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Fire alert algorithm based on kernel principal component analysis for invariant feature

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Abstract. Early fire smoke not only has the dynamic feature, but also has the static feature, and an early fire recognition algorithm combined with a canonical correlation analysis and BP neural network (CCA-BPNN) is proposed to improve the accuracy rate of early fire recognition. First of all, the main directivity, area growth, color, brightness and other relevant features of smoke is extracted. Then canonical correlation analysis algorithm is used to integrate these features. Finally, these features are input into BP neural network for training to establish early fire recognition model. The simulation results show that the CCA-BPNN algorithm improves the accuracy rate of early fire recognition, reduce the false alarm rate and missing alarm rate and can meet the requirements of the accuracy and real-time requirements for early fire recognition, compared to the contrast algorithm.

Key words. Fire identification, Feature, Principal component analysis, Canonical correla-tion analysis, Feature fusion.

1. Introduction

The fire rate is increasing every year, and the fire not only damages to life safety of people but also brings huge financial losses. It is an important topic [1] at present to take appropriate preventive measures in time for fire recognition especially the early fire recognition to reduce the loss caused by fire as much as possible.

Domestic and foreign scholars have conducted a lot of research for the problem of early fire recognition, in which, the traditional method is to use temperature sensor to monitor the air temperature and give alarm according to results. However, temperature is changed only in the late fire and the accurate recognition can not

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be realized by it for early fire since it is used in limited [2] scope. Because there is no obvious flame signal but only the smoldering and a lot of smoke, currently the smoke image detection is mainly used to research [3] the early fire. There is early fire recognition algorithm based on the static smoke features and dynamic features. The static features mainly include the color feature while the dynamitic featured mainly include smoke diffusion area growth rate, smoke energy change and smoke mobility [3–6]. It is difficult to describe all the information in current smoke change, accurately recognize the early fire if the single smoke feature is used due to the occlusion, illumination and other relevant influences, and these single smoke features can not be applied to the actual fire warning system [7]. Every feature can reflect the early fire state and more information can be provided by combining several features, so some early fire recognition algorithm are developed based on the combination of multiple features. With multiple feature algorithm, the shortcomings of recognition algorithm relying on a single smoke feature is overcome, accuracy of early fire recognition is improved and the results are more stable and reliable [8, 9]. However, the input dimensionality and training time of classifier are increased, real-time performance of early fire recognition is affected and more seriously, there are a large number of redundant information between the features since several features are combined, which is likely to result in accuracy of the early fire recognition lower than single feature recognition algorithm. Thus, these features shall be integrated to extract the effective feature vectors and delete the redundant information between features. Currently, features are integrated mainly by linear discriminant analysis, principal component analysis and independent component analysis which are only for similar features. Correlation relations between various types of features can be extracted to realize the integration of multiple feathers by canonical correlation analysis (CCA) which is widely used [10] in the field of image processing.

In order to improve the accuracy of early fire recognition, a new early fire recognition (CCA-BPNN) based on canonical correlation analysis and neural network is proposed. First of all, static features and dynamic features are extracted separately. Then, the two kinds of features are integrated by using CCA algorithm for extraction of effective recognized features. Finally, the integrated feature vectors are input into BP neural network for learning and establishment of early fire recognition model, with inspection of algorithm effectiveness with specific example.

2. Extraction of early fire smoke features

2.1. Suspicious area of smoke

The extraction of suspicious area of smoke and determination of target are the segmentation of image background, which are the basis [10] for accurate recognition of the early fire.

Step1: Suspicious area of the smoke is segmented according to the dynamic features and the static features such as the color and the brightness of the smoke video image.

(1) Dynamitic features. Smoke movement features make the number of each col-

umn of pixel highlight of smoke image regularly increase or decrease. It is supposed that the number of a line of highlights in the image is f (n) and the one of the lat line of highlights is f (n-1), the suspicious area S1 meeting smoke dynamitic features is determined by judging the value of x=f(n-1)/f(n).

$$S_1 = \begin{cases} fire\ flame\,, & if\ x \leq 1 \\ disturbance\,, & if\ x > 1 \end{cases} \tag{1}$$

(2) Brightness. Use the (2) and (3) to process the original image (A) and remove the background area to obtained suspicious area S2.

$$T = A - A \circ b\,. \tag{2}$$

$$S_2 = Th(A)\ \&\ Th(T)\,. \tag{3}$$

In the formula, b is a structural element, and TH is the binaryzation operation.

(3) Color. Firstly, the video image is converted from RGB space to YCbCr space, and then Mahalanobis distance between the color components Cb and Cr is used to segment the suspicious area S3 of smoke. The Mahalanobis distance formula is shown as follows:

$$Md = \sqrt{(x_i - x_j)^T C^{-1} (x_i - x_j)^{\frac{1}{2}}}\,. \tag{4}$$

In the formula, T is the transposition operation, {xi } and {xj } refer to two types of samples and C is the covariance matrix of sample.

Step2. Integrate the suspicious areas determined in the above steps and extract the last suspicious area S.

$$S = S_1 \& S_2 \& S_3\,. \tag{5}$$

2.2. Extraction of smoke features

Dynamitic features (main directivity and area growth rate of smoke) and static features (smoke color and brightness) are selected as the basis for early fire recognition according to determined suspicious area S of smoke.

(1) Dynamitic features of smoke

1) Main directivity. The early smoke spreads from down to up since it is driven by the heat. Several consecutive frames can reflect this phenomenon, and the smoke in the whole suspicious area moves upwards, at about 45°∼135°, while individual pixels in disruptors moves upwards but the main direction of pixel movement is horizontal and downward. Main movement direction (γ) of suspicious area are be defined as the rate of the number of pixels in the upward direction to the total number of pixels in suspicious area.

$$\gamma = \frac{\sum\limits_{\theta=2}^{4} \theta_{main}(\theta)}{\sum\limits_{\theta=1}^{8} \theta_{main}(\theta)}\,. \tag{6}$$

In the formula, 1~8 refers to 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315° respectively, and $\theta_{main}(\theta)$ is the value of movement direction of each pixel.

2) Smoke area growth rate. The smoke area of the early fire will continue to grow, so the area growth rate of suspicious area detected in the several consecutive frames can be used as the feature for the early fire recognition. It is supposed that G(t, t0) is the diffusivity measurement of suspicious area of smoke detected early, and the corresponding calculation formula is shown as follows:

$$G(t, t0) = \left| \frac{size(T)_t - size(T)_{to}}{t - t_0} \right| . \tag{7}$$

In the formula, *size* (T)t and *size* (T)t0 refer to the size of the suspicious area of smoke in the t frame and t_0 frame separately.

(2) Static features of smoke

1) Brightness significance. Internal brightness of the smoke area is relatively uniform and has more obvious brightness change than that of the surrounding area. Thus, the brightness significance in the smoke area can be calculated as follows:

$$f_i(p) = 255 - \max_{p' \in w} |I(p) - I(p')| . \tag{8}$$

In the formula, w refers to subarea centered by p, $f_i(p)$ refers to the value of brightness significance of pixel p, and p' refers to the adjacent point.

2) Color significance. The color significance of pixel p in the image can be calculated as follows:

$$f_e(p) = \sum_{n=0}^{255} f_n \|a_p - a_n\| . \tag{9}$$

In the formula, a_p refers to the pixel value corresponding to the pixel p, with a_n as the gray value of the R channel and f_n as the frequency of occurrence of a_n.

3. BP neural network and CCA algorithm

3.1. BP neural network

Neural network is a modern intelligent inference technique by which the human thinking inference can be imitated. The number and connection of neurons in artificial neural networks are complex and changeable, and the neural network still has the special calculative capability in case of strong nonlinearity, large amount of information and fuzzy parameters. It is supposed that training samples can be expressed as (X_K, Y_K), where $K = 1, 2, ...m$, X_K refers to the input sample, $X_K^T = (x_{1k}, x_{2k}, ...x_{nk})$ and n refers to the dimensionality value in sample, so the expected output of Y_k is calculated as follows:

$$E = \sum_{K=1}^{m} E_K . \tag{10}$$

In the formula, E_K refers to the local variable of error function, which can be worked out as follows:

$$E_K = \sum_{i=1}^{n} \varphi(e_{ik}) = \frac{1}{2}\sum_{i=1}^{n}(y_{ik} - \hat{y})^2 = \frac{1}{2}\sum_{i=1}^{n} e_{ik}^2 \,. \tag{11}$$

The weights and thresholds between the neurons of BP neural network are continuously adjusted by adding training samples. If there are L hidden layers in the BP network in total, the ith output will be calculated as follows:

$$\begin{aligned} \overset{\wedge}{y_{ik}} &= \sigma_0(\overset{-}{y_{ik}}), \\ \overset{-}{y_{ik}} &= W_{ik}^{(o)^T} \hat{H}_k^{(l)} = \sum_{j=1}^{nl} w_{ij}^{(0)} h_{jk}^{(l)} \,. \end{aligned} \tag{12}$$

Differential adjustment rules for the Pth line in weight matrix are shown as follows:

$$\begin{aligned} \frac{\partial E_K}{\partial W_{PK}^{(0)}} &= \frac{\partial E_K}{\partial epk} \cdot \frac{\partial e_{pk}}{\partial \overset{\wedge}{y_{pk}}} \cdot \frac{\partial \overset{\wedge}{y_{pk}}}{\partial \overline{y_{pk}}} \cdot \frac{\partial \overline{y_{pk}}}{\hat{y}_{pk}^{(0)}} \\ &= -e_{pk} \cdot \sigma_0'(\overline{y}_{pk}) \cdot \hat{H}_{pk}^{(1)} \,. \end{aligned} \tag{13}$$

$$\Delta W_{PK}^{(0)} = W_{PK}^{(0)} - W_{pk-1}^{(0)} = -\alpha \frac{\partial E_k}{\partial W_{pk}^{(0)}} \,. \tag{14}$$

According to the reverse recursion from the output layer to the input layer of BP network, it can be obtained that weight adjustment mode of the rth layer is shown as follows:

$$\begin{aligned} \Delta W_{pk}^{(r)} = W_{pk}^{(r)} - W_{pk-1}^{(r)} &= \alpha \cdot \varepsilon_{pk}^{(r)} \cdot \hat{H}_{pk}^{(r+1)} \,, \\ \varepsilon_{pk}^{(r)} &= \sigma_r'(\overline{h}_{pk}^{(r)}) \cdot \sum_{i=1}^{n_r - 1} \varepsilon_{ik}^{(r-1)} w_{ip}^{(r-1)} \,. \end{aligned} \tag{15}$$

The number of nodes of hidden layer in BP neural network can be selected according to the following formula.

$$H = \sqrt{N + M} + a, 1 < a < 10 \,. \tag{16}$$

In the formula, H, N and M refer to the number of nodes of hidden layer and that of input and output respectively.

The process of establishing BP neural network model is a one of continuous optimization and change of weights and thresholds in fact.

3.2. Evidence theory of CCA algorithm

After obtaining the L *Traini* dynamic feature subsets and the static feature *Trainx*, every local feature subset can make up a training set couple (*Traini*, *Trainx*) with the global features, namely features can be integrated in CCA, and the specific process is shown as follows:

In the L dynamic feature subsets *Traini* $(i = 1, 2, \ldots L)$, every *Traini* includes N image sample in which every one has the dimensionality of k. For the static feature *Trainx*, the optimal CCA projection matrix couple $\left(W_y^i, W_x^i\right)$is constructed by using the training set couple (*Traini*, *Trainx*) to minimize the correlation between internal elements of two groups of low dimensional feature vectors obtained by projecting the initial sample based on this projection matrix couple and maximize the correlation between the two groups of low dimensional feature vectors.

$$\begin{aligned}[W_y^i W_x^i] &= [(w_{y1}^i w_{y2}^i \ldots w_{yr}^i), (w_{x1}^i w_{x2}^i \ldots w_{xr}^i)] \\ &= \arg \max_{{w_{yq}^i}^T w_{xq}^i} \frac{{w_{yq}^i}^T S_{yx}^i w_{xq}^i}{\sqrt{{w_{yq}^i}^T S_{yy}^i w_{yq}^i {w_{xq}^i}^T b S_{xx}^i w_{xq}^i}} \,.\end{aligned} \tag{17}$$

In the formula, S_{yy}^i is defined as the covariance matrix of *Traini*, $S_{yy}^i = E[yy^T]$ and S_{xx}^i is defined as the covariance matrix of *Trainx* and $S_{xx}^i = E[xx^T]$. The cross covariance matrix between the two groups of feature vectors is $S_{yx}^i = E[yx^T]$.

Formula (17) must meet the following conditions to ensure the optimal $[W_y^i,W_x^i]$.

$$\begin{cases} {w_{yq}^i}^T S_{yy}^i w_{yq}^i = {w_{xq}^i}^T S_{xx}^i w_{xq}^i = 1\,, \\ {w_{yq}^i}^T S_{yy}^i w_{yj}^i = {w_{xq}^i}^T S_{xx}^i w_{xj}^i = 0\,, \\ j = 1, 2 \ldots, r, \quad j \neq k\,, \\ w_{yq}^i \in R^k, w_{xj}^i \in R^{k_2}\,, \end{cases} \tag{18}$$

According to the principle of CCA method, we can know that W_y^i and W_x^i meet the following conditions:

$$\begin{cases} S_{yx}^i S_{xx}^{-1} S_{xy}^i W_y^i = S_{yy}^i W_y^i \wedge^i\,, \\ S_{xy}^i (S_{yy}^i)^{-1} S_{yx}^i W_x^i = S_{xx}^i W_x^i \wedge^i\;. \end{cases} \tag{19}$$

Formula (19) is a generalized eigenvalue problem, where $\wedge^i$ represents a diagonal matrix formed by the first r largest positive features of the problem and the column vectors of W_y^i and W_x^i are the feature vectors corresponding to these feature values.

Construct the above CCA projection matrix by using all the local features subset *Traini* $(i = 1, 2, \ldots L)$ separately and the global features, and then obtain the L projection matrix couple $\left[W_y^i, W_x^i\right]$,=] ($i = 1, 2, \ldots, L$), finally extract the features of the corresponding feature subset with this projection matrix.

4. Early fire recognition model of CCA-BPNN

In the early fire recognition based on CCA-BPNN, CCA algorithm is used to integrate the main directivity, smoke area growth rate and other dynamitic features and the brightness, color and other static features and then the same is used as the input vector of BP neural network by which the optimal early fire recognition model is learned to be set up to obtain the target type (early fire or interference) to be recognized. The early fire recognition model with integration of multiple features and neural network is shown in Fig.1.

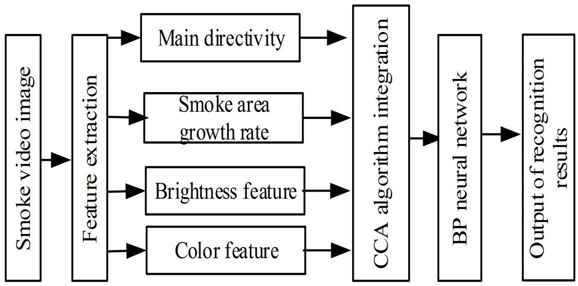


Fig. 1. Early Fire recognition model based on CCA-BPNN

Early fire is recognized according to the following steps in CCA-BPNN algorithm:

(1) Collect smoke video image for preprocessing.

(2) First, extract and determine the suspicious area of smoke, and then separately extract the main directivity, area growth rate, brightness and color of smoke.

(3) Naturalize the feature vectors and zoom the same into the range of [0 1].

(4) Use the CCA algorithm to integrate the main directivity, area growth rate, brightness and color of smoke to obtain the effective feature vectors.

(5) Input the effective feature vector into BP neural network to learn and set up the optimal early fire recognition model.

(6) Recognize the sample to be recognized by using the constructed early fire recognition model and output the recognition results.

5. Simulation experiment

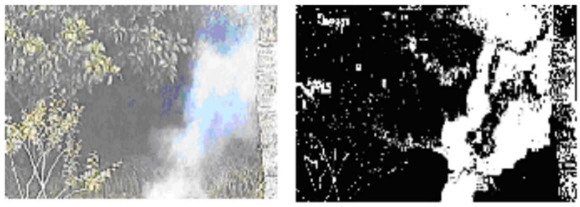
5.1. Experimental data

Table 1. Experimental data description

Number of experimental group	Experimental environment	Fire source materials	Interferent
1	Within community	Leaves	Pedestrian
2	Operating field	Wood	Pedestrian and fluorescent lamp
3	On the road	Plastic	Automotive lamp and pedestrian

The fire ignition experiments were simulated in the indoor and outdoor environments to verify the effectiveness of CCA-BPNN for early fire recognition, which were divided into 3 groups. 400 images were obtained from the same and 300 images were selected to make up the training set while the remaining was for the test set. 3 groups of video are described as shown in Table 1.

Suspicious area of smoke in an image is shown in Fig.2.



(a) Original image (b) Extraction of suspicious area

Fig. 2. Determination of suspicious area of smoke

Features are extracted for the suspicious area of smoke and the normalized results of the feature values of 500 samples are shown in Fig. 2. $x1$ represents the main direction, with $x2$ as the smog area growth rate, $x3$ as feature value of brightness significance, $x5$ as the feature value of color significance and y as the output type, where “1” represents the early fire (smoke) and “-1” represents the interferent (fluorescent lamps, alarm lamps, automotive lamp and pedestrians).

Table 2. Image feature value of sample set

Sample number	$x1$	$x2$	$x3$	$x4$	y
1	0.4695	0.3443	0.8669	0.5005	1
2	0.3947	0.0820	0.3420	0.7070	-1
3	0.0923	0.8987	0.8656	0.0585	1
4	0.4856	0.4102	0.6817	0.2550	1
5	0.0731	0.2765	0.8084	0.2080	1
6	0.6037	0.7905	0.9324	0.7561	-1
7	0.7494	0.2384	0.6565	0.2670	-1
8	0.4578	0.3883	0.3638	0.5661	1
...	...	...	...	...	...
500	0.2670	0.2654	0.1825	0.1244	-1

5.2. Results and analysis

(1) Early fire recognition results

In order to make the early fire recognition results of CCA-BPNN algorithm convincing, the single feature (dynamic and static features), dynamic features + static features, PCA are compared with the integration of multiple features algorithm, using the average accuracy rate, false alarm rate and missing alarm rate as the quality evaluation standard, and the experimental results of all the above algorithms are shown in Fig. 3∼5.

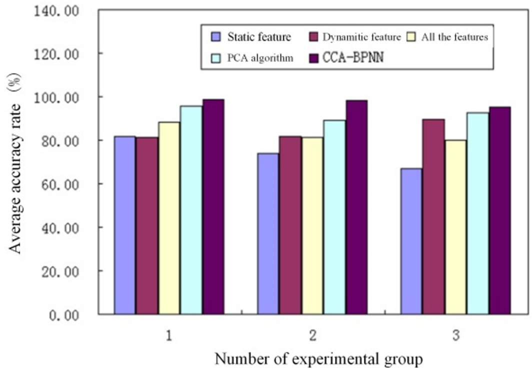


Fig. 3. Comparison of the accuracy rates of different early fire recognition algorithms

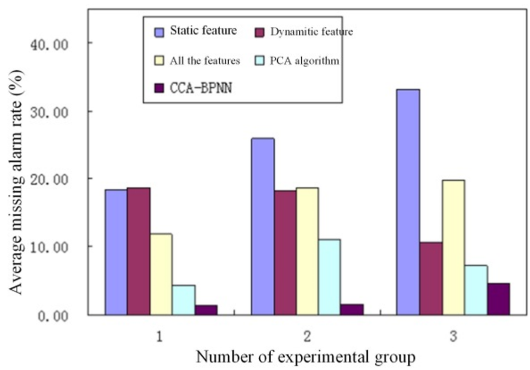


Fig. 4. Comparison of the missing alarm rates of different early fire recognition algorithms

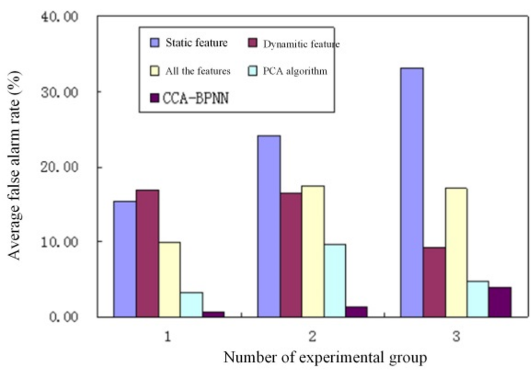


Fig. 5. Comparison of the false alarm rates of different early fire recognition algorithms

By comparing the results of Fig. 3∼5, we can get the following conclusions:
1) The accuracy rate of early fire recognition is low by using either the static

features or dynamitic features, with high false alarm rate and missing alarm rate, which is mainly caused by that the early fire state can be reflected only from one aspect but can not be described comprehensively if the single feature recognition algorithm is used. Thus, the overall results of single feature recognition algorithm are not satisfactory.

2) Compared with the single feature recognition algorithm, the global features combination algorithm is superior in the average recognition performance. However, it is inferior to the single feature recognition algorithm in the recognition accuracy rate sometimes, which is mainly caused by that there is not a simple linear relationship between the number of features and output type and there is redundant feature. Its recognition accuracy needs to be further improved.

3) PCA algorithm is superior to other algorithms in the performance, which is mainly caused by that the redundancy between features can be removed by PCA in a certain extent to decrease the input dimensionality, reduce the adverse effects of redundant information on early recognition results, improve the recognition accuracy rate and reduce the false alarm rate and missing alarm rate.

4) In all recognition algorithms, CCA-BPNN algorithm has the highest recognition accuracy and more stable and reliable recognition result, which is mainly because multiple features can be better integrated by using CCA algorithm to better eliminate the adverse effects of redundant information on early recognition results. It is an effective and feasible early fire recognition algorithm.

(2) Fire recognition speed comparison

Recognition speed is critical in the early fire recognition applications. In Matlab environment, TIC and TOC commands are used to calculate the average recognition speed of early fire recognition algorithm and the results are shown in Table 3. We can kwon from Table 3 that the CCA-BPNN is faster than other feature combination algorithms but slightly slower than the single feature recognition algorithm. However, CCA-BPNN has higher accuracy rate of recognition, which indicates that the input dimensionality of BP neural network is decreased with the CCA-BPNN algorithm so that the training time is shortened and early fire recognition speed is improved.

Table 3. Comparison of detection speeds of different models

Recognition algorithm	Average recognition time (s)
Static feature recognition algorithm	4.072
Dynamitic feature recognition algorithm	1.584
Global features recognition algorithm	19.071
PCA recognition algorithm	1.757
CCA-BPNN recognition algorithm	1.908

6. Conclusion

In view of the shortcomings of the single feature algorithm for early fire recognition, an early fire recognition algorithm with combination of canonical correlation analysis and neural network is proposed by taking advantages of CCA algorithm and BP neural network. The simulation results show that the accuracy rate of early fire recognition was improved with CCA-BPNN algorithm by which early fire can be recognized accurately and in real time and the requirements for early fire detection in different environments can be met.

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