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Pre-processing study of multi-sensor data

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Abstract

For multi-sensor data with multi-source heterogeneity, data pre-processing is required for data fusion. This paper proposes a data pre-processing method, firstly, the image data is binarized using the designed image binarization algorithm and flame area extraction algorithm, and the flame area information in the fire image is extracted into one-dimensional data, then the five one-dimensional data of ambient temperature, temperature-sensitive cable, CO2, CO and flame area are noise reduced using the designed wavelet noise reduction algorithm, and finally the final pre-processed data is calculated by the selected normalization formula. The results of the study show that the method can improve the effectiveness of multi-sensor data fusion.

Keywords

Flame images; Feature extraction; Wavelet noise reduction.

1. Introduction

With the development of society and the improvement of people's safety requirements, the traditional fire warning and firefighting system has been difficult to meet the needs of modern firefighting, and the artificially intelligent fire warning and firefighting system has gradually become the trend of modern firefighting development. The traditional fire warning system mostly uses a single sensor for fire alarm, which has delayed alarm and false alarm phenomenon, while the use of multi-sensor data fusion fire alarm technology can to a certain extent solve the defects of the single sensor, which has a multi-dimensional and more comprehensive fire information, can more accurately identify fire and timely alarm.

The principle of multi-sensor data fusion fire alarm is to pre-process the data obtained from the experiment, and then input these pre-processed data into the data fusion algorithm model to obtain the corresponding fusion results. Research on pre-processing of multi-sensor data and feature extraction has been carried out by domestic and foreign scholars. Wang et al. [1] used neural networks for multi-sensor fire detection and applied wavelet filtering for feature extraction of the collected data to filter out noisy signals, avoiding the signal from being swamped by the noise associated with the maximum and minimum measurements through normalization, and performing data fusion on the feature part of the signal to identify fires. Tlig [2], Otabek [3], and Wu [4] studied multi-sensor data fusion systems for fire detection, and they all used principal component analysis (PCA) for feature extraction of the acquired data and conducted fire alarm studies based on the feature values of the acquired data. Derbel et al. [5] studied multi-sensor fire detection system and divided into pre-processing unit, feature extraction unit and classification unit, where the pre-processing method of data is Fourier transform, which is achieved by generating a new one-dimensional signal to Fourier transform spectrum. Ren Shougang et al. [6] conducted a study on time series feature extraction and came up with methods to classify from shape features, time-dependent features, and sequence transformation features, comparing and analyzing the differences between the research methods used and traditional methods in extracting high-dimensional information, noise processing, and time-dependence, and elaborating the future development trend of time series feature extraction methods. In the study of fire warning, Zhang Rencheng et al. [7] applied the process feature extraction method to the CO feature parameter data and concluded that the size of the parameter m0 in the process feature extraction method affects the error and response time of the alarm. Wang Xuegui et al. [8] introduced the principal element analysis method, Raw Data method, local prior embedding method (LLE), etc., and used wavelet filtering method to process and normalize the data to obtain the feature extraction data.

In summary, researchers at home and abroad have conducted research on multi-sensor fire alarms for fire scenarios such as ship fires and indoor fires, and relatively little research has been conducted on multi-sensor data fusion for transformer fire scenarios. The previous group built a multi-sensor test platform for transformer pool fires and conducted fire tests, but the collected multi-sensor data has the characteristics of multi-source heterogeneity and requires data pre-processing for data fusion. These raw data include temperature, temperature-sensitive cable, CO2, CO and image data. For image data, because of its multi-dimensional characteristics, it needs to be transformed into one-dimensional flame area feature data, and for the one-dimensional data of ambient temperature, temperature-sensitive cable, CO2, CO and flame area, it needs to be processed for noise reduction and normalization due to the disturbance of external environment. Therefore, this paper will carry out the research on the pre-processing of multi-sensor data to achieve the purpose of multi-sensor data dimensionality reduction and noise reduction, and provide pre-processing data support for multi-sensor data fusion

2. Algorithm Fundamentals

2.1. Image feature extraction

2.1.1 Image binarization algorithm

In the fire image, the flame area as a proportion of the whole fire image can be expressed as:

$$\varpi_1 = \frac{N_1}{M \times N} \tag{1}$$

Where: ϖ_1 is the percentage of flame area in the fire image, N_1 is the number of pixels in the fire image with grayscale greater than a set threshold, and $M \times N$ is the total number of pixels in the fire image.

The background area as a percentage of the entire fire image can be expressed as:

$$\varpi_2 = \frac{N_2}{M \times N} \quad (2)$$

Where: ϖ_2 is the percentage of environmental area in the fire image, and N_2 is the number of pixels in the fire image with grayscale less than a set threshold.

The summation of the flame area and the ambient area can be expressed as:

$$N_1 + N_2 = M \times N \quad (3)$$

The sum of the flame area and the percentage of the ambient area can be expressed as:

$$\varpi_1 + \varpi_2 = 1 \quad (4)$$

The average grayscale of the fire image can be expressed as:

$$\mu = \mu_1 \times \varpi_1 + \mu_2 \times \varpi_2 \quad (5)$$

Where: μ is the average grayscale of the fire image, μ_2 is the average grayscale of the environment area, and μ_1 is the average grayscale of the flame area.

The interclass variance can be expressed as:

$$g = \varpi_1 \times (\mu - \mu_1)^2 + \varpi_2 \times (\mu - \mu_2)^2 \quad (6)$$

Where: g is the interclass variance.

Figure 1 is a diagram of the binarization process of flame image. The code of the binarization algorithm part is as follows:

(a)Original image (b) Grayscale image (c) Binarized image

Fig.1 Flame binarization data processing diagram

```
fire=VideoReader('D:\matlab\A\40-10-110-1.mp4');% Read-in video
background=imread('00.jpg');% Read into the background
nframes=get(fire,'numberofframes');% Frame Rate
nframes=500;
graybackground=rgb2gray(background);
[width,height]=size(graybackground);% Read grayscale image size
show=zeros(width,height);% Zero matrix of equal dimensions to the picture
```

2.1.2 Flame area extraction algorithm

In this paper, we need to extract the feature information and reduce the dimensionality when converting the high-dimensional image into a binarized image, specifically by counting the white pixel points in the binarized image to derive the white pixel area, and after the scale adjustment to obtain and output the one-dimensional data of the flame area, part of the code for flame area extraction is as follows:

```
flamearea=0;     % Area
for u=1:width     % Counting white pixel dots
    wd1=0;
    for v=1:height
        if pbw(u,v)==1
          flamearea=flamearea+1;       % Find the area
          wd1=wd1+1
        end
    end
end
```

2.2. One-dimensional data processing

2.2.1 Wavelet noise reduction processing algorithm

The equation for the noise reduction process can be expressed as:

$$\overline{w}_{i,j} = \begin{cases} \operatorname{sgn}\left(w_{i,j}\right)\left(w_{i,j} - \lambda\right), \left|w_{i,j}\right| \geq \lambda \\ 0, \left|w_{i,j}\right| < \lambda \end{cases} \tag{7}$$

Some of the code for data noise reduction is as follows:

```
level=5;
xm=wden(Y,'heursure','s','one',lev,'db4');
figure.(3)
plot(X,xm)
xlabel(' Horizontal coordinate ');
ylabel(' Vertical coordinate ');
title(' Noise reduction ');
set(gcf,'Color',[1 1 1])
```

2.2.2 Normalized calculation

The calculation of data normalization can be expressed as:

$$X_j = \frac{X_i - X\min}{X\max - X\min} \tag{8}$$

Where: X_i is the ith data in a certain set of data from the multi-sensor. X_j is the normalized value of the ith data. X_{max} is the maximum value of a data signal in a group of multi-sensors. X_{min} is the minimum value of a data signal of a group of multi-sensors.

3. Results and Discussion

3.1. Feature extraction of fire images

3.1.1 Video capture and image interception

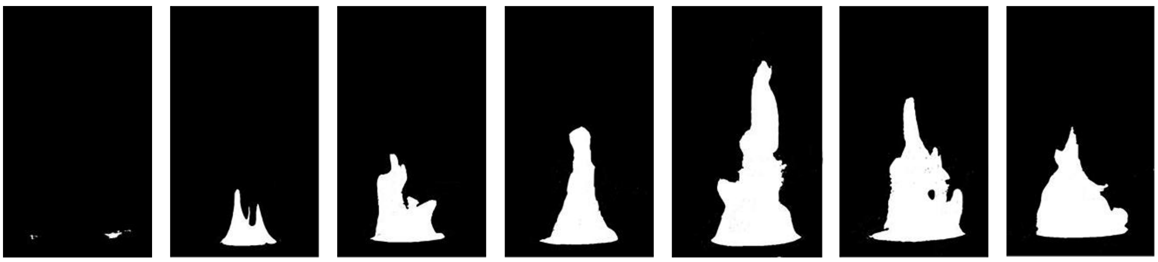
The image data is based on the Sony NEX-FS700 high-speed camera for acquisition, specifically, the camera is fixed 2 m away from the fire source to shoot to obtain the transformer oil flame burning video, the acquired video will be applied to the image split frame interception technology to obtain each frame picture. Figure 2 shows the burning process of transformer oil, from the figure can be seen that the burning process of transformer oil pool fire has the characteristics of pulsation, and the size of the flame height fluctuates in a certain range [9].

(a) (b) (c) (d) (e) (f) (g)

Fig.2 Transformer oil combustion process diagram

3.1.2 Image binarization

Figure 3 shows the binarization image. The image is divided into black and white areas, where the white area is the flame area in the transformer oil fire image, and the black area is the environmental background area in the fire image, and the binarization algorithm can clearly distinguish the flame area and the environmental background area in the image



(a) (b) (c) (d) (e) (f) (g)

Fig.3 Binarized images

3.1.3 Flame area extraction

Figure 4 shows the flame area map. It can be seen from the figure that the flame area feature information can be successfully extracted by image binarization and flame area extraction algorithm, and the corresponding one-dimensional flame area data can be obtained. By observing the graph of flame area change with time, it can be found that the flame area size in the time domain first shows a trend of gradually increasing, and then fluctuates within a certain range. This is because the oil pool fire is in the growth stage at the beginning of the combustion process, the flame area is increasing, and then in the stable combustion stage, the flame area at this time fluctuates in a certain range [10].

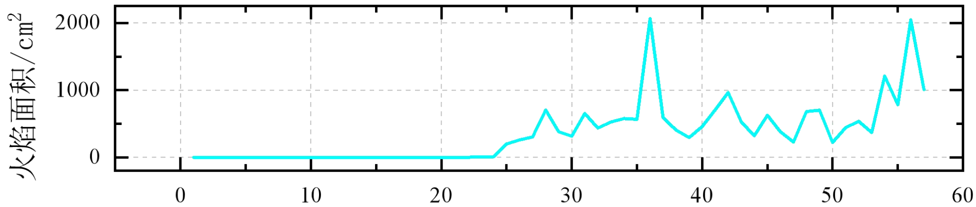
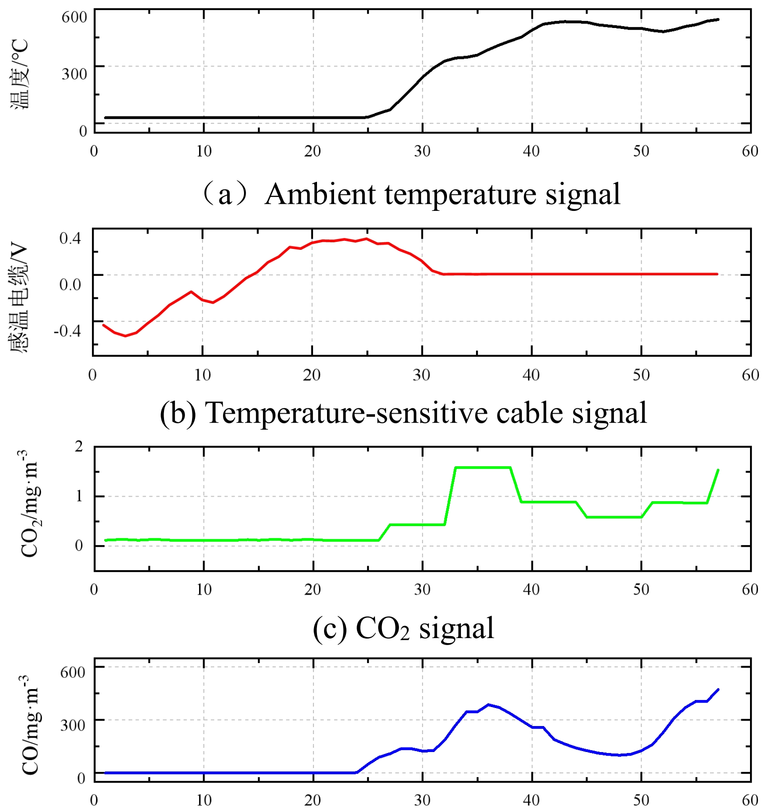


Fig.4 Flame area diagram

3.2. Processing of one-dimensional data

3.2.1 One-dimensional raw data

The original one-dimensional data of the five sensors were collected and processed, and a one-dimensional plot of the original data was obtained by graphing them, as shown in Figure 5. It can be seen from the figure that the response time of multiple sensors for transformer fires is different because different sensors receive different signals for the fire parameters [11].

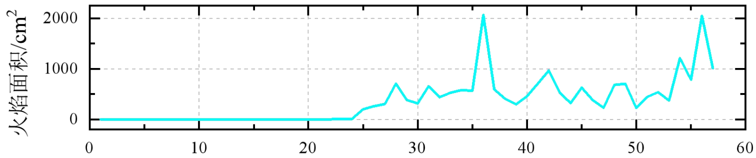


（a） Ambient temperature signal

(b) Temperature-sensitive cable signal

(c) CO_2 signal

(d) CO signal

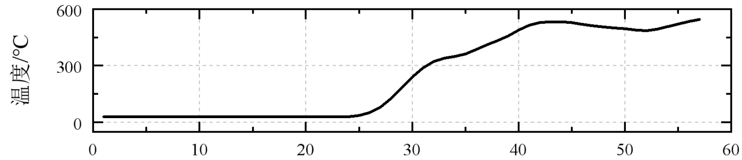


(e) Image signal

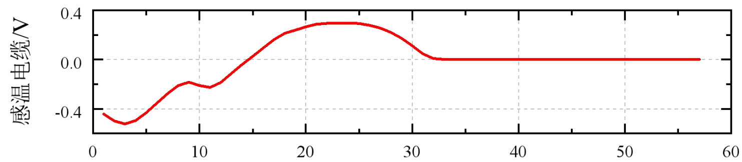
Fig.5 Trend chart of raw data

3.2.2 Wavelet noise reduction

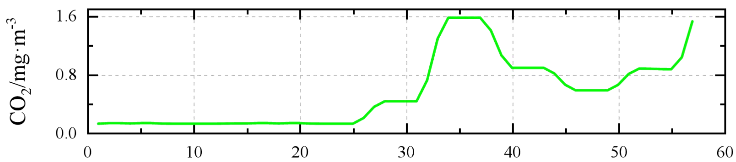
Figure 6 shows the graph of wavelet noise reduction data. he trend graph of the data processed by wavelet noise reduction algorithm is smoother than the trend graph of the original data, because wavelet noise reduction removes part of the noise signal and distortion signal, and removes the influence of environmental interference factors on the data signal, and the one-dimensional data processed by wavelet noise reduction does not change the characteristics of the original data itself [12].



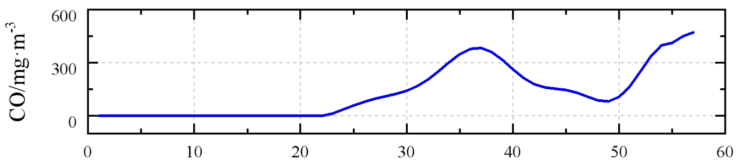
(a) Ambient temperature signal



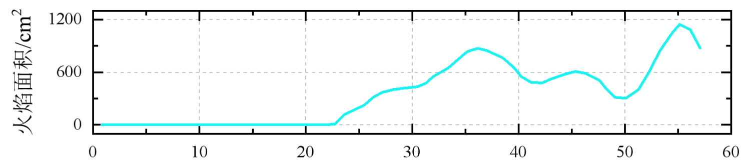
(b) Temperature-sensitive cable signal



(c) CO_2 signal



(d) CO signal



(e) Image signal

Fig.6 Trend chart of wavelet denoising data

3.2.3 Normalization process

Figure 7 shows the normalized data trend graph. Comparing the normalized data trend graph with the wavelet noise reduction data trend graph, we can see that the normalization process scales the wavelet noise reduction data to the (0,1) interval equally, and the normalized trend

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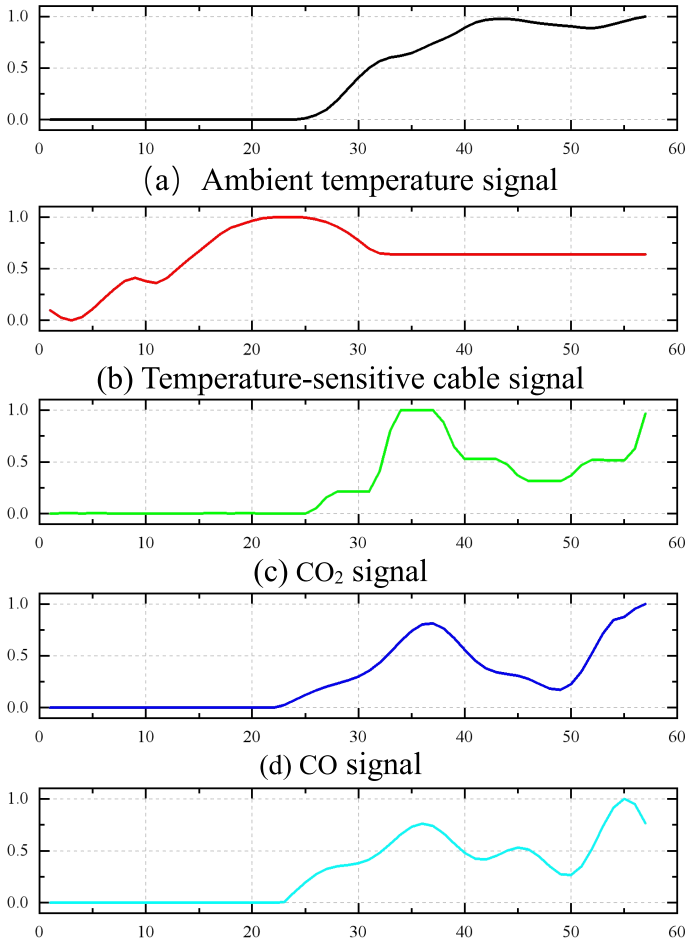
graph does not change the trend direction of the data, thus also does not change the nature of the multi-sensor data itself.



(a) Ambient temperature signal

(b) Temperature-sensitive cable signal

(c) CO_2 signal

(d) CO signal

(e) Image signal

Fig.7 Trend chart of Normalized data

4. Conclusion

Through binarization of fire images and extraction of flame area features, as well as wavelet noise reduction and normalization of five sensor data, the pre-processed data of ambient temperature, temperature-sensitive cables, CO2, CO and image signals of transformer fire alarm test were obtained, which realized the purpose of extracting image data into one-dimensional feature information data and noise reduction of one-dimensional data to remove interference signals, providing more effective and reliable pre-processed data support for data fusion.

5. Acknowledgements

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