Algorithm for Early Fire Detection Base on Neural Network and FT-IR Using Feature Extraction

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A specific experiment system is set up based on FT-IR technology. Through experiments of real fire sources and nuisance alarm sources, we get all kinds of fire parameters, including concentration of CO and CO2, fire videos, alarm time of conventional fire detectors, and environment temperatures. Trough analyzing the concentration of CO and CO2 collected in fire process by Curve fitting method, the characteristic parameters including gas concentration fitting values, change rate and acceleration are extracted. Based on theoretical and experimental studies, we establish an algorithm with LVQ neural network suitable for early fire detection. The network input is the change rate of CO concentration, the acceleration of CO concentration and the change rate of CO2 concentration. The output is real fire and nuisance fire. After the network training and validation, the results prove that this method can provide a 3 to 21 minutes earlier alarm then the conventional fire detectors as far as the alarm time by comparing, and can achieve the goal of early fire detection warning.

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1. Introduction

Fire occurs frequently and it is one of the most devastating disasters. According to statistics, about 6,000,000-7,000,000 fires appear around the world each year, which cause 65,000 to 75,000 people's deaths worldwide. [1] Therefore, a timely and accurate detection alarm to fire is very important.

There are still many problems for fire detection algorithm of present fire detection systems in case of nuisance alarm immunity, accuracy and reliability, although various types of complex fire detection algorithm constantly appear which greatly improved the forecasting ability of fire detection systems. In this contribution, a new fire detection system using FT-IR technology is introduced. Based on a large number of experiments we collected concentrations of target gases in fire process. The characteristic parameters which can represent the overall information of fire processes are extracted by curve fitting. Combined with LVQ neural network, a fire detection algorithm is set up, which can achieve the purposes of accurate and reliable early fire warning.

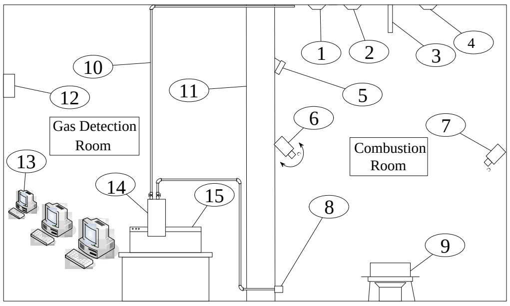
2. The choice of target gases

The gases useful for fire sensing would be ubiquitous to early fires. Nonflaming pyrolysis produces significant amounts of carbon monoxide, carbon dioxide, fluorophosgene, hydrogen chloride, hydrogren cyanide, sulfur dioxide, methane, ethylene, and water vapor. Carbon monoxide is the most characteristic of smoldering fires and chemically stable enough to survive, which can transport from the fire source to the measurement location quickly. So we include CO despite its relatively small absorption cross section because it is generated by nearly all types of combustion. Carbon dioxide is included because its presence is virtually guaranteed under all conditions. The two target gases are particularly useful for fire sensing because they can be detected at sub-ppm concentrations.[2]

3. Experiments

The experiment system mainly include the Thermo Nicolet NEXUS Fourier transform infrared spectroscopy, 10 meters gas cell, heating device, auxiliary sensors, gas pipe and other accessories distributed in the comustion room and the gas detection room. The details of the experiment system are shown in Figure . 1. The experiment system is depend on the FT-IR technology which can provide the concentration of target gases according to the absorption of specific wavelength with high accuracy, and can measure trace gases.

In experiments the MCT-A detector was used in the spectroscopy with the resolution of $4cm^{-1}$, 64 scans, and 1 minute interval of spectral acquisition time. The Quantitative analysis band of CO is $739cm^{-1} \sim 722cm^{-1}$ and $772cm^{-1} \sim 746cm^{-1}$, The Quantitative analysis band of CO2 is $2183cm^{-1} \sim 2165cm^{-1}$ and $2203cm^{-1} \sim 2188cm^{-1}$. [3] Based on the different properties of materials, we take a great deal of tests of real fire sources and nuisance sources, such as paper, chipboard, wood, washrag, plywood, Plastic, smoking, candle, LPG, Cables, generally covering the six stages of the whole combustion, including heating, pyrolysis, fume, diffusion, complete combustion and attenuation.



1:photoelectric smoke detector, 2:ionization smoke detectors, 3:thermocouples, 4:fixed temperature detectors, 5: CO/CO2 monitor; 6:camera, 7:infrared temperature monitor ; 8:exhaust fan, 9:heating device, 10 :gas pipe; 11: wall, 12: temperature and smoke alarm controller, 13:computers, 14:10 meters Gas cell, 15: Fourier transform infrared spectroscopy.

Fig. 1 The structure of the experiment system

In each of the tests we have collected the gas spectral data, the video of combustion process, surface temperature of material, ambient temperature, alarm time of smoke detector and so on. Through quantitative analysis of spectral data, we acquire the concentrations of CO and CO2 during the process of combustion. Figure.2 shows the video capture image when wood blocks heated. Figure.3 and Figure.4 respectively shows the spectra waterfall of CO and CO2 when wood blocks heated. Figure.5 shows the concentration curve of CO released in heating process of four kinds of materials.

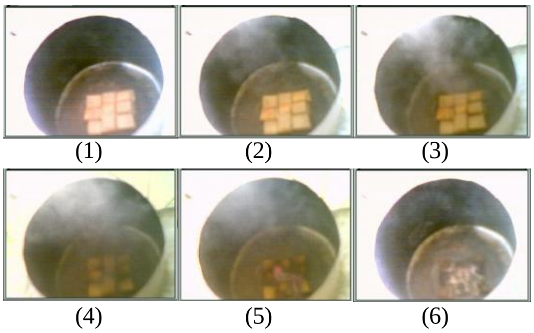


Fig. 2 Images of wood blocks when heated

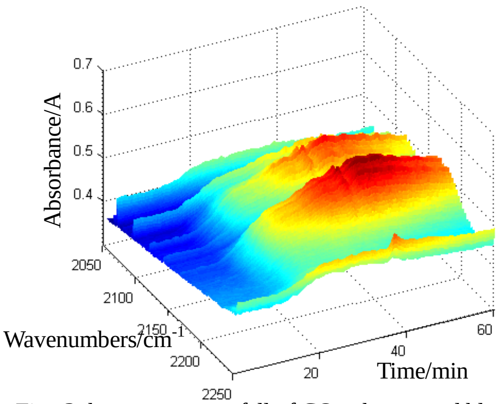


Fig. 3 the spectra waterfall of CO when wood blocks heated

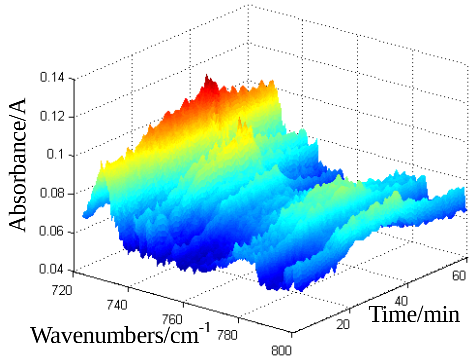


Fig. 4 the spectra waterfall of CO2 when wood blocks heated

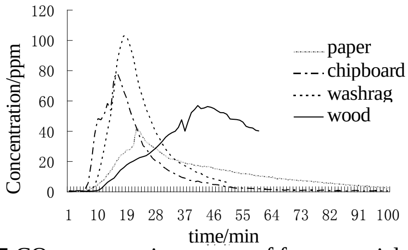


Fig. 5 CO concentration curves of four materials when heated

4. LVQ Algorithm

Learning vector quantization (LVQ) neural network is widely used in pattern recognition and optimization. It's a hybrid neural network composed of competitive learning algorithm and supervised learning algorithm. LVQ neural network generally includes an input layer, a competition layer and an output layer. when training samples input the network, it will calculate the Euclidea distance between input layer and competition layer. The neurons with a minimum Euclidea distance win the competition. The output layer map the result of competitions to the user-defined target classification.[4]

4.1 The structure and learning algorithm of LVQ

The structure of LVQ neural network is shown in Figure. 6. Supposing the input layer contains N neurons, fully connected with the competition layer. The competitive layer is consisted of M neurons. The output layer is formed by L neurons.

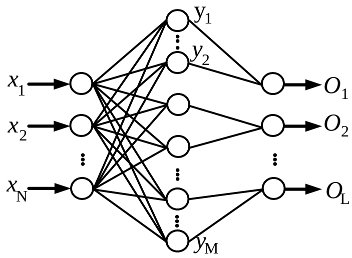


Fig. 6 The structure of LVQ neural network

In the training process of LVQ network, the connection weights between the input layer and competitive layer are gradually adjusted to the cluster center. When the input samples are sent to the LVQ network, the competitive layer produces the winning neuron by the learning rules of winner-takes-all, the output of winning neuron is 1, the output of other neurons is 0. Specific steps of learning algorithm is as follows: [5,6]

(a). Initialize the weight vector of the competitive layer neurons with random decimal. The weight vector is $w_i^1(0)$ $(i=1, 2,\cdots M)$. Initialize the initial learning rate $\eta(0)$ and the number of training epochs K.

(b). Input the sample vector $\boldsymbol{X}$.
(c). Find the winning neuron i^*.

$$\| \boldsymbol{X} - \boldsymbol{W}_{i^*}^1 \| = \min_i \| \boldsymbol{X} - \boldsymbol{W}_i^1 \|, \quad i=1,2,\cdots,M$$

(d). Adjust connection weights of winning neuron according to the Correctness of classification on the basis of different rules. When the classification results of network accord with the teachers signals, we should adjust weights to the direction of the input samples:

$$\boldsymbol{W}_{i^*}^1(k+1) = \boldsymbol{W}_{i^*}^1(k) + \eta(k)[\boldsymbol{X} - \boldsymbol{W}_{i^*}^1(k)]$$

Otherwise, adjust weights to the opposite direction of the input samples:

$$\boldsymbol{W}_{i^*}^1(k+1) = \boldsymbol{W}_{i^*}^1(k) - \eta(k)[\boldsymbol{X} - \boldsymbol{W}_{i^*}^1(k)]$$

The weights of other neurons weights keep unchanged.
(e). Update the learning rate

$$\eta(k+1) = \eta(0)(1 - \frac{k}{K})$$

When $k<K$, then $k = k+1$, go to step 2, input the next sample, and repeat the steps until $k = K$.

4.2 Feature extraction of Characteristic Parameters

The curve of discrete data measured from fire tests can be expressed as follow:

$$\hat{x}(i+v) = a_0(i) + a_1(i)\cdot v + \frac{1}{2}a_2(i)\cdot v^2$$

In which i represents the time t, v represents Δt, $v \in (-v_{\max}, v_{\max})$, $v_{\max} = \frac{\Delta t_{\max}}{\Delta t}$.

The error on both sides of point i can be expressed as follow:

$$\Delta x(i+v) = \hat{x}(i+v) - x(i+v)$$

Process the discrete data with symmetric Hamming window function $w(v)$, square the difference Δx according to least square method. We get the summation $\boldsymbol{J}$:

$$J = \sum_{-v_{\max}}^{v_{\max}} w(v)^2[\hat{x}(i+v) - x(i+v)]^2$$

Order the derivation of expression $\boldsymbol{J}$ to zero, we get the following expression:

$$\sum_{-v_{\max}}^{v_{\max}} w(v)^2[\hat{x}(i+v) - x(i+v)](v^k/k!) = 0 \quad (k=0,\ 1,\ 2)$$

$$W = V\cdot A$$

$$W = \sum_{-v_{\max}}^{v_{\max}} w(v)^2 \begin{bmatrix} x(i+v) \\ vx(i+v) \\ v^2x(i+v) \end{bmatrix},$$

$$V = \sum_{-v_{\max}}^{v_{\max}} w(v)^2 \begin{bmatrix} 1 & 0 & v^2/2 \\ 0 & v^2 & 0 \\ v^2 & 0 & v^4/2 \end{bmatrix}, \quad A = \begin{bmatrix} a_0(i) \\ a_1(i) \\ a_2(i) \end{bmatrix}$$

Because the expression $V\cdot A$ is nonsingular, so we can get the estimated value of $a_k(i)$:

$$A = V^{-1}\cdot W$$

When v equal to zero, then $\hat{x}(i)$ equal to $a_0(i)$, the value of $a_0(i)$ represent the gas concentration itself, the values of $a_1(i)$ and $a_2(i)$ respectively represent the change rate and acceleration of gas concentration.

$a_0(i)$, $a_1(i)$ and $a_2(i)$ are continuously extracted from the $2v_{max}+1$ data (called data window width) removed from measured data as the data window sliding with the timeline. Figure.7 shows CO concentration fitting curve when paper heated. Figure.8 Figure.9 and Figure.10 respectively show the change rate curve of CO concentration, the acceleration curve of CO concentration and the change rate curve of CO2 concentration when paper heated.

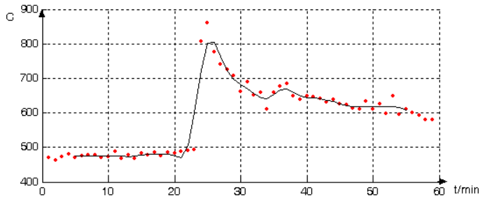


Fig. 7 CO concentration fitting curve when paper heated

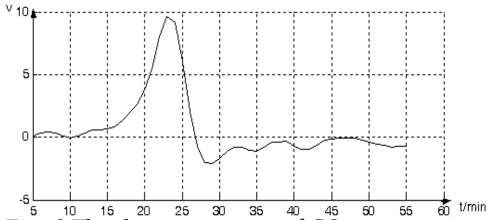


Fig. 8 The change rate curve of CO concentration when paper heated

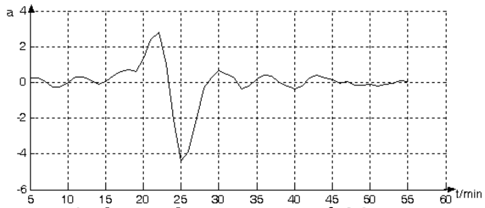


Fig. 9 The acceleration curve of CO concentration when paper heated

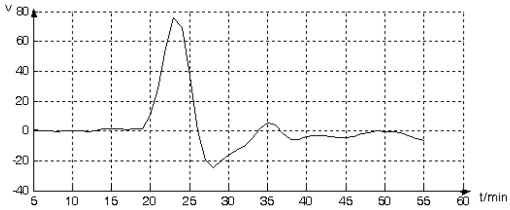


Fig. 10 The change rate curve of CO_2 concentration when paper heated

4.3 The building of alarm algorithm based on LVQ

On the basis of the feature extraction from fire data, a Learning Vector Quantization(LVQ) neural network has been built and tested. The inputs of the network are the change rate of CO concentration, the acceleration of CO concentration and the change rate of CO2 concentration, that is, the input vector is $[v_{co}, a_{co}, v_{co2}]^T$. The output of the network is the vector $[y_1, y_2]^T$, which represent the classification of the input data as a real source fire when the output is [1,0], or a nuisance source fire When the output is [0,1].

200 samples have been randomly drawn from the normalized data of feature extraction from fires tests, in which 100 samples are used to train the LVQ neural network, 100 samples are used to validate the LVQ neural network. Part of the training data are shown in Table. 1.

Table. 1 Part of training data

输入[v_{co} a_{co} v_{co2}]	输出[y_1 y_2]	状态
0.1627 0.1606 0.1815	0 1	N
0.1634 0.1643 0.2127	0 1	N
0.1808 0.1676 0.2390	0 1	N
0.1833 0.1619 0.2440	0 1	N
0.2001 0.1824 0.2681	0 1	N
0.2313 0.1988 0.2896	1 0	F
0.2683 0.2042 0.2833	1 0	F
0.3509 0.1990 0.3043	1 0	F
0.3618 0.1283 0.4777	1 0	F
0.1710 0.1651 0.1839	0 1	N
0.1664 0.1548 0.1546	0 1	N
0.1603 0.1568 0.1499	0 1	N
0.2572 0.2099 0.2275	1 0	F
0.3164 0.2315 0.4151	1 0	F

N：Nuisance fire；F：Real fire

The training step of the network is 100 steps. After a 35-step training, the network reach to a stable error 0.0667. Figure. 11 shows the training error curve of LVQ neural network.

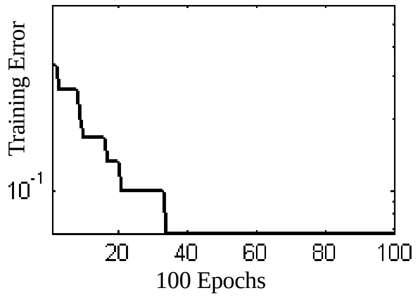


Fig. 11 The training error curve of LVQ network

4.4. Results

In the 100 samples used to validation, 97 samples are correctly classified. By adding sliding window to the collected data, we extract the characteristic parameters of fires, and obtain the alarm time by continuously determining whether the fire occurs or not, using the LVQ neural network. Through comparing the alarm time of the LVQ algorithm with the photoelectric smoke detector, ionization smoke detector and fixed temperature detector, we get the results of Comparison shown in Table. 2.

Table. 2 The result of comparison (unit: min)

Material	Conventional fire detectors			LVQ（sliding window）
	fixed temperature	photoelectric	Ionic	
Wood	—	32	33	14
Veneer	—	—	—	18
Washrag	—	20	20	17
Cotton thread	—	17	17	14
Paper	—	22	22	11
Chipboard	—	23	22	13
Wastebin	—	53	52	31
Candle	—	—	—	N
Smoking	—	—	—	N
LPG	—	—	—	N

—：No alarm；N：Nuisance fire

From Table. 2, we can see that the algorithm of LVQ neural network based on feature extraction can accurately identify the real fires and nuisance fires, and provide 3 to 21 minutes earlier alarm then the conventional fire detectors, which will greatly reduce the loss of fires

5. Conclusion

It is always a key issue that improving the accuracy and reliability of early fire detection. In this paper, FT-IR measurements of numerous real fire and nuisance fire sources have been conducted. By means of feature extraction process for concentration of CO and CO2, we take advantage of the learning vector quantization neural network for early fire detection research, and achieve the purpose of early warning of fires.

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