Image Based Forest Fire Detection Using Dynamic Characteristics With Artificial Neural Networks

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***Abstract* - In this paper, we propose a real-time forest fire detection algorithm using artificial neural networks based on dynamic characteristics of fire regions segmented from video images. Fire region is obtained from image with the help of threshold values in HSV color space. Area, roundness and contour are computed for fire regions from each 5 continuous frames. The average and mean square deviation of them are used as dynamic characteristics, and taken as input of the artificial neural network. The trained BP network can help identify forest fire, even distinguish it from moving car or flying flag with red color. Experimental results of our method prove its value in forest fire surveillance.**

Keywords - color segmentation; feature extraction; dynamic characteristics; BP neural network

I. INTRODUCTION

The monitoring of forest fire has mainly depended on manpower and satellite for a long time. In recent years, with the development of video surveillance, the method of image-based automatic forest fire detection has received more and more attentions from researchers [1-3]. Compared with the way of satellite surveillance, video-based fire detection is much cheaper and can work in real-time.

Different with the other fires, forest fire monitoring has its own properties. Its view range is not limited, can be 3-5 km generally or even 8 km. Focal length of the cameras is changeable, and the size of objects in recorded images is not constant. The cameras are usually installed on the top of mountains, and they are not very stable because of wind blow. All of them cause a great deal of trouble for fire detection. Therefore it is necessary to specially study the case of forest fire recognition.

Until now there have been some reported algorithms for automatic fire recognition, but the accuracy of them is still not satisfactory, especially for distinguishing between fire and its similar objects [4-7]. In our paper, a novel method is proposed for image based forest fire detection using some dynamic characteristics with the help of BP neural network, and it has good performance in recognizing forest fire from its likenesses.

The structure of our paper is: fire segmentation by color space is introduced in section 2, extraction of fire features is described in section 3, dynamic characteristics are defined in section 4, application of BP neural network is provided in section 5, results and conclusion are given in section 6 and 7.

II. SEGMENTATION BASED ON COLOR

Compared with RGB color model, HSV (hue, saturation, value) is very suitable for providing a more people oriented way of describing the color, because the hue, saturation and value components are intimately related to the way in which human beings perceive color. Thus we convert the images from RGB to HSV color space, and define it as

$$V = \{x \mid x(H) \in [0,359], x(S) \in [0,255], x(V) \in [0,255]\} \quad (1)$$

where x is a pixel in HSV color space, $x(H)$, $x(S)$, $x(V)$ are H, S, and V component value of x respectively. The fire color distribution is obtained from sample images containing fire regions, and the collected sample color values form a 3D point cloud, as shown in Fig. 1. Then the 3D shape of the point cloud can be represented by Gaussian mixture model, and the pixel whose color lies within the range of the distribution model can be taken as a fire pixel.

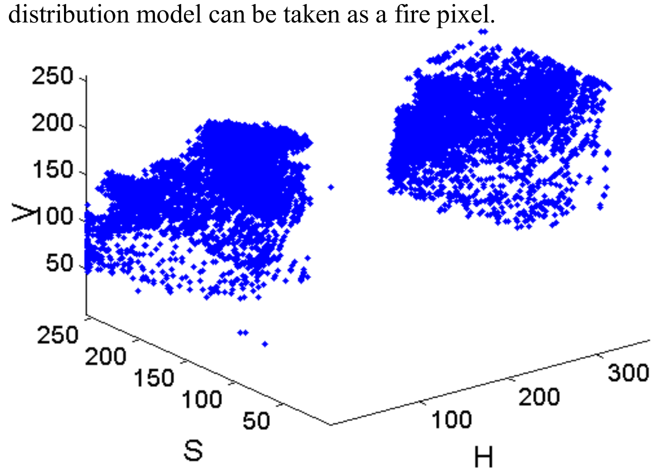

Figure 1. The sample color values in 3D HSV color space

To further reduce the computational cost, we use three 2D projection planes instead of the 3D distribution model, i.e. sample fire colors are projected onto HS plane, HV plane and SV plane. In each plane, the range of color distribution can be easily represented by one or two rectangles, and thus a relative simple 2D color distribution is defined as

$$Vx = \{x \mid x(H) \in [0,36] \cup [345,359], x(S) \in [69,255]\} \quad (2)$$

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Based on the color range, the images are segmented and candidate fire regions are obtained, as shown in Fig. 2. The segmentation method is ideal for images with forest fire, but it can also get some fire like objects whose color is within the same color range, such as the flying red flag or the moving red car, as illustrated in Fig. 3. Therefore, besides the color based segmentation, the other fire features have to be adopted for more accurate recognition from the candidate fire regions.

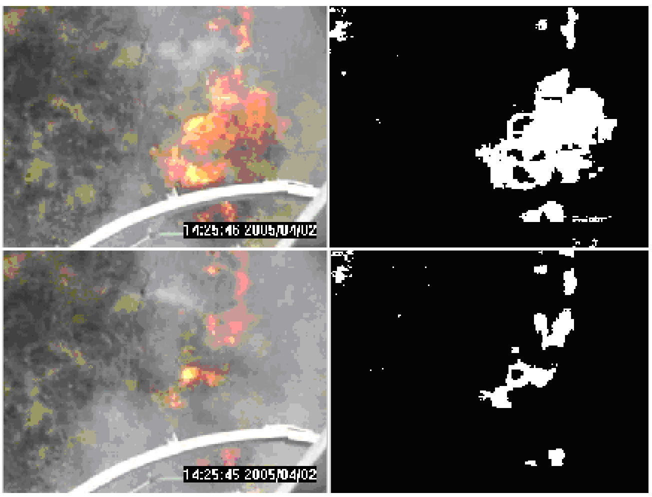

Figure 2. Fire region segmentation based on color

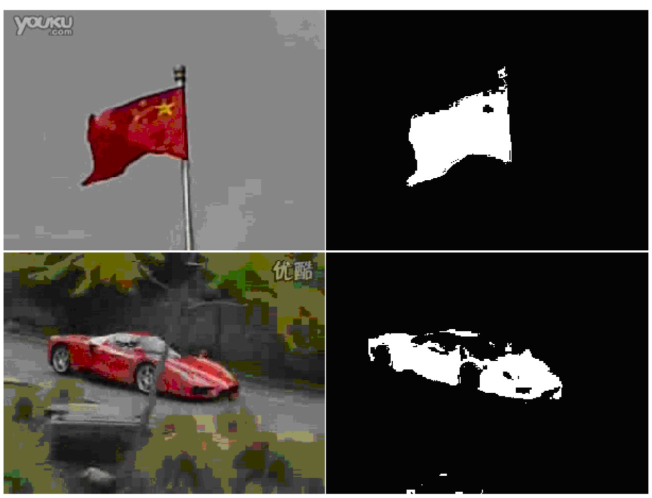

Figure 3. The segmentation of fire-like objects

III. EXTRACTION OF FIRE FEATURES

After segmentation of possible fire regions from video images, the features of them including area, roundness and contour can be calculated, and then the features are used for further decision.

A. Area

The early forest fire is an instable and developing flame, i.e. the fire area represented by the number of fire pixels is consecutively increasing. Thus area is an important feature of fire. To identify a fire's growth, we can calculate the size variations of fire area from two consecutive images. If the result is more than a predefined threshold value, there is a likely fire's growth.

B. Boundary chain code and roundness

Given a segmented fire region, we retrieve its boundary using a classical Laplacian operator $\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$, and then it is convenient for us to retrieve its 8-connected boundary chain code [8]. From the chain code, we can easily calculate the perimeter L of the boundary. Based on the perimeter and the area of fire region, we calculate the roundness as L^2/S, which describes complexity of the shape, i.e. more complex shape has greater value. Roundness can help to get rid of the inerratic bright subjects in the early time.

C. Contour

Since the shape of fire region is changeable owing to air flowing, we can calculate the contour fluctuation to measure the disorder. Assume there are N points on the boundary, and they are expressed in the complex form $\{z_i \mid z_i = x_i + jy_i\}$, where (x_i, y_i) are the coordinates of the ith point on the boundary of fire region traversed clockwise. The coefficients of the Discrete Fourier Transform (DFT) [9] of z_i are then calculated as

$$F_w = \frac{1}{N}\sum_{i=1}^{N} z_i \exp(-j\frac{2\pi}{N}iw) \tag{3}$$

F_0 represents the centre of gravity of the 1-D boundary, which does not carry shape information, so we neglect it to achieve the translation invariance. Experiments show that only a few dozens of the Fourier coefficients are really needed to describe the contour, thus we choose the front 32 ones $D = (\|F_1'\|_2, \|F_2'\|_2, ..., \|F_{32}'\|_2)$, and the difference of two consecutive Fourier descriptors is

$$D_i = \sum_{w=1}^{32} \left| \|F_w^{i'}\|_2 - \|F_w^{i-1'}\|_2 \right| \tag{4}$$

If D_i is greater than Td and lasts for a time period longer than Tm, where Td and Tm are statistical threshold values from experiments, it means that there is a drastic change in shape and probably a fire.

IV. DEFINITION OF DYNAMIC CHARACTERISTICS

Since forest fire is continuously developing, the dynamic characteristics of fire features from continuous video frames are very important for fire detection, which makes it possible to identify fire from the similar objects.

We define the dynamic characteristics for one video clip including n consecutive video images. To make sure that fire detection performs in real time, n should be a relative small number. As a common sense, the flames flicker with a characteristic flicker frequency of around 10 Hz independent of the burning material and the burner [10], and the recorded videos have 30 frames per second. Based on the facts, n is assigned with the value of 5. That is, dynamic characteristics are defined for the fire features from every 5 consecutive video frames.

Therefore, a nxm matrix is constructed for fire features of a video clip, where n=5 is the number of consecutive frames in the video clip, while m=3 is the number of fire features including area, roundness and contour. Suppose $X(i, j)$ is one element of the matrix corresponding to the ith frame and the jth fire feature, dynamic characteristics based on the matrix are defined as the average

$$E(j) = \frac{1}{n}\sum_{i=1}^{n} X(i, j) \tag{5}$$

and the mean square deviation

$$S(j) = \sqrt{\frac{1}{n}\sum_{i-1}^{n} (X(i, j) - E(j))^2} \tag{6}$$

Now, for any video clip, there are six related dynamic characteristics, i.e. average and mean square deviation of area, roundness and contour.

V. CONSTRUCTION OF BP NEURAL NETWORK

The BP neural network proposed in our paper is three-tier model, as shown in Fig. 4. The dimension of the input vector is six. If x is the input vector, x_1 and x_2 are the dynamic features of the area of fire region, x_3 and x_4 are the dynamic features of the roundness of fire region, x_5 and x_6 are the dynamic features of the contour of fire region. So the number of nodes in input layer is six, and the number of nodes in output layer is one. The output value is $r \in [0,1]$. When r is close to 1, it means that there is high possibility of fire in current video clip. When r is close to 0, it means that there is low possibility of fire.

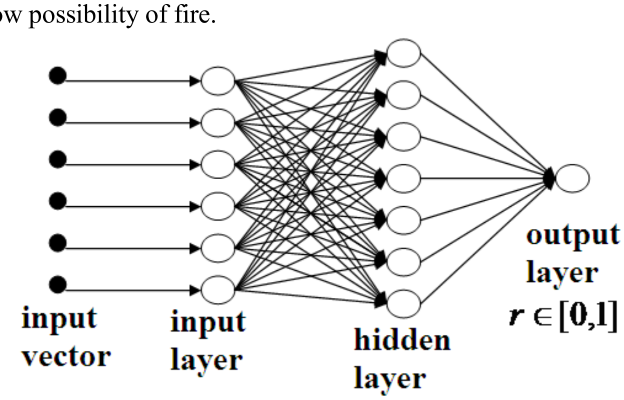

Figure 4. The proposed BP neural network

As for the number of nodes in hidden layer, there is no certain method for computation, since it is related with the numbers of nodes in both input and output layers, and more important, related with the properties of the problem. If the number of nodes in hidden layer is too small, the BP network will be less robust. If the number is too large, the learning time will be very long. Currently there are several empirical formulas for the number. Suppose i, o and h are the numbers of nodes in input, output and hidden layers respectively, the formulas are

$$\begin{aligned} h &= \sqrt{i+o} + d \\ h &= \log_2 i \\ h &= \sqrt{i \times o} + d \end{aligned} \tag{7}$$

where $d \in (0,10)$ is an integer value. Based on experiments, 7 is taken as the number of nodes in hidden layer.

When the BP neural network is set up, input and output samples are used for training. During training the threshold value and weighting parameters of the network are adjusted to implement the mapping relations between the input and output samples. In our work, LM algorithm is adopted to train the BP neural network as it can avoid the calculation of the Hessian matrix when adjusting the approximate rate of second-order training. In Newton algorithm, if the Hessian matrix is not positive, the direction of Newton may point to the local maxima or a saddle point. In this case a positive matrix can be added to the Hessian matrix to make it become positive. Levenberg and Marquardt introduce this concept in the problem of least squares.

The updating formula for threshold value and weighting parameters of BP network is

$$x_{k+1} = x_k - (H + \mu I)^{-1} f'(x) \tag{8}$$

where H is a second-order differential Hessian matrix for errors on weighting parameters, while μ is a scalar quantity. Depending on μ, the method changes smoothly between two extreme cases: Newton algorithm (when μ->0) and the steepest drop algorithm (when μ->∞). In this method, μ is self adaptively adjusted, at the same time the current error and the old weighting parameters need to be recorded. The self adaptive adjustment algorithm for μ can be described as the following codes:

```
if (err < currentErr)
{  μ*= 0.1;              // reduce μ
   currentErr = err;     // update the current error
}
else
{  μ*= 10.0;             // increase μ
   use the old weighting parameters
}
```

The adopted LM optimization algorithm can reduce the learning time and obtain better results. Of course, amount of memory is needed to store the Hessian matrix.

VI. EXPERIMENTAL RESULTS

Three digital videos including forest fire, flying red flag and moving red car respectively are taken as data in our experiments. Clips of the videos are used as training samples and testing samples. Dynamic characteristics of fire features from them are taken as input of the BP neural network, while the output value is $r \in [0,1]$.

Based on our experiments, it can be found that when the number of training is more than 1000, the convergence tendency becomes not obvious as illustrated in Fig. 5, thus we define the maximum number of training as 1000.

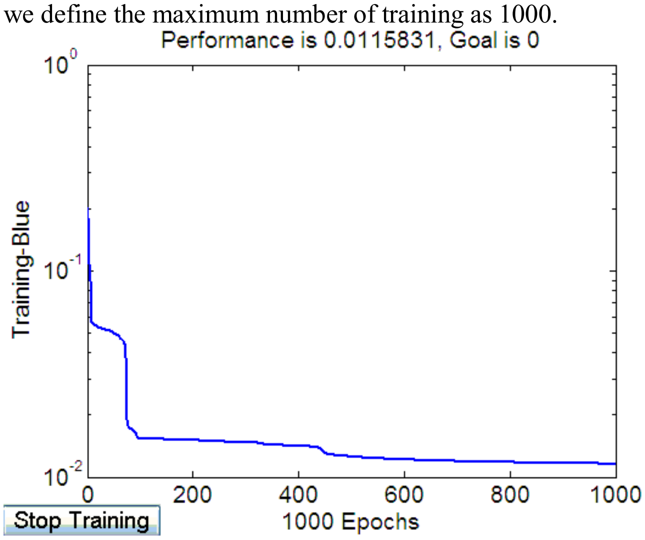

Figure 5. training process

After the BP neural network has been trained by the training samples, it can be used for the testing samples. If the output value lies within (0.75, 1], the related video clip is concluded as having fire, and then the alarm rings. The experimental results are listed in Table 1, from which we can find that the accuracy rate is 98.94%.

TABLE I. EXPERIMENTAL RESULTS

Video	Num of clips	Real fire clips	Alarm times
Forest fire	27	27	26
Flying red flag	291	0	1
Moving red car	58	0	2

VII. CONCLUSION

In our paper, an algorithm is presented for automatic forest fire detection from monocular video images, during which dynamic characteristics are considered with the help of BP neural network. Our method can recognize fire; even from the objects appear similar to it.

Possible fire regions are segmented from video image based on the fire range of HSV color space, while the fire range is defined from collected sample images. To save the computational time, the samples in 3D color space are projected onto 2D planes and a relative simple 2D fire range is obtained for quick segmentation.

Fire features including area, roundness and contour are defined for fire like regions, and then are used to define dynamic characteristics of video clips. We take every five consecutive frames as one video clip, and take the average and the mean square deviation of the three fire features as the dynamic characteristics of it.

BP neural network is applied to help detect forest fire based on the collected sample video clips. As the standard BP neural network is slow in convergence, we use LM to speed the training procedure. With the trained BP neural network, forest fire can be recognized effectively from the other similar objects such as the moving red car or the flying red flag.

For forest fire, sometimes the flames are covered with smoke and only little fire appears on the image, as shown in Fig. 6. In this case, the fire regions are very hard to be segmented. Compared with flame, smoke has less typical features and thus difficult to be recognized. Therefore, there are still many problems for automatic detection of forest fire with heavy smoke in the future.

Figure 6. The forest fire with heavy smoke

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