Forest Fire Smoke Recognition Based on Multiple Feature Fusion

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Abstract. In order to discover the forest fire at the early stage, the video based fire smoke detection system should be developed. Three static features and three dynamic features are selected to recognize the fire smoke through the analysis of forest monitoring video. To solve the fusion problem of different features, a cascade classifier based on BP neutral network is designed. Each feature vector would be assigned a classifier as the first stage of the cascaded classifier. The output of the first level of the classifier used as the input of the second level of the classifier. The weight for each feature that given by the trainer is more scientific. The result of the experiments show that the cascade classifier has better performance compared to the single BP neural network.

Keywords: Fire smoke, Feature extraction, Cascade classifier

1. Introduction

Forest smoke recognition algorithm based on video analysis determines whether there is fire smoke in video through a series of processing of forest monitoring video\([1][2]\). The feature based smoke recognition method is a tradition method in fire smoke recognition\([3]\). It extracts appropriate dynamic and static features and designs effective classifiers to fuse and classify features for smoke recognition.

Töreyin proposes to use spatial wavelet transform to monitor the change of the high frequency component of the image, especially the change of the edge of the image\([4]\). He thinks that the edge of the image can provide the local extremum in the wavelet domain, which suggest the emergence of the fire smoke. Lin Wang et al. extract color features from RGB and HSI space and use two-dimensional wavelet transform to extract the background fuzzy features\([5]\). From Kolesov’s point of view, the motion vector can be extracted as the motion feature by the optical flow method and SVM can be used as classifier which has a good performance\([6]\). Tiantian Tang introduces a local binary model to extract the texture features of the image and the experiment shows that the smoke texture features are effective in smoke recognition\([7]\). Chen T-H et al. determine whether the suspected region is a smog area through the static and dynamic features\([8]\). The static feature mainly refers to the color features extracted from the RGB space, while the dynamic feature refers to the diffusion characteristic of the smoke. Maruta H identifies the fire smoke by comparing the Hurst index of suspected smoke area and standard smoke image\([9]\). Ha C employs motion information for detecting the correct smoke block by
using the characteristics that smoke goes almost upward[10].

This paper extracts 6 kinds of static and dynamic features to recognize the fire smoke region. The static features include the color feature, the texture feature and the edge contour feature, while the dynamic features include the motion direction feature, the area growth feature and the periodic flutter intensity feature. In addition, a cascaded classifier based on the BP neural network is designed to realize multi-feature fusion. Each feature vector would be assigned a classifier as the first stage of the cascaded classifier. The output of the first level of the classifier used as the input of the second level of the classifier, which is more efficient and solves the fusion problem of different features.

2. Feature Extraction

2.1 Static Features

We mainly consider 3 static features, including color feature, the texture feature and the edge contour feature to identify the fire smoke region.

2.1.1 Colour Feature. Color moment is a simple, effective and low dimension color feature developed from the concept “moment” in linear algebra. The pixel values in the image are regarded as random variables. The color information is mainly distributed in the low order moment. So the first order original moment which shows in (1), the second order center moment which showed in (2) and the third order center moment which showed in (3) are the most common used to describe the characteristic of a colored image. $p_{i,j}$ refers to the probability of occurrence of pixels in the channel $i$ of the color image with the value of $j$, and $N$ represents the number of pixels in the image.

\[
\mu_i = \frac{1}{N} \sum_{j=1}^{N} p_{i,j} \]

\[
\sigma_i = \left( \frac{1}{N} \sum_{j=1}^{N} (p_{i,j} - \mu_i)^2 \right)^{\frac{1}{2}} \]  

\[
s_i = \left( \frac{1}{N} \sum_{j=1}^{N} (p_{i,j} - \mu_i) \right)^{\frac{1}{3}} \]

2.1.2 Texture Feature. The fire smoke is composed of fine particles. When the smoke density reaches a certain level, the smoke completely blocks the background area in the camera monitoring scene. The uneven diffusion of smoke can lead to the diversity of the surface texture of the smoke area and have a certain effect on the high-frequency components, which can help us to identify the smoke area. Texture features can be quantified by gray level co-occurrence matrix. The gray level co-occurrence matrix contains the information of the direction, distance and amplitude of the image by calculating the correlation between the 2 pixels separated by a certain distance and a certain angle in the image.

2.1.3 Edge Contour Feature. Smoke spreads to the surrounding area with the air flow, which leads to the change of contour. Compared to the objects with fixed shapes such as vehicles or human beings, the contour of smoke has the irregular shapes. We can see that the length of the contours of the smoke are always longer than human beings and vehicles when they have same area. Therefore, the contour of the smoke can be measured by the correlation between the circumference and the area, which shows in (4). $P$ refers to the circumference of the motion area while $s$ represents the area of the motion area.

\[
\gamma = \frac{P^2}{s} \]  

(4)
2.2 Dynamic Features
We take the motion direction feature, the area growth feature and the periodic flutter intensity feature into consideration as dynamic features of the fire smokes.

2.2.1 The motion Direction Feature. There will be a lot of heat at the place of forest fire. The fire smoke presents a general trend of rising due to the effect of the heat and the air flow. The moving direction of people and vehicles is obviously distinct with the smoke. The analysis of moving direction of the moving area can also be one of the features to recognize the fire smoke along with other moving object.

We can use the overlap rate to trace the motion area. As it shows in Figure 1, we extract the moving area A and moving area B from frame k and frame k+1 and then calculate the overlap rate $R_s$ following (5). In (5), $S_A$ refers to the area of region A, while $S_B$ refers to the area of the region B and $S_{A\cap B}$ represents the overlap area of region A and region B.

$$R_s = \frac{S_{A\cap B}}{\max\{S_A, S_B\}}$$ \hspace{1cm} (5)

Figure 1. Trace of the moving area

Threshold $T_s$ will be set and if $R_s > T_s$, area A and area B are regarded as the same moving area. The centroid of the region A and the region will be calculated respectively. The state of the moving area is fitted with the motion state of the centroid.

2.2.2 Area Growth Feature. As it shows in Figure 2, we extract the moving area in frame k and frame k+50. With the increasing of fire and the diffusion of smoke, the area of smoke region gradually grows. Detecting the relative growth rate of the area in the continuous frame can measure the diffusion characteristics of the smoke, which help us in fire smoke recognition.

We can assume that the area of region A in frame k equals to $S_{A,k}$ and area of region A in frame k-$\Delta$ equals to$S_{A,k-\Delta}$. So the relative growth rate of the area $V_{S_k}$ can be calculate in (6).

$$V_{S_k} = \frac{S_{A,k} - S_{A,k-\Delta}}{S_{A,k-\Delta}}$$ \hspace{1cm} (6)

2.2.3 Periodic Flutter Intensity Feature. In the case of forest fires, smoke has certain speed characteristics besides the movement direction characteristics under the influence of heat and air flow. Suppose that a series of centroid $X(t = 1, 2, 3, \ldots)$ of the motion region A is a two-dimensional vector. $X_t[1]$ and $X_t[2]$ respectively represent the transverse and vertical coordinates of the centroid. The position of the centroid of the smoke area is shown in Figure 3.
Figure 3. Position of the centroid of the smoke area

It can be seen that the moving direction of the centroid moves upward generally and the intensity of movement is regular. However, human beings have uncertain moving direction and irregular intensity of movement, as it shows in Figure 4.

Figure 4. Position of the centroid of human beings

We definite the intensity of the movement in (7) to distinguish the fire smoke and other moving area. \( W_T \) refers to the number of frames in the video.

\[
F(I^*) = \sum_{t=2}^{n_{WT}} \sqrt{ (C_{t-1}[1] - C_{t}[1])^2 + (C_{t-1}[2] - C_{t}[2])^2 }
\]  

(7)

3. Classifier Design

Considering that the selected features have different orders and the optimal parameters of the classifiers for each features are not uniform, it is not rational to combine the feature vectors directly. The feature like texture feature who has small order can hardly affect the final result and we can’t know the contribution of each feature to allocate the weight in the process of recognition. A cascaded classifier based on the BP neural network is designed in this paper. The specific structure is shown in Figure 5, where M is the number of selected features.

Figure 5. Structure of the classifier

The cascade classifier of double level BP neural network takes into account the self-learning and self-adaptive ability of the BP neural network. We use an independent BP neural network to train each type of feature as the first lever of the classifier. The second level of the cascade classifier uses a single BP neural network with M dimension inputs and one dimension output. The parameters for the classifier of each feature would not affect each other and the weights that given by the trainer are more scientific.

4. Experiment

In this paper, the recognition results are tested by 2 indicators, the recognition rate and efficiency rate, which show in (8) and (9), where \( N_{sc} \) refers to the number of smoke areas recognized correctly and \( N_{sf} \) refers to the number of smoke areas that are in fact exist. \( N_{dt} \) represents the number of smoke areas that are detected in total. The experiments are done from 2 aspects.

\[
\text{Recognition Rate} = \frac{N_{sc}}{N_{sf}}
\]  

(8)
Efficiency Rate = \frac{N_{sc}}{N_{dt}} \tag{9}

We would compare the recognition rate and the efficiency rate for the single BP neural network and our cascaded classifier. The results are shown in Table 1.

|                      | Single BP Neural Network | Cascade Classifier |
|----------------------|--------------------------|--------------------|
| Recognition Rate     | 0.7009                   | 0.9094             |
| Efficiency Rate      | 0.4033                   | 0.4098             |

We can see in Table 1 that the cascade classifier can get the recognition rate even higher than 0.9 while the single BP neural network only get about 0.7. Our cascade classifier has better performance. As it shows in Figure 6, the smoke area can be accurately recognized.

5. Conclusion
This paper extracts 3 static features and 3 dynamic features that suitable for fire smoke recognition. In order to solve the problem of the fusion of different features, a cascade classifier based on BP neural network is designed. The experiments show that the performance of the cascade classifier is good.

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