One Fire Detection Method Using Neural Networks[*]

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Abstract: A neural network fire detection method was developed using detection information for temperature, smoke density, and CO concentration to determine the probability of three representative fire conditions. The method overcomes the shortcomings of domestic fire alarm systems using single sensor information. Test results show that the identification error rates for fires, smoldering fires, and no fire are less than 5%, which greatly reduces leak-check rates and false alarms. This neural network fire alarm system can fuse a variety of sensor data and improve the ability of systems to adapt in the environment and accurately predict fires, which has great significance for life and property safety.

Key words: fire detection; neural network; multi-sensor information fusion; simulation

Introduction

Fires are chemical and physical processes accompanied by smoke, light, and heat. Fire detection system access fire information and turn this information into electrical signals for processing. Currently, the majority of domestic automatic fire alarm systems use a single passive sensor alarm system, which has some unavoidable problems. For example, some devices using photosensitive detectors are affected by sunlight and lighting. Smoke detectors can be affected by various gases with simple processing systems using threshold algorithms and trend algorithms. These methods and techniques can detect fires in simple situations, but with the increasing number of sensor installations, the false alarm rate based on simple algorithms will be greatly, so alarm systems will then result in many leak-checks or false

fire alarms. Thus, traditional fire detection systems are unable to meet the needs of real fire alarms[1,2].

Fire detection systems abroad are primarily smoke detectors. The false alarm rates, defined as the percentage of alarms with no verified smoke in the cargo compartment are very high. More complex fire detection algorithms used data from sensors for temperature, smoke, and combustion products[3]. Some chemical species included oxygen (O_2), carbon monoxide (CO), carbon dioxide (CO_2), water vapor (H_2O), hydrogen cyanide (HCN), acetylene (C_2H_2), and nitric oxide (NO). Simple fire alarm algorithms are based on thresholds for maximum values, rates of increase, and combinations thereof from multiple sensors. Alarm algorithms based on threshold values are very sensitive to signal offsets (due to background concentration fluctuations or slow drift in the calibration), so they need to be very accurate, and require accurate, frequent calibrations. To remedy some of these deficiencies, threshold values that adapt to changing environmental conditions have been developed based on comparisons between predicted and measured values in a time sliding window[4]. Rates of increase of CO_2 and CO

concentrations have been used to identify flaming and non-flaming fires, with comparisons to a commercial smoke detector[5]. Fire alarm algorithms that use CO and smoke[6] or CO_2 and smoke have reduced nuisance alarms and response times[7]. Ionization and photoelectric detectors, CO and CO_2 sensors using magnitude and slope information, and background subtraction have been used to evaluate a fire alarm algorithm based on a probabilistic neural network[8].

Traditional fire detection systems cannot meet the real needs of complex fire alarm systems. This paper presents a fire detection approach based on neural networks, which uses the fire temperature, smoke concentration, and CO concentration in the initial fire stage as a system input with a neural network simulation model for the fire detection using the self-learning and adaptive features of neural networks with multi-sensor signal fusion and network training and simulation. The method has strong fault tolerance and anti-jamming capability, increases early fire detection capability, and reduces the leak-check rate and false fire alarms which greatly affect safety monitoring.

1   Fire Detection Based on a Neural Network

1.1   Multi-sensor information fusion theory

Since fire information is not structured and quite uncertain, this study uses a neural network to collect temperature and smoke and use data fusion to generate a fire signal decision using the neural network adaptive, self-learning capability.

Thermal detectors, smoke detectors, and gas concentration detectors have continuous analog outputs. When one detector output exceeds the detection limit,
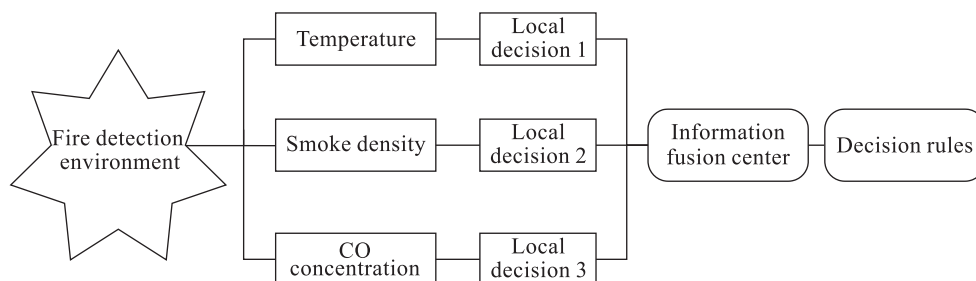
the hardware circuit sends a local fire indication to the system and the environmental characteristics to the information fusion center. When a single detector local fire signal is received, the information fusion center repeatedly queries the system detectors to generate a final decision[9].

The local decision-making systems use single-sensor detection with continuous readings to distinguish fires according to signal rate change exceeding some limit. The set of sampling signals can be given as

$$x(n) = [x_1(n), x_2(n), x_3(n)],$$

where the parameters $x_i(n)$ $(i = 1, 2, 3)$ are the sampled temperature, smoke level, and gas concentration signals. A cumulative function $a_i(m)$ is defined as the margin sum of multiple cumulative adjacent sample values $x_i(n)$.

$$a_i(m) = x_i(n+1) - x_i(n), \quad i = 1, 2, 3, \quad n = 0 \text{ to } m.$$

The local decision-making algorithm then uses

$$u_i = f(a_i(m) - \text{STD}_i),$$

where the function $f(\cdot)$ is a unit step function, u_i are the local decision-making results for the temperature, gas, and smoke signals and $\text{STD}_i (i=1, 2, 3)$ are the alarm thresholds.

Local test results are used to determine the weighting coefficients, w_i, and the decision thresholds STD_i according to statistical knowledge of the various local test signals. The decision function is then

$$U = \sum W_i U_i - \text{STU}.$$

However, the fire information is very uncertain and there are few statistical models of the local detector signals, so the decision criteria cannot be fixed. Thus the model shown in Fig. 1 uses a neural network with a non-linear approximation and self-learning for the data fusion.

Fig. 1   Multi-sensor information fusion detection system

1.2   Network structure

The core of the fire detection method uses intelligent

processing to improve reliability and reduce false alarms[10]. Artificial neural networks are intelligent information processing systems which mimic human

brain functions. The system function depends on the network structure, connection strength, and unit approach. Neural networks can be self-adaptive and self-organizing with strong learning ability and have been successfully used to resolve many complex practical problems in pattern recognition, system identification, signal processing, and forecasting due to these intelligent features[11].

Most existing fire detection artificial neural networks use the BP network. Due to its negative gradient descent method to adjust the weights, this method has some limitations, including slow convergence, long training times, and easily falling into local minimums. Therefore, this analysis uses a radial basis function (RBF) network for the fire detection to improve the fire detection accuracy since the approximation capability, classification ability, and learning speed are better for the RBF network than the BP network. The RBF network structure is shown in Fig. 2[12].
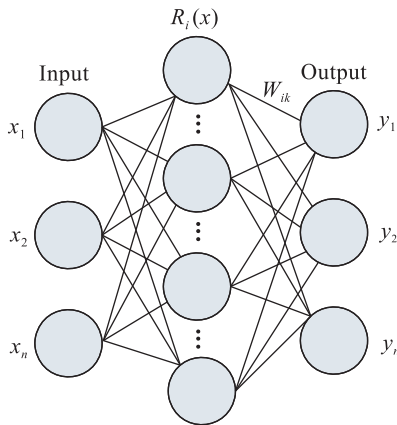
Fig. 2   RBF network structure

In an RBF network the input nodes only pass the input signal to the hidden layer. The hidden layer nodes are then made of functions like the radial Gaussian function. The role of the hidden nodes (basis functions) is to generate the local response to the input signal using local approximations. The output layer nodes simply use linear functions[12]. When the input signal is close to the central range of the basis function, the hidden layer nodes will have a greater output. Thus, the RBF network has the capacity of local approximation, also known as a local sensing field network.

1.3   Learning algorithm

The network model uses a two-phase hybrid learning algorithm. The first phase uses unsupervised self-organizing learning using the K-means clustering algorithm to cluster the radial basis function nodes in the hidden layer to determine the appropriate data center and the expansion rate of the hidden nodes based on the distance between centers. The second phase uses supervised learning to train the output layer weights using the gradient method[11].

Before the clustering determines the data center locations, the number of the centers (M) which are generally decided through experiments must be estimated to determine the number of hidden nodes. Since the data center which gets through the cluster is not the sample data X^p itself, then $c(k)$ is the center of the k-th iteration. The K-means clustering algorithm is used to determine the data center.

(1) Initialization. Select M different vectors as the initial cluster centers: $c_1(0), c_2(0), \cdots, c_M(0)$.

(2) Calculate the Euclidean distance between the input sample points and the clustering center,
$$\|X^p - c_j(k)\|, p = 1, 2, \cdots, P; j = 1, 2, \cdots, M.$$

(3) Similarity match. j^* is the subscript of the hidden nodes competing to win. The classification $j^*(X^p)$ of each input sample X^p is determined by the minimum Euclidean distance from the cluster center, that is, when $j^*(X^p) = \min\limits_{j} \|X_p - c_j(k)\|, \ p = 1, 2, \cdots, p$.

X^p is classified as j^* class. Thus all samples are divided into M sub-sets: $U_1(k), U_2(k), \cdots, U_M(k)$, with each subset forming a cluster domain represented by a cluster center.

(4) Update all the cluster centers. Two methods can be used to update the cluster centers. One method is to average samples in each cluster domain, when $U_j(k)$ is the j-th cluster domain and N_j is the number of samples in the j-th cluster domain:
$$c_j(k+1) = \frac{1}{N_j} \sum_{X \in U_f(k)} X.$$

(5) $k + 1$, go to (2) step. Repeat this process until the change in c_k is less than some limit.

After the cluster centers are determined, the distance between the centers is used to determine the expansion rate of the radial basis function.
$$d_j = \min\limits_{i} \|c_j - c_i\|.$$

The expansion rate $\delta_j = \lambda d_j$, where λ is the overlap factor.

After the centers and expansion rate of the radial

basis function are calculated by the K-means clustering algorithm, the second step in the mixed learning process is a supervised learning algorithm to get the output layer weights using a pseudo inverse method. For X^p as the input, the output of the j-th hidden node $\varphi_{pj} = \varphi(\| X^p - c_j \|)$, $p = 1, 2, \cdots, P$, $j = 1, 2, \cdots, M$, given by the hidden layer output matrix is

$$\hat{\phi} = (\varphi_{pj})_{P \times M}.$$

If the output weights of the RBF network are $W = (w_1, w_2, \cdots, w_M)$, the network output vector is

$$F(X) = \hat{\phi} W.$$

The network output vector set equals the mentor signal d, so W can be obtained using the pseudo inverse of $\hat{\phi}$,

$$W = \hat{\phi}^+ d,$$

$$\hat{\phi}^+ = (\hat{\phi}^{\mathrm{T}} \hat{\phi})^{-1} \hat{\phi}^{\mathrm{T}}.$$

2 Simulation

2.1 Simulation model

The current model uses the RBF network input layer neurons to represent the temperature, smoke density, and CO concentration as the input signals. The output layer gives the probabilities of the three fire states for fire, smoldering fires, and no fire.

This analysis used 8 typical group samples listed in Table 1 for the RBF network training. After the network training in MATLAB, the relationship between the multiple information judgments and the input signals was transformed into the neural network weight matrix for the data fusion process.

Table 1   BF network training samples

Sample number	Input samples			Expected value		
	Temperature (℃)	Smoke density (mg/m³)	CO concentration (mg/m³)	Fire probability	Smoldering fires probability	No fire probability
1	25	0.3	7	0.03	0.04	0.93
2	30	0.5	10	0.05	0.05	0.90
3	35	1.0	15	0.05	0.15	0.80
4	40	1.4	21	0.10	0.20	0.70
5	45	1.9	39	0.15	0.35	0.50
6	59	2.5	46	0.60	0.30	0.10
7	75	3.2	53	0.70	0.20	0.10
8	85	4.0	62	0.80	0.15	0.05

2.2   Simulation results analysis

The MATLAB environment used newrb (**P**, **T**, goal, spread, MN, DF) to create the RBF network, in which: **P**, input matrix; **T**, desired output matrix; goal, root mean square error target; spread, basis function radius;

MN, number of hidden layer neurons; DF, increase in the number of neurons between the input and output.

The network training results in Fig. 3 show that the model has fast convergence and a short training time.

The sim () function is used for the simulations with the results listed in Table 2.

Table 2   Comparison of simulation results with expected values

| Sample number	Simulation results			Expected value		
	Fire probability	Smoldering fires probability	No fire probability	Fire probability	Smoldering fires probability	No fire probability
1	0.0313	0.0405	0.9293	0.03	0.04	0.93
2	0.0504	0.0513	0.9019	0.05	0.05	0.90
3	0.0459	0.1461	0.7979	0.05	0.15	0.80
4	0.1031	0.2026	0.7013	0.10	0.20	0.70
5	0.1498	0.3497	0.4997	0.15	0.35	0.50
6	0.5972	0.2972	0.099	0.60	0.30	0.10
7	0.7061	0.2058	0.1028	0.70	0.20	0.10
8	0.7954	0.1458	0.0483	0.80	0.15	0.05
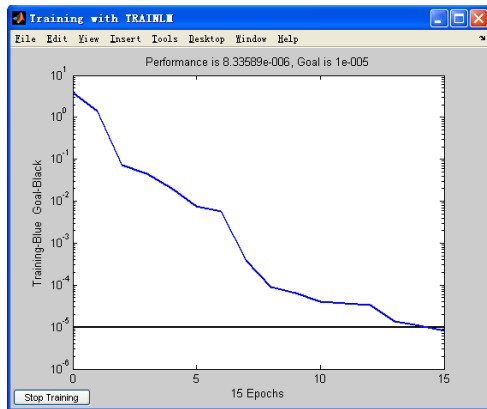
Fig. 3   Network training process

Comparison of the simulation results and the expected values shows that the average fire identification error probability is 2.3%, the average error probability for detecting smoldering fires is 1.8%, and the average error probability of no fire identification is 1.0%. Thus, the fire detection neural network after training has a high accuracy recognition rate for fires, which will greatly reduce false alarms and leak-checks and improve the reliability and credibility of automatic fire alarm systems.

3   Conclusions

This paper describes a neural network using temperature, smoke concentration, and CO concentration to detect and predict fires. The following conclusions can be drawn.

(1) The fire detection neural network has a fire prediction error rate for three fire states of less than 5%. The high recognition rate of this neural network will greatly reduce the risk of false alarms and leak-checks of fire alarm system.

(2) This neural network fire alarm system can analyze a variety of sensor data at the same time and can improve the ability of systems to adapt in their environment and correct for interference to accurately predict fires.

(3) The paper also describes how neural networks can combine sensor data in an intelligent automatic fire alarm system to effectively identify fires which has great significance for safety.

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