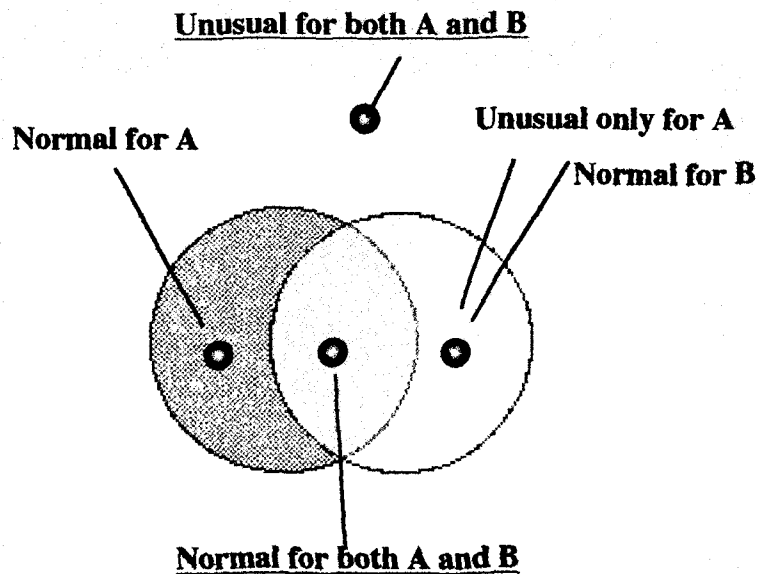


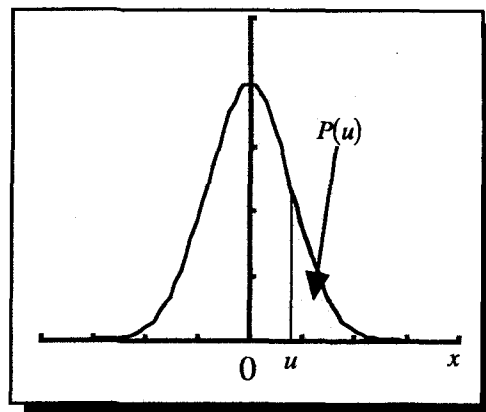
Fig. 1 Normal and unusual state regions for room A and B

which can be regarded as being rare enough, or anomalous, you could find appropriate threshold value for the discrimination from this procedure.

**Table 1 Upper Probability Integrals of the Normal Distribution**

$u$	$P(u)$	$u$	$P(u)$
1	0.158655	6	0.0 <sup>9</sup> 986588
2	0.0227501	7	0.0 <sup>11</sup> 127981
3	0.0 <sup>2</sup> 134960	8	0.0 <sup>15</sup> 622096
4	0.0 <sup>4</sup> 316712	9	0.0 <sup>18</sup> 112859
5	0.0 <sup>6</sup> 286652	10	0.0 <sup>23</sup> 761985

$$P(u) = \int_u^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$



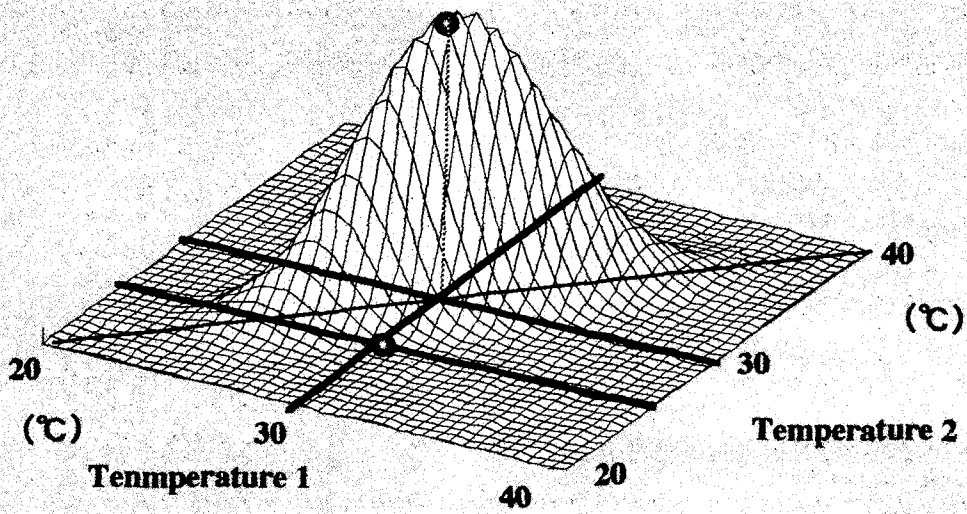
According to the characteristics of the normal distribution, the deviation from the mean value can be normalized by the standard deviation. This normalized deviation can be treated as a normalized distance from the mean which represent the rareness. This procedure is known as the discriminant analysis by the statistical theory. We can extend this normalized distance for 1 dimensional distribution to multi valuable distribution and get the Mahalanobis' distance  $D$  given by the following formula.

$$D^2 = (\mathbf{x} - \mathbf{m})^T \mathbf{S}^{-1} (\mathbf{x} - \mathbf{m}) \dots\dots (2)$$

where,  $\mathbf{S}$  is the covariance matrix,  $\mathbf{x}$  is the valuable vector and  $\mathbf{m}$  is the mean vector.

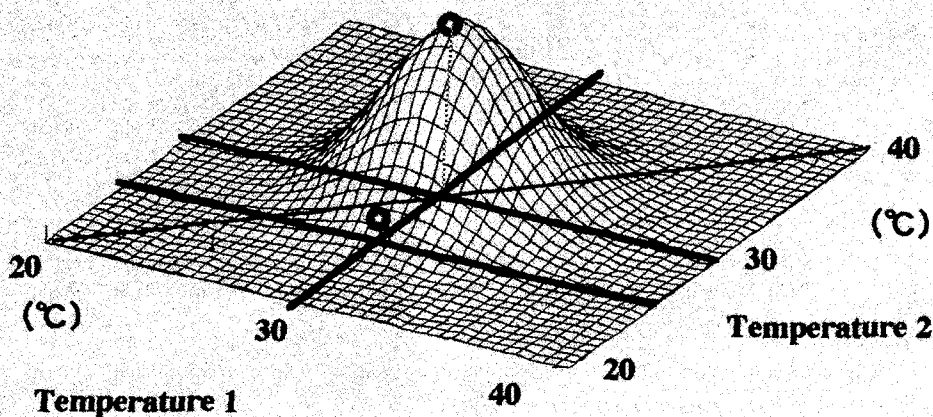
This Mahalanobis' distance takes the correlation between valuables into account. Rooms of a company are often air-conditioned with one central equipment and hence the temperature of rooms show a strong correlation to each other. Fig. 2(a) shows an example of frequency distribution of temperature observed at two rooms with strong correlation, and Fig. 2(b) shows an example for weak correlation. For the case of Fig. 2(a), it is reasonable to decide 25°C of temperature1 anomalous when temperature2 is 30°C. On the contrary, for the case of Fig. 2(b), the same situation should be regarded as normal. As is shown here, when the observed valuable have some mutual correlation, by taking these correlation into account, it becomes possible to distinguish anomalous state from normal one better. To calculate this Mahalanobis' distance for given situation, all what required are the mean values and the covariances, and these values can be derived from temperature or other stored data.

Moreover, if we limit the period of time long enough for the data to be statistically stable, and short enough for the system to adopt itself to the environment change, this algorithm enable us to construct a self learning flexible fire detector.



a correlation coefficient  $r=0.8$

(a) strong correlation



a correlation coefficient  $r=0$

(b) weak correlation

**Fig. 2 Ordinates of 2 variables Normal Distribution**

### STATISTICAL CHARACTERISTIC OF ROOM TEMPERATURE

As proposed in the previous section, when the observed valuables obey the normal distribution, the Mahalanobis' distance can be used as a measure to distinguish abnormal situation from normal one. The issue left to be solved is the statistical properties of the valuables obtained by sensors now in use, such as temperature, rate of temperature change, smoke density and so on. To clarify this issue, we have conducted continuous measurements of temperature in two rooms, one of which(room A) was not air-conditioned and the other(room B) was. The CA thermocouples were installed beneath the ceiling, and measured data were stored on a micro-computer. Fig. 3 is a time course of temperature in the room A, and period of the measurement was 9days. The room A wa

2.4m in height, 3.5m in width and 2.6m in depth. There was no one staying in this room, and air conditioner has been turned off.

The cyclic ups and downs in temperature clearly appears day by day. You can see the frequency polygon of temperature in Fig. 4.

The solid line in the figure represents a normal distribution whose mean and standard deviation are adjusted to the measured temperature. This figure indicate that the temperature of a room without air-condition can be roughly assumed to obey the normal distribution.

Fig. 5 is a frequency polygon of the rate of temperature change in the room A, and the solid line in the figure represents

the normal distribution, whose mean value and standard deviation are equal to the observed temperature change. As is shown in Fig. 5, the rate of temperature change concentrate on the

region around the mean value when compared with the normal distribution. However, from a view point of the rough estimation of the probability of appearance for right edge of the distribution, this frequency polygon can also be treated as the normal distribution.

Fig. 6 shows the time course of temperature in the room B, which was air conditioned. The period of measurement was 21days. During the daytime, this room was used as an office for 2 or 3 workers. The room was 2.6m in height, 5.6m in width and 11m in depth. This figure clearly shows the effect of the air-conditioner on room temperature during daytime, and this type of temperature

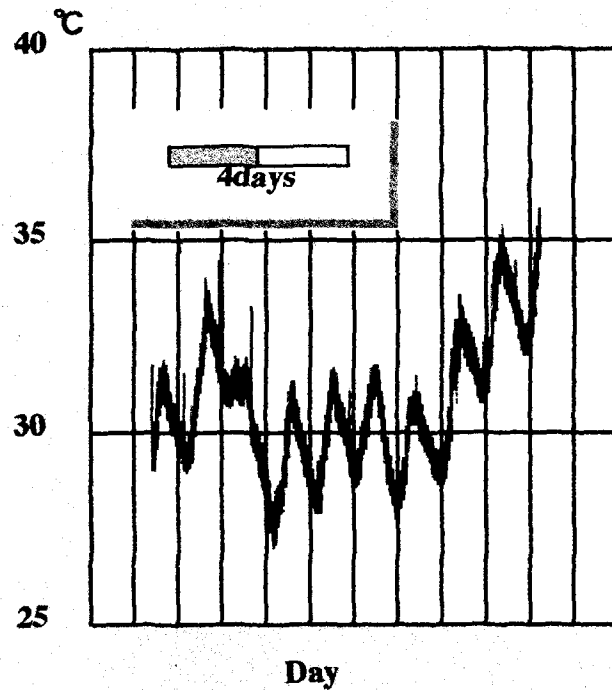


Fig. 3 Temperature history of room A

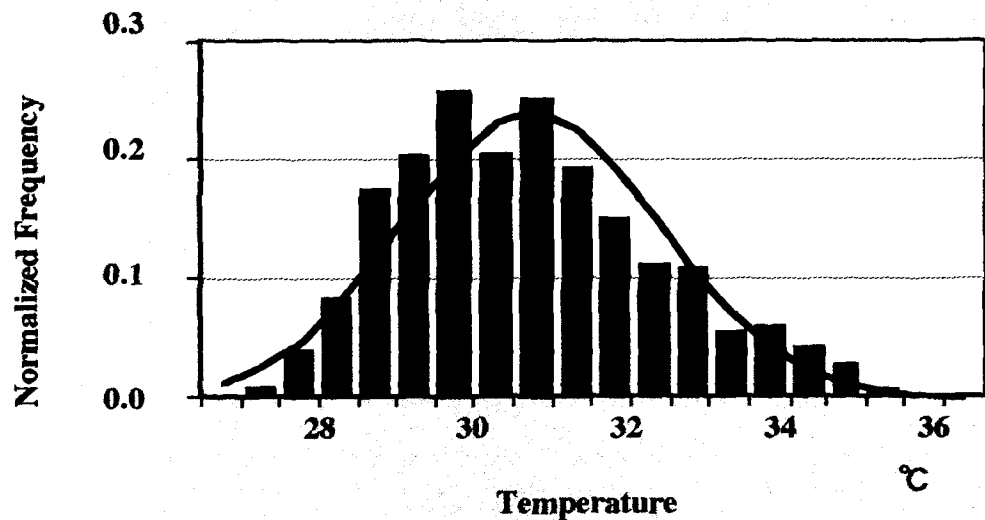
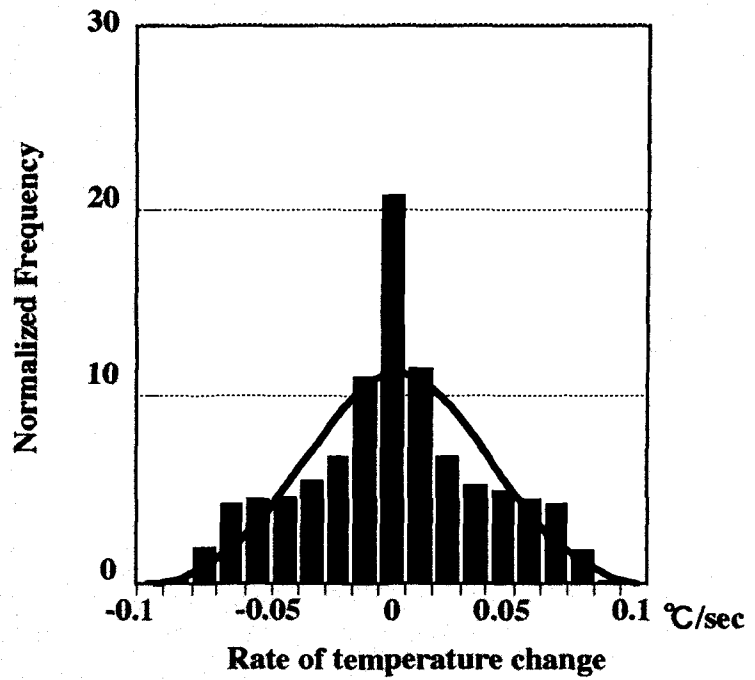
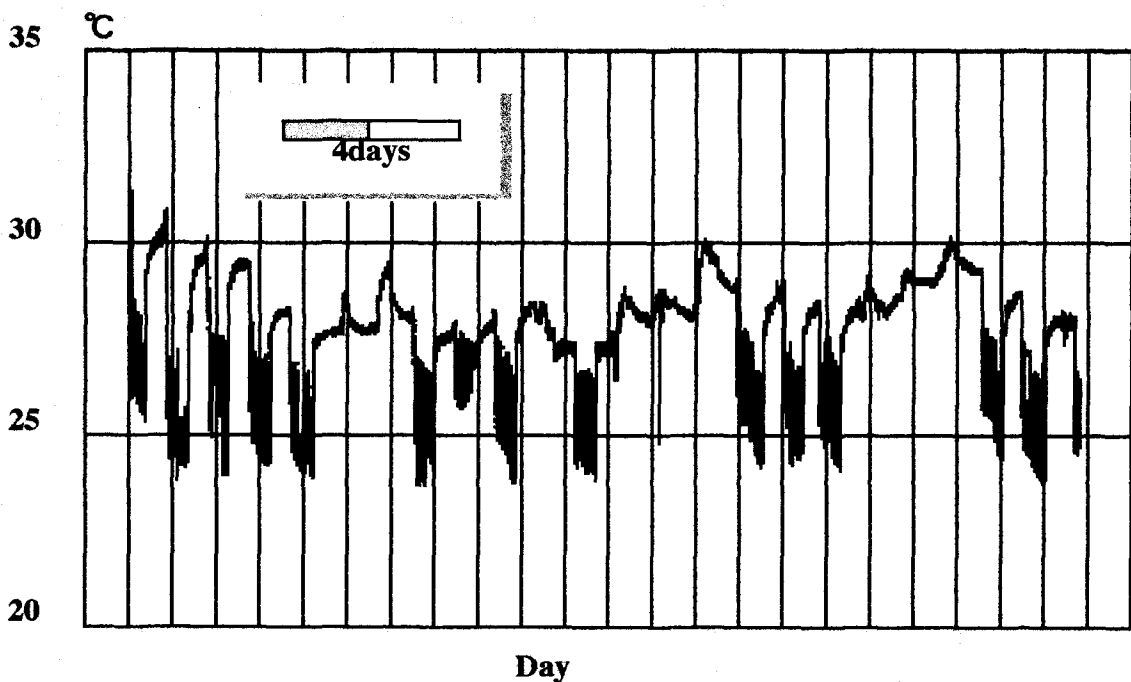


Fig. 4 Frequency polygon of temperature in Room A

profile may be common in the real offices. Fig. 7 is the frequency polygon of the temperature shown in figure 6, and figure 8 shows the polygon of the rate of temperature change for the same data. In these figures the solid lines represent the normal distributions. The distinctive feature of these data obtained in the air-conditioned room is the existence of 2 peaks in Fig.7. As for the frequency polygon of the room temperature, the probability based on the normal distribution gives an overestimation for high temperature region. However, it offers an conservative decision for the anomalous state. As for the polygon of the rate of temperature change, the figure says that this distribution can be treated as the normal distribution for the purpose mentioned.



**Fig. 5 Frequency Polygon of the rate of temperature change in room A**



**Fig. 6 Temperature history of room B**

**DISCUSSION**

When a figure of 0.000000287 is acceptable for the probability of false alarms, we can take the threshold of  $m + 5\sigma$ , according to Table 1. For the room A, this deviation corresponds to 38.9°C in temperature, and 0.17°C/sec in rate of temperature rise. For the room B, the deviation of  $5\sigma$

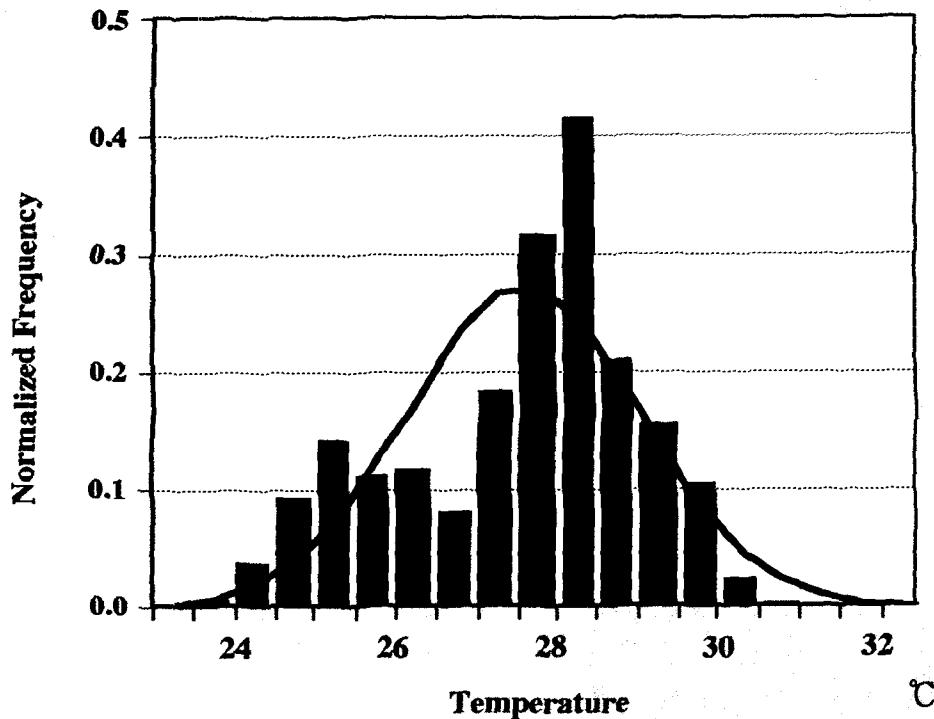


Fig. 7 Frequency polygon of temperature in Room B

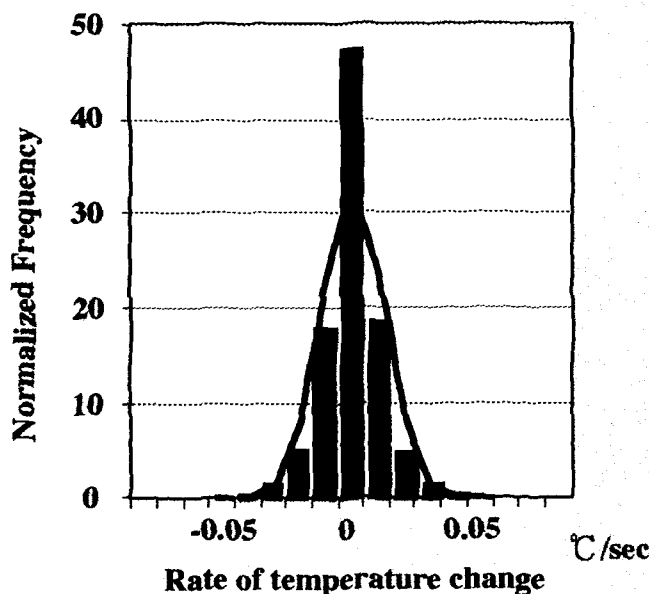


Fig. 8 Frequency Polygon of the rate of temperature change in room B

corresponds to 34.8 °C in temperature, and 0.06°C/sec in rate of temperature rise. The same procedure is applicable to decide a threshold value corresponds to given probability of false alarm, and data obtained on site can be used for a set of normal condition because the probability to meet a fire is as small as  $10^{-3}$  (fire/year\* house) for a house [5].

Based on the mean and the standard deviation for each room, thresholds for the room are derived through simple arithmetic calculation. If the period of the data correction is short, the number of data is too small for the statistical treatment. However, by limiting the period and revising the statistical parameters periodically, we can give adaptability to the system. Such system can adapt itself to a change after its installation, such changes like the seasonal change, change of uses and so on.

The determination of appropriate time period for the data storage is left for further discussion. Although the algorithm is extendable to multi-valuable

treatment as explained in the previous part of this paper, the selection of the combinations is another issue left for discussion. Recent trend that various types of fire detectors with multiple sensors are coming in use gives an insight that combination between smoke, temperature and the rate of their change might be hopeful. The combination of data from several rooms can be another selection.

## CONCLUSION

First of all, we present an algorithm of discrimination of anomalous situation based on the statistical theory. The major difference of this idea presented here from existing similar proposals[6],[7] is the usage of the last data of limited past period which will be obtained on-site, and this gives a flexibility to the decision system. And then, we presented the experimental results to clarify the adoptability of this algorithm. We studied statistical characteristics of the temperature gathered in rooms with and without air-conditioning and showed that the temperature and their rate of change can be treated as the normal distribution as an approximation for the both cases. Some issues such as the determination of appropriate storage period, and of the combination of data, are left for the future discussion.

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