Fire Detection System by Multi-Layered Neural Network with Delay Circuit

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ABSTRACT

To recognize a fire, a person usually considers all information he can obtain such as the size of flame, the amount of smoke generated by the source, the location of flammable materials and other related conditions. The criteria for recognizing a fire are unclear and vary from person to person but human judgment is generally correct. This paper describes a fire detection system which uses a multi-layered neural network, which has been considered effective in recognizing and judging a situation with obscure factors such as a fire. This system uses the output of three different sensors: temperature, smoke and gas, and processes their output data to obtain information about the fire source, such as the heat release rate and the generation rate of smoke and gas. The real time data values and the previously collected data are then applied to a multi-layer neural network to obtain judgments about the state of the fire. After intensive studies, a new type of fire detection system has been achieved, which can not only form a proper analysis of gradually spreading fires but can also resolve one of the existing problems, false alarms caused by transient inputs, by identifying then suppressing them.

KEYWORDS: Fire detection, fire alarm system, false alarm, neural network.

INTRODUCTION

When a person sees and recognizes a fire, the criteria include the size of the origin, the degree of flame spread, and the environmental conditions. These criteria are unclear and vary from person to person because they may depend on that person's experience and impressions made by various types of information. However, most people can handle those types of information properly and form a judgment which is generally correct. We have directed our attention to a neural network, which is an information processing system similar to the human judgment mechanism and has been considered effective in recognizing and judging a situation with "fluctuating" and "obscure" factors. If fire recognition were performed in a similar manner to that of humans by the neural network, false alarms would be reduced.

Neural networks are roughly classified into two types: multi-layered and interconnecting. Since real-time processing is desirable for fire analysis, we have adopted a multi-layered network which has a simple structure and can be modified through training signals at any time. However, incorporation of this multi-layered neural network alone has little effect in identifying the effect of transient inputs (N.B. caused by cigarette smoke) which may cause false alarms in existing fire detection systems. To resolve this problem, we have arranged the input layer of the neural network to form a delay circuit enabling to include previously collected data as inputs. This type of approach was found successful as described hereafter.

SYSTEM CONSIDERATION

For fire judgment, a person may perform multivariate analysis of physical and chemical phenomena caused by a fire with his all senses. Thus, an intelligent fire alarm system should be based on multivariate measurement utilizing the outputs of different sensors. It is also important to note that people generally consider the condition of the fire source and its environment directly. Information such as the temperature and the smoke concentration near the ceiling is rather less important than the size of flame and the smoke generation rate. Thus, the information obtained by the ceiling mounted sensors should be converted to the parameters representing the conditions of the fire source itself[1-5]. In addition, some routines should be added which forms a judgment which closely resembles the process humans follow during information processing.

Fig. 1 shows a block diagram of the fire detection system used in this study. The outputs obtained from the sensors are temperature T, extinction coefficient μ_{sp}, and gas concentration G_p. To obtain the source information, a mathematical fire model ASET-B is used, which is a

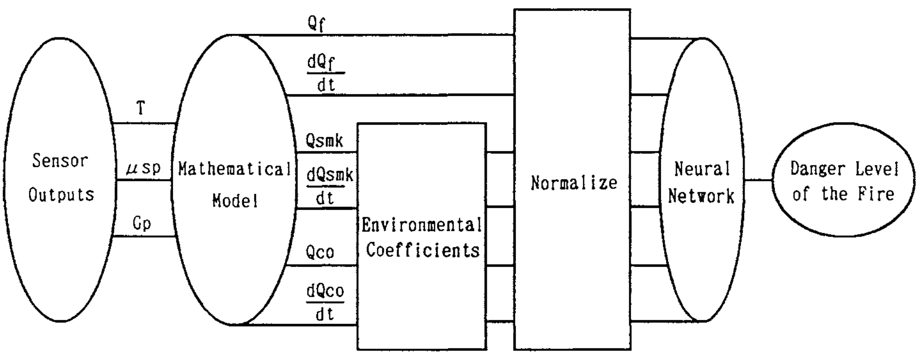

FIGURE 1 Block diagram of fire detection system.

simple zone model to calculate the averaged values for temperature, smoke concentration and gas concentration near the ceiling using as input the fire source conditions such as the heat release rate, smoke generation rate and gas generation rate[6-8]. In our system, this model is used in 'reverse' to obtain the source information of heat release rate (Q_f), smoke generation rate (Q_{smk}), and gas generation rate (Q_{co}) from the corresponding sensor outputs. The temporal differentials dQ_f/dt, dQ_{smk}/dt, and dQ_{co}/dt are also calculated. These quantities are then normalized with the respective predetermined normalization coefficients. These normalized quantities are then applied to the neural network. It should be noted that the normalization coefficients should be determined by how the room is used, since human judgment concerning these quantities is generally different. Finally, the neutral network outputs the danger level of the fire.

MODEL FIRE EXPERIMENTS

Materials and method

In order to analyze the human criteria of the judgment, a series of model fire experiments have been made. The size of the test room was 6.26 m (L) x 10.12 m (W) x 3 m (H). Temperature, smoke, and gas sensors were installed on the ceiling with 1 m horizontal distance from the center. A C-A (chromel-alumel) thermocouple was used as the temperature sensor, an extension-type smoke density meter was used as the smoke sensor and a semiconductor (SnO_2) gas sensor was used for gas concentration measurement. This gas sensor is sensitive to CO gas which may be the most harmful to humans amongst the various gases generated from combustion.

Real fires may start in a variety of conditions, thus the combustion materials for the experiments were selected to produce conditions as similar as possible to those of real ones. As typical liquid fuels, normal heptane and ethanol were used. Wood was used to produce a flaming fire and a smoldering fire. The shape and weight of these combustion materials and the method of ignition conformed to appropriate ISO standards or EN standards for testing fire detection systems. In addition to these standard materials, curtains, fusumas (Japanese papered sliding doors), and chairs were used to attempt to produce fires like those actually observed in a real situation. Moreover, smoking cigarettes, fish and chicken being grilled with a gas cooker, a kerosene heater and a gas heater, were used to produce false alarm conditions. The position of the source in every case was at the center of the test room.

Human judgment of fire

Judgment by sight

As mentioned previously, the human criteria used to judge whether the situation is dangerous or not may include the size of the fire source, the degree of the flame spread, and other environmental conditions. In order to find how these criteria are related to actual parameters such as the heat release rate and the smoke generation rate, some view tests were conducted.

13 males aged 21 to 24 years were used as the test subjects of the view test. During the view test, the test subjects were asked to form a judgment when they thought the situation was

dangerous, while observing the changing conditions of the fire sources. During the initial stage of the test fire, the percentage of test subjects who thought the situation was dangerous is small, but the percentage gradually increased as the fire source developed with an increasing heat release rate and smoke generation rate. By plotting this percentage with the quantities of actual parameters such as the heat release rate, a logistic curve can be obtained showing at about what quantity a person usually think that the situation has become dangerous. Similar experiments were repeated to obtain similar logistic curves for smoke generation rate and CO gas generation rate. It should be noted here that any generated CO gas cannot be seen with human eyes, so the correlation has been made assuming that human judgment of the CO gas is similar to that of smoke.

It is expected that not only the actual quantities of the source parameters such as the heat release rate but also their temporal differentials are important in the human judgment, because people may judge the situation more dangerous when they see a fire quickly spreading than when they see a slowly spreading fire. Thus similar correlation has been made with the temporal differentials of the above mentioned three parameters.

The logistic curves thus obtained for the six parameters -- the heat release rate, smoke generation rate, gas generation rate, and their temporal differentials -- were then used to obtain the lesson signal for the neural network, which is described in more detail in the latter section.

Normalization

Further adjustment is needed to the above mentioned parameters, because the actual quantities handled by the neural network are not the actual values of the fire parameters but the logistic values between 0 to 1.0. To normalize each quantity and its differential form, therefore, data collected from the numerous fire and non-fire experiments previously made were used.

Fig. 2 shows two examples of the normalization factors: (a) heat release rate, (b) differential

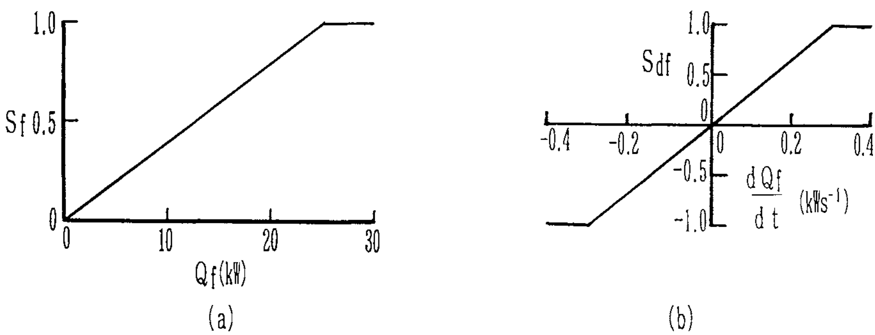

FIGURE 2 Normalization of quantities and their differential forms: (a) Heat release rate; (b) Differential of heat release rate.

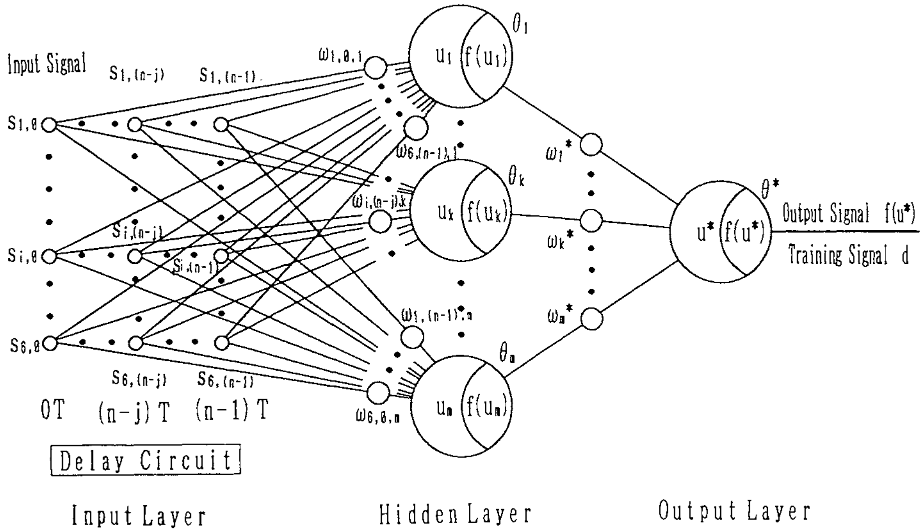

FIGURE 3 Neural network with delay circuit.

of heat release rate. The maximum values of the normalization factor S_f, S_{smk}, and S_{co} corresponding respectively to the quantities of generated heat, smoke, and CO gas were 25 kW, 0.2 $g \cdot s^{-1}$, and 2.5 $g \cdot s^{-1}$. The maximum values of the normalization factor S_{df}, S_{dsmk}, and S_{dco} used for the differential forms were 0.3 $kW \cdot s^{-1}$, 3.0 $mg \cdot s^{-2}$, and 19 $mg \cdot s^{-2}$, respectively. To represent the degree of decrease in each quantity a negative value is also used for normalization.

Neural Network Design

<u>Multi-layered Neural Network Incorporating a Concept of "Time"</u>

Fig. 3 shows a multi-layered neural network incorporating a concept of "time". This network consists of three layers: an input layer with 6 × n units, a hidden layer with m units, and an output layer with 1 unit.

The vertical axis of the input layer shows 6 different input signals corresponding to the actual quantities and their time differential forms. The horizontal axis of the input layer shows the time of the delay circuit, which is a product of the unit delay time T and the delay count (n-j). For example, $S_{1,(n-j)}$ through $S_{6,(n-j)}$ correspond to the quantities and their time differential forms obtained (n-j)T seconds before the current time.

Assuming that a set of input signals were applied at a certain point in time. The k'th unit has an internal condition u_k in the hidden layer and the output has a condition $f(u_k)$ as represented by the following expressions (1) and (2), respectively:

$$u_k = \sum_{i=1}^{6}\sum_{j=1}^{n} S_{i,(n-j)} \cdot \omega_{i,(n-j),k}, \tag{1}$$

$$f(u_k) = \frac{1}{1+\exp(-u_k + \theta_k)}, \tag{2}$$

where $\omega_{i,(n-j),k}$ is the weight coefficient of the paths between the input and hidden layers and θ_k is the threshold for the hidden layer units.

The output layer has an internal condition u^* and an output $f(u^*)$ represented by the following expressions (3) and (4), respectively:

$$u^* = \sum_{k=1}^{m} f(u_k) \cdot \omega_k^*, \tag{3}$$

$$f(u^*) = \frac{1}{1+\exp(-u^* + \theta^*)}, \tag{4}$$

where ω_k^* is the weight coefficient of the paths between the hidden and output layers and θ^* is the threshold for the output layer unit.

For optimizing the weight coefficients, a commonly used technique, the back-propagation method[9], was applied.

Lessons Given to the Neural Network

The characteristic of the neural network is generally modified through a repetition of lessons of similar patterns. However, since each fire has its own process, no two fires have the same pattern. The lessons used in this study are the sets fire data which varies with time and the lessons were done as such that each set of data applied at each sample timing is a separate lesson. More specifically, the values of the weight coefficient shown in Fig. 5 are corrected with the back-propagation method at each timing when the h'th combination of an input signal $S_{i,(n-j)}$ and a training signal d is applied. The values of the weight coefficient ω and the threshold θ are corrected to minimize the value of the error function E, defined as follows with the difference between the values of the training signal $d^{(h)}$ and the output signal $f(u^{(h)*})$:

$$E = \frac{1}{2}\sum_{h=1}^{p}\left\{d^{(h)} - f\left(u^{(h)*}\right)\right\}^2, \tag{5}$$

where p is the number of combinations of the input signal $S_{i,(n-j)}$ and the training signal d.

Now the error signal $\delta^{(h)*}$ can be expressed as follows:

$$\delta^{(h)*} = \frac{\partial E^{(h)}}{\partial u^{(h)*}}. \tag{6}$$

Then the correction value $\Delta\omega^{(h)}{}_k{}^*$ for the weight coefficient $\omega^{(h)}{}_k{}^*$ can be calculated by the following equation:

$$\Delta\omega^{(h)}{}_k{}^*=\eta\cdot\frac{\partial E^{(h)}}{\partial\omega^{(h)}{}_k{}^*}+\alpha\cdot\Delta\omega^{(h-1)}{}_k{}^*=\eta\cdot\delta^{(h)*}\cdot f\left(u^{(h)}{}_k\right)+\alpha\cdot\Delta\omega^{(h-1)}{}_k{}^*, \tag{7}$$

where η is a lesson constant and α is a convergence constant. This means that the error signal $\delta^{(h)*}$ of the output layer is inversely transferred to the hidden layer through $\Delta\omega^{(h-1)}{}_k{}^*$ of the previous combination (h-1).

Accordingly, the corrected weight coefficient $\omega^{(h+1)}{}_k{}^*$ can be expressed as follows:

$$\omega^{(h+1)}{}_k{}^*=\omega^{(h)}{}_k{}^*+\Delta\omega^{(h)}{}_k{}^*. \tag{8}$$

Similarly, the error signal $\delta^{(h)}{}_k$ for the k'th unit in the hidden layer is given by the following expression:

$$\delta^{(h)}{}_k=\frac{\partial E^{(h)}}{\partial u^{(h)}{}_k}=f\left(u^{(h)}{}_k\right)\cdot\left(1-f\left(u^{(h)}{}_k\right)\right)\cdot\delta^{(h)*}\cdot\omega^{(h)}{}_k{}^*, \tag{9}$$

which means the error signal $\delta^{(h)*}$ of the output layer can be inversely transferred to the hidden layer.

Then the correction value $\Delta\omega^{(h)}{}_{i,(n-j),k}$ for the weight coefficient $\omega^{(h)}{}_{i,(n-j),k}$ between the input and hidden layers can be given by the following expression:

$$\begin{aligned}\Delta\omega^{(h)}{}_{i,(n-j),k}&=\eta\cdot\frac{\partial E^{(h)}}{\partial\omega^{(h)}{}_{i,(n-j),k}}+\alpha\cdot\Delta\omega^{(h-1)}{}_{i,(n-j),k},\\&=\eta\cdot\delta^{(h)}{}_k\cdot S^{(h)}{}_{i,(n-j)}+\alpha\cdot\Delta\omega^{(h-1)}{}_{i,(n-j),k},\end{aligned} \tag{10}$$

which means that the error signal $\delta^{(h)}{}_k$ of the hidden layer was inversely transferred to the input layer.

Accordingly, the corrected weight coefficient $\omega^{(h+1)}{}_{i,(n-j),k}$ can be expressed as follows:

$$\omega^{(h+1)}{}_{i,(n-j),k}=\omega^{(h)}{}_{i,(n-j),k}+\Delta\omega^{(h)}{}_{i,(n-j),k}. \tag{11}$$

For a value of h, the weight coefficient is corrected with Eq. (8) with the values for k=1 through m and then corrected again with Eq. (11) with the values for i=1 through 6, j=1 through n, and k=1 through m. Similar correction is also made to the thresholds $\theta^{(h)*}$ and $\theta^{(h)}{}_k$. Completion of these operation through the combinations h=1 through p in time series constitutes a single lesson in our sense, which should be repeated as necessary.

ACTUAL LESSONS GIVEN TO NEURAL NETWORK

Training Signals for Fire and Non-fire Situations

Training signals for fire situations

Actual data of the heat release rate (Q_f), smoke generation rate (Q_{smk}), and CO generation rate (Q_{co}) collected through fire experiments using such as wooden chair, polyurethane foam, cloths and other materials were used as training signals (d) for the fire situations

Fig. 4 shows the burning wooden chair experiment. In this case, the heat release rate $Q_{f,}$, the smoke generation rate Q_{smk} and the CO generation rate were rather small during the initial stage while the seat surface was smoldering. The peak of the smoke generation rate at about 400 second shows the instant when the flame was about to ignite the seat back of the chair. During the initial stage, Q_f shows a small increase at about 150 seconds, and Q_{smk} shows a small increase at about 200 second. The training signal was designed to give a rise to 0.2 and a succeeding fall represent these variations. To match another increase in the quantity Q_{smk} at a point of 380 seconds, the training signal was design to give another rise to 0.2. When the seat back ignited at approximately 420 seconds, Q_f and Q_{smk} showed a steep increase and Q_{co} started to increase with some delay. This stage corresponds to the point in time when the flame had spread to the entire chair. The training signal was set to show a steep rise so that it

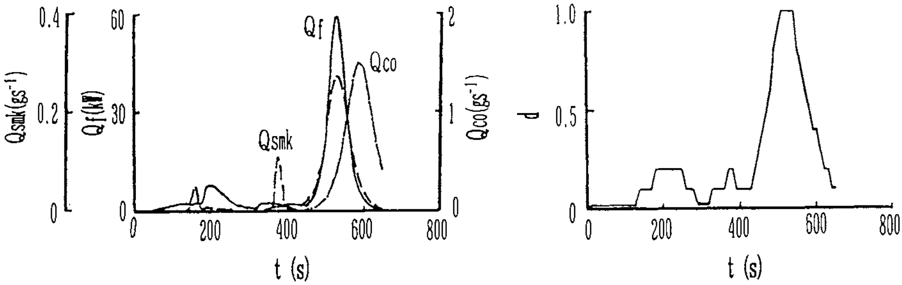

FIGURE 4 Quantities of heat, smoke and CO generated in a fire experiment and the corresponding training signal.

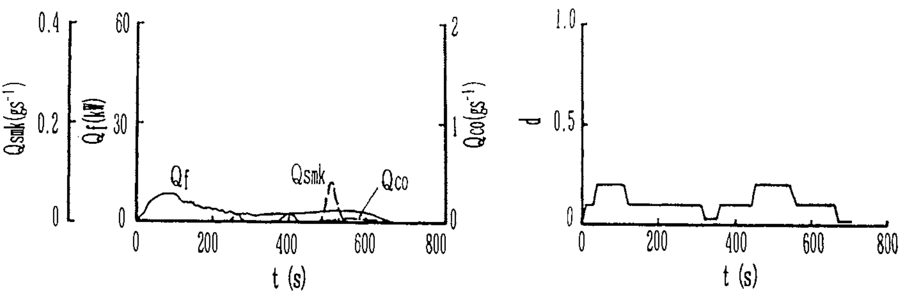

FIGURE 5 Quantities of heat, smoke, and CO generated in a non-fire experiment and the corresponding training signal.

reaches 1.0 after approximately 500 seconds when Q_f reaches approximately 25 kW.

Training signal for non-fire situations

The training signal for non-fire situations was generated with simulated false alarm sources such as grilling of fish over a gas cooker. This kind of situation may usually cause the existing fire alarm systems to give a false alarm because an sufficient amount of smoke is generated. Fig. 5 shows the variation of the three parameters and the training signal designed for this experiment. Q_f shows a peak at about 200 second but keeps rather constant during the whole experiment. The designed training signal has a rise to 0.2 and the succeeding fall to show this stage. Once the fish started to bake, Q_{smk} shows some peaks after 250 seconds. The existing fire alarm systems may give a false alarm at about the point of 507 seconds, but the training signal was designed to give a peak of 0.2 at this stage.

Optimizing Number of Units in the Hidden Layer

With the neural network tuned as above, the effect of parameters such as the number of delay units (n), and the number of hidden layer units (m) were studied. In this study, the unit delay time T of the delay circuit was set as 5 seconds. The number of delay units (n) studied was 5 to 9 (which means 30 to 54 units in the input layer), and the number of hidden layer units (m) studied was 5 to 10. The number of combinations of input and training signals (h) was 45, and the number of lessons applied was up to 1000. In addition, a lesson constant h of 0.25 and a convergence constant a of 0.9 were used.

With 5 hidden layer units (m=5), the deviation curve showed some uncertainty after 300 to 600 lessons had been given. However, when the number of units was more than 6, the deviation curve converged to a certain value with no uncertainty and produced a result that was virtually identical to that with the minimum number (m=5). This means that 6 hidden layer units (m=6) is sufficient to minimize the deviation. Similarly, the deviation curve did not show any considerable difference with the number of delay units more than 6. Thus, with 5 second unit delay time, 6 delay units in the input layer (n=6) and 6 units in the hidden layer (m=6) were considered to be a best combination .

VERIFICATION

$f(u^*)$ for Fire Situations

To test the neural network optimized with the lessons as described above, signals obtained from experimental fires were applied. Fig. 6 shows the variation of Q_f, Q_{smk}, and Q_{co} and the output signal $f(u^*)$ during an experimental curtain fire. All the three parameters began to rise approximately 45 seconds when the lower edge of the curtain was ignited. At approximately 55 seconds, the Q_f exceeded 25 kW, the level which everyone feels is dangerous. Similarly, the quantity Q_{smk} exceeded the threshold 0.2 $g \cdot s^{-1}$ at a point of approximately 67 seconds. With these input signals, the output signal $f(u^*)$ representing the danger level reached 1.0 at approximately 70 seconds indicating that the fire had become dangerous. At approximately 75 seconds when the curtain was burned out but still smoking, the quantity Q_{co} reached approximately 2.6 $g \cdot s^{-1}$ while the quantities Q_f and Q_{smk} decreased to low but non-zero values.

The signal f(u*) remained at 1.0, indicating that the fire was still dangerous. Similar successful results were obtained with other experimental fires such as of liquid fuels and wood.

f(u*) for Non-fire Situations

As a test for non-fire situations, chicken was skewered and grilled over the open flame of a gas cooker. Fig. 7 shows the variation of the three sourse parameters and the output signal f(u*). The quantity Q_f increased slightly to approximately 7 kW after the gas cooker was lit. The quantities Q_{smk} and Q_{co} were slightly increased by smoke and gas generated when the chicken was grilled. The output signal f(u*) showed a slight rise up to approximately 0.23 at the highest. This curve is different from that of the former example of the real fire case, indicating that a discrimination between fire and non-fire situations is possible. Similar results were obtained with other experiments using cigarrette smoke, gas and kerosene heaters.

f(u*) for Transient Inputs

Finally, the non-fire phenomena caused by transient inputs were studied, which may be caused when cigarette smoke is directly blown in to the sensor. Pseudo inputs were used for this investigation.

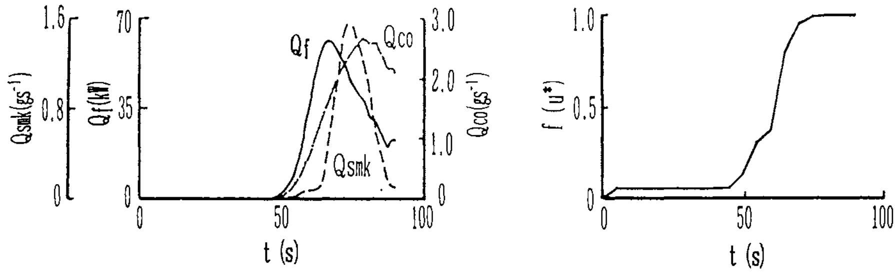

FIGURE 6 Quantities of heat, smoke, and CO and output signal f(u*) of the neural network for a fire situation (a curtain fire).

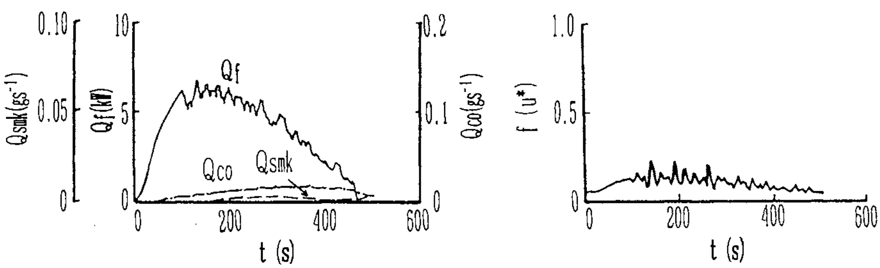

FIGURE 7 Quantities of heat, smoke, and CO and output signal f(u*) of the neural network for a non-fire situation (chicken was grilled on a gas cooker).

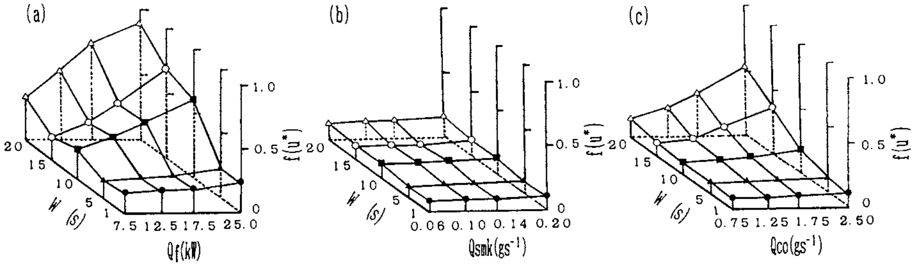

FIGURE 8 Output signal f(u*) of the neural network for transient inputs (each quantity of (a) heat, (b) smoke, or (c) CO is applied seperately).

Fig. 8 shows the variation of the maximum output signal f(u*) with different peak values and pulse width (W) of transient rectangular inputs. Fig. 8 (a), (b) and (c) shows respectively the seperate effect of Q_f, Q_{smk}, and Q_{co}. In the case of Q_f, the effect is rather steep. With the pulse width less than 5 seconds, the output signal f(u*) remains lower than 0.2 showing that f(u*) is suppressed properly. If the pulse width aproaches 20 seconds, however, the value of f(u*) increases up to approximately 0.75 with the peak heat release rate of 17.5 kW. This output is considered approproate, because this heat release rate is comparable to that of normal heptane pool fire of 200 mm pan size.

In Fig. 8 (b) of the Q_{smk} case, in the range of smoke generation rate between 0.06 and 0.2 $g{\cdot}s^{-1}$, the output f(u*) is not become more than 0.2 with the pulse width shorter than 20 seconds. Thus the present system may not give false alarms even though cigarette smoke is directly blown in to the sensor. Fig. 8 (c) shows the case of Q_{co}. The output becomes higher only when a large quantity of CO gas (0.75 to 2.5 $g{\cdot}s^{-1}$) is generated. which is considered to give harmful effect to humans. With rest of the conditions, the output f(u*) remains less than 0.2 indicating the similar suppression effect of the smoke case. The test results shown in Figs. 8 (b) and (c) indicate that the output f(u*) is suppressed properly because these situations may not occur in any real fire situations.

CONCLUSION

A fire detection system incorporating a multi-layered neural network with a concept of "time" has been proposed. After intensive studies on the performance of the system, we found that:

1) The proposed system can make a highly reliable judgment on fire and non-fire situations based on the output f(u*) calculated from the singnals of three different sensors.

2) The neural network with a delay cuicuit, which handles the the previously collected data as well as the actual data obtained from different sensors, can reduce false alarms caused by transient variation of output of a single sensor.

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