Statistical Algorithm of Early Fire Based on Improved Time-series Test

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Focused on the solution of mutual restraint between timeliness and accuracy in fire detection, a new algorithm based on improved time-series test and fire signature was presented. According to national standard fire, a series of fire test had been performed in the NEXUS FT-IR spectrometer based fire detection system. As an important early fire signature, CO concentration was measured during the burning test. A two-component mathematical model of CO was established. One is the signature function of early fire including CO concentration and its changing rate and acceleration, the other is a zero-mean Gaussian noise. Based on improved time-series test, a recursion formula of likelihood function L(X) is built up using the probability density functions in cases of fire and non-fire, one of the two improvements is adding a reject region in observation space and give an upper threshold λ_1 and a lower threshold λ_0 corresponding to the allowable false positive and negative rate, the other is keeping observation number invariable. The algorithm makes fire decision if $L(X) > \lambda_1$, or non-fire decision if $L(X) < \lambda_0$, otherwise rejects any decision and waits for the next sample to iterate the likelihood function until making a certain decision of fire or non-fire. The results of experiment have showed that the presented technology can distinguish early fire from non-fire with lower false positive and negative rate.

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1. Introduction

Fire signature extraction and fire distinguish algorithm are key technologies of early fire detection. The existing fire detection methods use smoke-sensing detector or heat-sensing detector.[1-3] But in early stages of fire, few smoke and heat are likely to come out unless fire already spreads in large-scale, so above techniques can hardly alarm early fire fleetly and reliably. 'Fire signature' proposed by Custer RLP and Bright RG in 1974 has been researched widely.[4] William, Jackson and Daniel T had made in-depth study on early fire gases in laboratory, they found that CO and CO_2 are relatively ideal parameters in early fire detection; especially CO concentration would increases obviously in the initial stage of smoldering fire. [5-7] In the other hand, traditional fire algorithms include threshold algorithm, trend algorithm and statistic algorithm etc. The first two make fire alarm according to whether the variation of fire variables or its changing rate exceed a given threshold, the last estimates the statistical parameters of fire variable in time domain or frequency domain firstly, and then makes fire decision using intelligent classification methods such as artificial neural network. In fact, any given threshold value can hardly be suitable for all kinds of fire sources, and the algorithms based on the variation of fire variable could be influenced by many random factors. Consequently current fire algorithms often make fire alarm with high false positive and negative rates.

To solve the mutual restriction between false positive rate and false negative rate in fire detection, it is seems necessary to bring forward a new early fire algorithm. In this paper, CO concentration is counted as fire variable, from which early fire process signature is extracted, and a statistical fire detection algorithm has been proposed based on improved time- series test and fire signature, so as to improve the timeliness and accuracy of fire detection with lower false positive and negative rates.

2. Experiment

According to national standard fire, a series of fire test have been performed in fire detection system based on NEXUS FT-IR spectrometer with a 10-meter gas pool, the infrared absorption wavebands of CO is from 2165 cm^{-1} to 2183 cm^{-1}, the spectrum detector is MCT-A with resolution of 4cm^{-1}, and the sample frequency

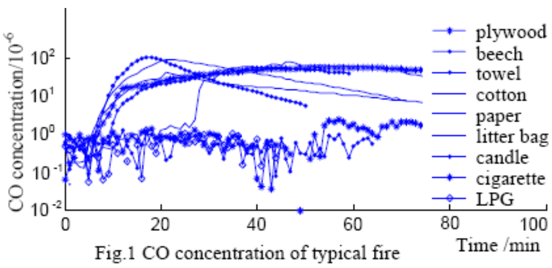

Fig.1 CO concentration of typical fire

is 64 times per minute. CO concentration is obtained during the burning process by using FTIR quantitative analysis. [3]

The experiment materials include 6 kinds of real fire source, such as pieces of plywood, beech block, towel, cotton rope, paper and litter bag which was filled with some scraps of paper and ignited by a smoldering cigarette, and 3 kinds of non-fire nuisance source such as burning candle, cigarette smoke and burning liquefied petrochemical gas (LPG). The test results show that CO concentration of real fire begins to increase obviously about 6 to 8 minutes later after heating, but that of non-fire has no regular change and keeps in small values during the whole combustion process as show in Fig.1.[8] This character offers a possibility to distinguish real fire from non-fire nuisances in early stages of fire.

3. Extraction of early fire process characteristic

The essential difference of the two fire sources is in their different variation behaviours of CO $x(i)$. Supposing $x''(i)$, the changing acceleration of CO concentration, is invariable; all the influencing factors, including the variation of $x''(i)$ if it exists, measurement uncertainty, and unpredictable error resulted by combustion materials etc, are equivalent to a zero-mean Gaussian noise $n(i)$ with standard deviation σ_n^2. Then at time $i+k$, CO concentration $x(i+k)$ can be expressed as Eq.(1).

$$\begin{cases} x(i+k) = s(i+k) + n(i+k) \\ s(i+k) = x(i) + kx'(i) + \dfrac{1}{2}k^2 x''(i) \end{cases} \tag{1}$$

Where $x'(i)$ is the changing rate of $x(i)$ at time i, $s(i)$ is a signature function of fire eigenvector $[x(i), x'(i), x''(i)]^T$ which completely describe the process signature of early fire, i=1,2,3,…, k.

To make the eigenvector optimal, the square error sum of $n(i)$ must be minimum in the neighborhood of time i, say $k=-m\sim m$. Thus, the eigenvector can be obtrained as Eq.2. [9]

$$\begin{pmatrix} x(i)\\ x'(i)\\ x''(i)\end{pmatrix} = \left[\sum_{k=-m}^{m} w^2(k)\cdot \begin{pmatrix}1&0&k^2/2\\0&k^2&0\\k^2&0&k^4/2\end{pmatrix}\right]^{-1}\left(\sum_{k=-m}^{m} w^2(k)\begin{bmatrix}x(i+k)\\k\cdot x(i+k)\\k^2\cdot x(i+k)\end{bmatrix}\right) \tag{2}$$

The half-breadth of the weight function m has greatly influence on the signature function. if m is big, the signature function curve will become smoother and well reflect the microscopic features of fire process, but this could impair the promptness of fire alarm; if m is too small, the sensitivity of fire alarm increases, but the eigenvector is affected by more stochastic errors so that the accuracy of fire alarm reduce correspondingly.

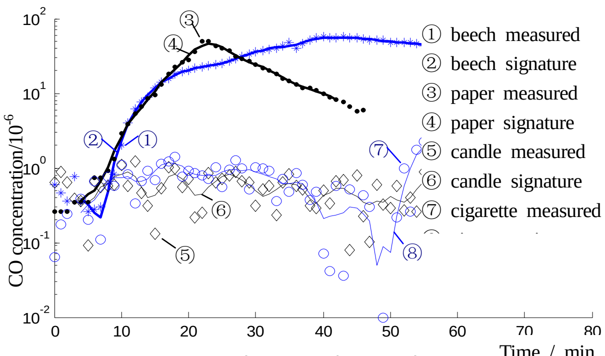

Fig.2 Signature functions of typical fire sources

The signature functions of typical fire materials are extracted as in Fig.2, where k=4. It is evident that the signature functions of real fire source increase fleetly in the in early stage of fire, but that of non-fire nuisance sources change infinitesimally in all the process of combustion.

4. Algorithm of Early Fire Based on Improved Time-series Test

4.1 Statistical detection model of fire signal

In general, the occurrence and development of fire is a lengthy gradual process. When a fire occures, the detected signal $x(i)$ can be expressed by $x(i) = s(i) + n(i)$. The purpose of fire detection is to determine whether a fire occures on the principle of the location of fire variable value sampled in observation space as show in Fig.3. where $H=\{H_0, H_1\}$ is a set of alternative assumption including two mutual exclusion domains. H_0 is the original hypothesis which means no fire occures, H_1 is the alternative hypothesis which means fire ocuures. $Z=\{Z_0, Z_1\}$ is a set of decision domain. The model gives fire alarm if the observation is located in region Z_1 otherwise gives non-fire alarm if the observation is located in region Z_0.

Assuming $X=\{x_1,x_2,\ldots,x_r\}$ is a periodical sample series of fire variable. If no fire takes place $x_i=n_i$, and if fire has occurred $x_i=s_i+n_i$, where i=1,2,3,…,r. both random signals of x_i and (x_i-s_i) are as the law of normal distribution $N(0,\sigma_n^2)$. In both situations, the probability density functions are

$$\begin{cases} p(X\,|H_0) = \left[\dfrac{1}{\sqrt{2\pi}\sigma_n}\right]^r \exp[-\dfrac{\sum_{i=1}^{r} x_i^2}{2\sigma_n^2}] \\ p(X\,|H_1) = \left[\dfrac{1}{\sqrt{2\pi}\sigma_n}\right]^r \exp[-\dfrac{\sum_{i=1}^{r}(x_i - s_i)^2}{2\sigma_n^2}] \end{cases} \tag{3}$$

Under the allowable false-alarm probability α with corresponding threshold λ_{NP}, the likelihood function based on detection probability maximum priciple is constructed below.

$$\begin{cases} l(X) = \dfrac{p(X\,|H_1)}{p(X\,|H_0)} = \exp\{\dfrac{\sum_{i=1}^{r} x_i^2}{2\sigma_n^2} - \dfrac{\sum_{i=1}^{r}(x_i - s_i)^2}{2\sigma_n^2}\} \\ l(X) \begin{matrix} < \lambda_{NP}, accept\, H_0 : non-fire \\ > \lambda_{NP}, accept\, H_1 : \ fire \end{matrix} \end{cases} \tag{4}$$

This method, named multiple observation Neyman-Pearson criterion, has the advantages of high reliability and low false alarm rates, but it is not well suited for fire detection for the reasons below. Firstly it is bounded to cause high false positive or negative rates to make selection in two mutual exclusion domains per an observation, especially in the initial stage of fire occurrence. Secondly observation number r is changeless and difficult to predetermine; its value restricts the timeliness and accuracy of fire detection.

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4.2 Time-series test and its improvement

To improve above disadvantages, add a rejection region Z_2 in observation space as show in Fig.4. If a fire signature is not obvious to distinguish and the observation is located in area Z_2, the algorithm rejects to make any decision and waits for the next detection cycle. Moreover, keep the observation number r to be incremental, and make hypothesis test according to Neyman-Pearson criterion, if the decision is rejected then let $r=r+1$, make a longer fire signature time-series ended with the new signature extracted in the next cycle, and make hypothesis test again until the observation is located in either domain Z_0 or domain Z_1. So time-series test can distinguish fire at once the fire take place theoretically.

In fact, fire is a very small probability enent, the observation number r will increase gradually as time goes on. In the initial stage of fire, useless massive history data would reduce the timeliness of algorithm because of too much computation. In our work, the observation unmber r is regarded as an appropriate constant, it must be large enough to extract early fire signature reliably within a given period of time. Suppose $X_N=\{x_{N-r+1},x_{N-r+2},\ldots,x_{N-1},x_N\}$ is the sampled time-series before time N, $X_{N+1}=\{x_{N-r+2},x_{N-r+3},\ldots,x_N,x_{N+1}\}$ is the sampled time-series before time $N+1$, then the likelihood functions of N times observation are expressed as Eq.5

$$\begin{cases} l(X_N)=\dfrac{p(X_N\,|\,H_1)}{p(X_N\,|\,H_0)}=\exp\{\dfrac{\sum_{i=1}^{r}x_{N-i+1}^2}{2\sigma_n^2}-\dfrac{\sum_{i=1}^{r}[x_{N-i+1}-s_{N-i+1})]^2}{2\sigma_n^2}\} \\ l(X_{N+1})=\dfrac{p(X_{N+1}\,|\,H_1)}{p(X_{N+1}\,|\,H_0)}=\exp\{\dfrac{\sum_{i=1}^{r}x_{N-i+2}^2}{2\sigma_n^2}-\dfrac{\sum_{i=1}^{r}[x_{N-i+2}-s_{N-i+2})]^2}{2\sigma_n^2}\} \end{cases} \quad . \quad (5)$$

Thus, the recursion formula of the log likelihood fountions from $l(X_N)$ to $l(X_{N+1})$ is obtrained as Eq.6

$$\begin{cases} \ln l(X_{N+1})=\ln l(X_N)+\ln l(x_{N+1})-\ln l(x_{N-r+1}) \\ \ln l(x_{N+1})=\dfrac{x_{N+1}^2}{2\sigma_n^2}-\dfrac{(x_{N+1}-s_{N+1})^2}{2\sigma_n^2} \\ \ln l(x_{N-r+1})=\dfrac{x_{N-r+1}^2}{2\sigma_n^2}-\dfrac{(x_{N-k+1}-s_{N-r+1})^2}{2\sigma_n^2} \end{cases} \quad . \quad (6)$$

Where $l(x_{N+1})$ and $l(x_{N-r+1})$ are respectively the single observation likelihood functions at time $N+1$ and $N-r+1$. Under the allowable false positive probability a and false negative probability β with corresponding decision threshold λ_{NP0} and λ_{NP1}, the fire decision formula is constructed below.

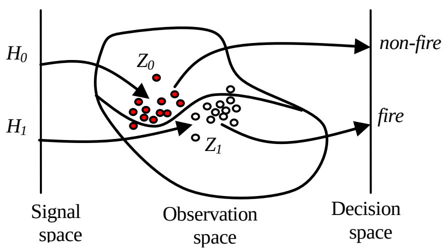

Fig.3 Statistical detection model of fire signal

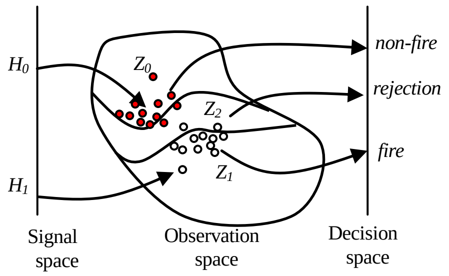

Fig.4 Statistical detection model of fire signal

$$\ln l(X_N)\begin{cases} <\ln\lambda_{NP0} & ,accept\ H_0\text{: } non-fire \\ >\ln\lambda_{NP1} & ,accept\ H_1\text{: } fire \\ \in(\ln\lambda_{NP0},\ln\lambda_{NP1}) & ,reject \end{cases} \quad (7)$$

Where $\lambda_{NP0}=\beta/(1-a)$, $\lambda_{NP1}=(1-\beta)/a$.[10], When a rejection appear, the algorithm iterates the next likelihood function l(XN+1) from $l(X_N)$ and the new fire signature extracted at next detection, and makes a decision again and again by using Eq.6 and Eq.7 until hypothesis H_0 or H_1 is accepted.

4.3 Fire identification using improved time-series test

Applied above improved time series test algorithm to some typical fire source, the graphs of log likelihood function in fire identification process are achieved as shown in Fig.5. where a=0.01, β=0.005, the corresponding thresholds vlues of ln(λ_{NP0}) =-5.27, ln(λ_{NP1})=4.60, r=2m+1=9. the standard deviation of observation σ_n^2=0.3098 according to the statistical analysis to a lot of experimental data.

In Fig.5, the likelihood functions of real fire source, such as paper and beech block, increase from non-fire region to fire region rapidly at about 15 minutes after heating; but that of non-fire nuisance sources, such as smoking cigarette and lighting candle, are almost less than the lower decision threshold λ_{NP0} in whole the combustion process, although in some short time they rise to rejection region. The major reason for mentioned algorithm to alarm fire accurately is that non-fire sources could generate small amounts of CO without the fire signature like real fire in all the burny process. The fire warning time can be estimated from Fig.5. In order to investigate the timeliness of the presented method, the earliest warning time of fire detectors, such as ionic smoke detector, photoelectric smoke detector and temperature detector fixed in laboratory, had been recorded. The comparison is shown in Table 1. Obviously presented algorithm fire alarm is much early than any others.

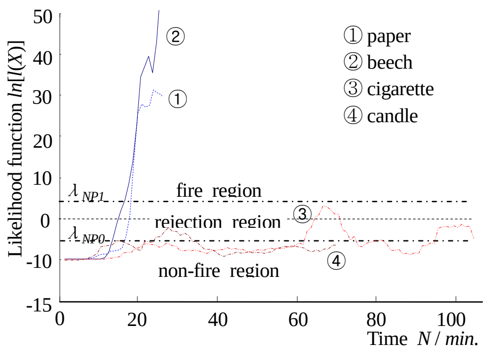

Fig.5 Likelihood functions of typical fire sources

5 Conclusions

Fire process signatures were setup by using moving average filter, a recursive formula of linklihood function was put forward based on an improved time-series test, and a new algorithm of early fire detection has been presented using fire signature. The results of experiment have shown that fire signature can better reflects the nature characteristic of early fire; adding a rejection domain in observation space can effectively reduce false positive and negative rate; the algorithm mentioned above is suitable for early fire detection with high timeliness and accuracy.

materials	presented method*	other methods
paper	20	24
wood	22	32
cigarette	not alarm	false alarm
candle	not alarm	not alarm

Table.1 Comparison of alarm timeliness [min.]

* alarm time = estimated time at the cross of likelihood function curve and upper level dotted line+4

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