Contour Based Forest Fire Detection Using FFT and Wavelet

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Abstract—In the methods of video based fire detection, wavelet was usually used to test whether a pixel belongs to fire region, while Fast Fourier Transform was used to describe the contour of fire area. We try these two methods on images with forest flame, and develop one new approach combined both wavelet and FFT. In our method, contour of fire is found firstly, then is presented by FFT, and then temporal wavelet is employed to analyze the FFT descriptors from all frames of a video clip. Our approach avoids the setting of contour threshold value in FFT method, and also detects more accurate fire frames than wavelet method. The novel approach is tested with some video clips of forest fire, and the experimental results are satisfying.

Keywords: Forest fire; Region contour; FFT; Wavelet

I. Introduction

The fire disaster not only causes property losses, but also damages a variety of resources such as forest resources. There are two traditional methods to detect fire. In buildings, the fire sensors are used to detect the presence of certain particles generated by smoke and fire. In other places, such as forest, some people are employed to monitor the situations. But both of these traditional methods have limits, e.g. the detectors must be set near the fire point and may be out of order, human resources are expensive.

The analysis of image and video contents has been studied by many researchers [1,2]. If the content is fire, one new kind of fire recognition approach has been adopted, i.e. video based flame detection method [3-5]. Phillips et al. [3] used color and temporal variation as clues. Whether a pixel belongs to fire area depends on its color and significant temporal variation. Giuseppe Marbach et al. [4] used temporal variation of fire intensity to capture candidate regions and extract characteristic color features to detect fire. Thou-Ho Chen proposed a fire-color model with RGB and saturation value to detect fire-colored region and then use region's spread as a clue to check it [5]. Yuan et al. [6] took a series of static features including color, texture, etc. and the temporal variation of flame contour as clues to detect fire in video. In their method, Fourier descriptor is used to represent the contour information of fire region which is also an important factor in our method. Then one threshold value T_d is set to measure whether the temporal variation is large enough to represent fire, and the threshold value may vary in different fire scenes thus hard to be defined. Toreyin et al. [7] developed a wavelet method for detecting whether a pixel is fire or not. They keep on tracking the history of red channel for each pixel which is part of fire contour in a relative short time, and take them as the input of wavelet method. In their method, the two-channel decomposition filter coefficients are $\{-0.25, 0.5, -0.25\}$ and $\{0.25, 0.5, 0.25\}$, which are the same coefficients used in our method. They apply wavelet method at pixel level, but in fact the flickering frequency is more accurately represented by the whole shape of fire region.

In our method, based on the fact that flames flicker with a characteristic frequency around 10 Hz independent of the burning material, we use the temporal wavelet to analyze Fourier descriptors representing the variation of flame contour in a relative short period. Therefore, we can avoid setting the threshold value for FFT while more accurately detect forest fire than wavelet method only.

II. Fire Detection Algorithm

Our approach for forest fire detection includes three steps: segment fire region and achieve the flame contour, use FFT method to describe the contour, analyze the calculated Fourier descriptors with temporal wavelet and provide decision.



A. Contour of Fire Region

Based on the fact that fire and smoke always exist together in forest, the method of [8] is used to segment the images from forest surveillance video. Taking gray value as the input of Otsu method, fire and smoke regions are segmented from the background. Since the shape of forest smoke is normally continuous in one image, the smaller and isolated regions are deleted as noises. Then taking R value in the RGB color space as input of Otsu method, the fire region is segmented from the left large and continuous regions. After the fire region is obtained, we then use the

classical Laplacian operator
$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \ \ \text{to achieve its}$$

boundary, and then the eight-connected boundary chain code can be easily retrieved to represent the fire contour.

B. Fourier Descriptors

We can calculate the contour fluctuation to decide whether the region is fire or not due to the shape of fire that changes every frame. We assume that the boundary has N points which are expressed in complex form

$$\{z_i \mid z_i = x_i + jy_i\} \tag{1}$$

where (x_i, y_i) are the coordinates of the ith point on the boundary. The coefficients of the Discrete Fourier Transform (DFT) [9] of z_i are calculated as

$$F_{w} = \frac{1}{N} \sum_{i=1}^{N} z_{i} \exp(-j\frac{2\pi}{N}iw)$$
 (2)

 F_0 is about the centre of gravity of the 1-D boundary and it does not include shape information, therefore, we do not take it into consideration. Experiments show that a few dozens of the Fourier coefficients are enough to describe the contour, therefore we choose the front 32 ones as Fourier descriptor $D = (\|F_1^{\perp}\|_2, \|F_2^{\perp}\|_2, \dots, \|F_{32}^{\perp}\|_2)$, and calculate the variance of two consecutive Fourier descriptors [10] as

$$D_{i} = \sum_{w=1}^{32} \left\| \left\| F_{w}^{i'} \right\|_{2}^{i} - \left\| F_{w}^{i-1'} \right\|_{2}^{i} \right\|$$
 (3)

As a common sense, flames flicker with a characteristic flicker frequency of around 10 Hz independent of the burning material and the burner. Therefore, the contour of flame should fluctuate with the similar frequency. Based on this fact, in our method, we use the temporal wavelet to analyze the variance of two consecutive Fourier descriptors.

C. Temporal Wavelet Analysis

We keep track of the variance of two consecutive Fourier descriptors in a relatively short time and analyze the sequence of variance with temporal wavelet. The video capture rate should be high enough to capture flicker. For example, if there is 10Hz flicker in video, the video capture rate should be at least 20Hz. In our experiment, the digital camera can get 30 frames per second, so it works.

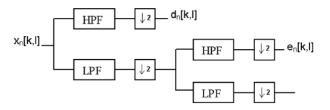
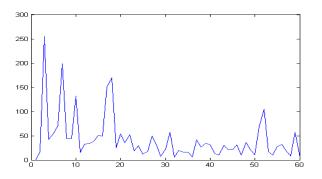


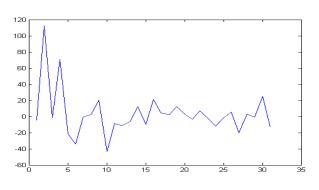
Figure 1. A two-stage filter, HPF represents high-pass filter and LPF represents low-pass filter.

In Fig.1, $x_n[k, l]$ is used to represent the variance of Fourier descriptors between the nth frame and the n+1th frame. Each $x_n[k, l]$ in a relatively short time is assigned to a two-stage filter bank as shown in Fig.1. The two-channel decomposition filter is constituted of high-pass filter ($\{-0.25, 0.5, -0.25\}$) and low-pass filter ($\{0.25, 0.5, 0.25\}$). If the nth frame has high frequency action, high-band sub-signals d_n and e_n should be non-zero. On the contrary, if the nth frame stay stationary compared with the consecutive frame, these two sub-signals should be equal to zero or very close to zero due to high-pass filters. The number of zero crossings of the sub-band signals d_n and e_n in a few seconds, i.e. flicker frequency of the region's contour, is used to discriminate between real flame and an ordinary fire-colored object. If this number is above the predefined threshold value, an alarm can

be issued for the current frame, and we consider the current fire-colored region is real fire.



(1) The variance of consecutive Fourier descriptors



(2) The value of d_n

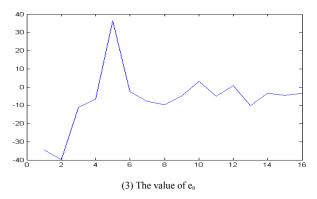


Figure 2. Variance of consecutive Fourier descriptors and the corresponding wavelet signals, (1) the x-axis represents the frame number and the y-axis represents the variance of Fourier descriptors, (2) and (3) reveal the flickers, the x-axis represents the index of wavelet transform, and the y-axis represents the value of d and e respectively.

The temporal feature of the variance between consecutive Fourier descriptors and the corresponding wavelet signals are shown in Fig.2. The contour flickers for n = 3, 5, 6, 7, 10, 15,

17, 18, 20, 22, 31, 51, 52, 59. The sub-signals d_n and e_n reveal the flicker at the corresponding nth frame with peak value. The length of wavelet signals is halved after each stage of sub-band filtering because of a down-sampling operation during wavelet computation. As a result, the value of a sample in a sub-band signal corresponds to several samples in the original signal. For example, the value of $d_6[10, 39]$ corresponds to the values of $x_{12}[10, 39]$ and $x_{13}[10, 39]$, and the value of $e_6[10, 39]$ corresponds to the values of $x_{24}[10, 39]$, $x_{25}[10, 39]$, $x_{26}[10, 39]$, $x_{27}[10, 39]$ in the original signal.

III. Experimental Results

We compare our method with the wavelet method [7] based on two kinds of video clips. One is the early fire, and the other is the blazing fire. The early fire and extracted contours of fire region are shown in Fig.3, while the blazing fire and extracted fire contours are illustrated in Fig.4.



(1) The first five frames of an early fire



(2) The contours of fire regions

Figure 3. The type of early fire



(1) The first five frames of a blazing fire



(2) The contours of fire regions

Figure 4. The type of blazing fire

The threshold value for flicker frequency is set to 3, and the results are listed in Table 1. The first frame, the last frame, and the number of frames detected as fire are used to compare the efficiencies of two methods. Obviously, our method can provide more accurate detections. Other thresholds, such as 4 and 5 are also tried, and the same conclusion can be achieved from the experimental results.

IV. Conclusion

Based on the experimental results, we can find that the wavelet method and our method both give a satisfying result for early fire. This exactly meets our common sense that the shape of early fire varies every time and the region of early fire is small, therefore the pixels keep on changing their regions, fire or background. However, when the fire becomes blazing, our method is obviously better than the wavelet method. In the situation of blazing fire, most pixels are always in fire region or non-fire region, only the fire contour keeps on changing. Thus the flickering frequency is more accurately described by the whole shape of fire region, and our method is a better choice.

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|-------------|-----------|------------------|----------|------------------|----------|------------------|-----------|--------------|
| Video clips | Number of | The firs | st frame | The las | st frame | Number | of frames | Description |
| | frames | detected as fire | | detected as fire | | detected as fire | | |
| | with fire | Wavelet | Our | Wavelet | Our | Wavelet | Our | |
| | | method | method | method | method | method | method | |
| Movie 1 | 60 | 1 | 1 | 60 | 60 | 60 | 60 | early fire |
| Movie 2 | 60 | No | 1 | No | 60 | 0 | 59 | blazing fire |
| Movie 3 | 60 | 3 | 1 | 60 | 60 | 15 | 58 | early fire |
| Movie 4 | 71 | No | 1 | No | 71 | 0 | 64 | blazing fire |

Table 1. Experiment results of four video clips