Early forest fire smoke detection based on aerial video

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Abstract. The early detection of forest fire smoke has more research value than the detection of forest fire flames. This article mainly introduces the content of early forest fire smoke detection based on background blur model and aerial video. First, the background image of the video is extracted by establishing a background model. Then, through wavelet transform, the energy value of the background composite image is compared with the energy value of the target composite image when smoke appears, and the presence of smoke is detected by threshold processing. Experimental results show that the average recognition rate of smoke is as high as 96.94%.

1. Introduction

The occurrence of forest fires can generally be divided into three stages, namely the preheating stage, the gas burning stage and the charcoal burning stage. Among them, the preheating stage only produces smoke, not flames, so the identification of fire smoke at this stage has more research value. In the past, the biggest interference factor in the smoke recognition of forest fire videos was the sky, clouds and fog in the video background. Yu Suping and Gu Xiaowen [1] improved the existing sky-earth line segmentation algorithm with few digits to eliminate the interference of clouds and fog on early forest fire smoke detection, and their smoke detection rate was only 77%.

Traditional forest fire video surveillance is based on a watchtower. The smoke in the video image is relatively small, and the movement of the smoke is not obvious. In addition, there are other interference factors, as shown in Figure 1. With the development of drones, drones equipped with video surveillance are not uncommon. The video smoke movement is obvious, the movement area is large, and the interference factors are few, as shown in Figure 2. This article will improve the traditional wavelet transform to improve the recognition rate of aerial video smoke.

Figure 1. Traditional forest fire smoke video surveillance composition.
Figure 2. Aerial photography forest fire smoke video surveillance composition.
2. Experimental design
For the video data of the experiment, it is required to use a multi-rotor aircraft with long endurance and strong stability to hover for more than 4s to obtain the video source data. The main content of the experiment includes background extraction, wavelet transform, feature identification and so on. The main steps of the experiment are:

(1) Input video and get every frame of video.
(2) Establish a background model and obtain a video background image.
(3) Perform grayscale processing on the original frame image and background image respectively, and obtain the processed target image and background image respectively.
(4) Perform wavelet decomposition and reconstruction on the target image and background image respectively, and obtain the target reconstruction image and background reconstruction image respectively.
(5) Perform block processing on the target reconstructed image and background reconstructed image after the wavelet processing, respectively, to obtain the target image sub-block and the background image sub-block.
(6) Perform threshold processing on the sub-blocks obtained in (5) and compare them to determine the suspected smoke area in the target image.
(7) Determine the red marking of the moving smoke boundary, and count the number of image frames that correctly identify the smoke.

3. Background extraction based on background fuzzy features
Early forest fire smoke has features such as background ambiguity, diffusivity, and main direction angle. Research has found that smoke usually partially obscures other objects. It appears as background blur in the airspace and attenuation of high-frequency signals in the frequency domain; In smoke video images, non-smoke images usually completely obscure the background. The feature of background ambiguity is better for detecting smoke in aerial images of aircraft, so this article uses the feature of background ambiguity to identify smoke.

3.1. Background extraction
This paper uses two background difference methods, the mean method and the median method, to extract the background of the video.

The mean background model regards moving targets as noise, and eliminates noise by means of cumulative averaging. The specific calculation formula is:

$$I_{B}(x, y) = \frac{1}{N} \sum_{i=1}^{N} I_i(x, y)$$  \hspace{1cm} (1)

Among them, $I_B(x, y)$ is the average background image pixel, $N$ is the video image sequence, and $I_i(x, y)$ is the pixel of the i-th frame of the target image.

The median background model is a background model based on ranking theory, which can effectively suppress noise. The specific calculation formula is:

$$I_B(x, y) = \text{Median}(I_i(x, y))$$  \hspace{1cm} (2)

Select a sliding window with a size of (m, n), and sort all the pixel gray values of the target window centered at the point (x, y) in order. If the pixels in the sliding window are odd, the median value is used as the gray value of a point, if the number of pixels in the sliding window is an even number, the average of the two intermediate values is taken as the gray value of the point.

4. Background blur detection

4.1. Judgment basis
Studies have found that smoke partially occludes other objects under normal circumstances. In the spatial domain, the background becomes blurred, and in the frequency domain, it appears as high-frequency signal attenuation; non-smoky images usually completely occlude the background. According to the characteristics of smoke, we can use two-dimensional discrete wavelet transform to
extract the background texture of the smoke image, distinguish the characteristics of the texture becoming blurred, and detect the existence of smoke.

4.2. Two-dimensional discrete wavelet transform

The main feature of wavelet transform is that the transformation can fully highlight the characteristics of certain aspects of the problem, localized analysis of time and space frequency, and multi-scale refinement of the signal through scaling and translation operations, and finally achieve time subdivision at high frequencies. The result of frequency subdivision at low frequencies.

The two-dimensional discrete wavelet transform of images [2, 3] can be divided into two processes: decomposition and reconstruction. The decomposition process will get a low-frequency (LL) component sub-image and three high-frequency component sub-images. The specific decomposition process is shown in Figure 3. Among them, the three high-frequency component sub-images include the horizontal direction (HL), the vertical direction (LH) and the diagonal direction (HH). The reconstruction process is to perform row and column one-dimensional discrete wavelet inverse transformation on the decomposed image. In order to improve the speed and recognition rate of image processing, the method of block operation and threshold processing is added in the reconstruction process. The reconstruction process is shown in Figure 4.

![Figure 3. Two-dimensional discrete wavelet decomposition process.](image)

![Figure 4. Two-dimensional discrete wavelet decomposition process.](image)

In the above reconstruction process, if there is smoke in the fused image, the energy value of its component sub-images will generally be reduced. Suppose the fusion image of the i-th frame is \( F_i(x, y) \), see formula 3. In this paper, a 4×4 block matrix is used to divide the fused image into several rectangular blocks of the same size. The high frequency information of the pixels in the j-th image sub-block of the i-th frame image is represented by \( E_{i,j}(e_1, e_2) \), see formula 4.

\[
F_i(x, y) = |LH_i(x, y)|^2 + |HL_i(x, y)|^2 + |HH_i(x, y)|^2
\]

\[
E_{i,j}(x, y) = \sum_{x}\sum_{y} F_i(x, y) \lambda_{i,j}(e_1, e_2)
\]

At this time, the suspected smoke area is judged according to the background blur characteristics of the smoke, and the smoke area should satisfy formula 5.

\[
0 < E_{i,j}(e_1, e_2) < \lambda B_{i,j}(e_1, e_2)
\]

In the above formula, \( \lambda \) is the threshold, and \( B_{i,j}(e_1, e_2) \) is the high frequency information of the background sub-block corresponding to the high frequency information of the pixel in the j-th image sub-block of the i-th frame image. Then, the smoke area that meets the conditions. Set the pixel value in the sub-block satisfying formula 5 to 0, that is, \( LH_i(e_1, e_2) = 0, HL_i(e_1, e_2) = 0, HH_i(e_1, e_2) = 0 \), \( cA_i(e_1, e_2) = 0 \). The target image is restored by wavelet inverse transformation. At this time, the target image lacks the pixel value of the smoke area, and then the restored target image is binarized and reversed to complement the smoke area.
5. Experimental results and analysis
Through the above algorithm, this article first uses the mean background model and the median background model to extract the video background of the video background, as shown in Figure 5 and Figure 6.

Figure 5. Mean background image.  Figure 6. Median background image.

The movement of the bottom of the smoke is more consistent, resulting in the small movement characteristics of the bottom of the smoke in the two frames before and after. Therefore, part of the smoke will be regarded as the background, and the top of the smoke with obvious movement characteristics may be detected more.

This article selects 5 groups of hovering aerial videos of early forest fire smoke. The average number of video frames is about 203. The recognition results of early forest fire smoke are shown in Figure 7, and the statistical results of the recognition rate are shown in Table 1.

![Early smoke detection results of forest fires](image)

| Video name | Velocity (ms⁻¹) |
|------------|-----------------|
| Video_1    | 94.02%          |
| Video_2    | 97.09%          |
| Video_3    | 100%            |
| Video_4    | 96.06%          |
| Video_5    | 97.55%          |

Table 1. Statistics of early forest fire smoke detection rate in aerial photography.
Through the video analysis results, it can be seen that the more violent the movement of the smoke, the wider the movement range, and the better the detection effect.

6. Conclusion
This article first extracts the background of the smoke video by establishing a background model, and then detects the smoke through the background blur features. The experimental results show that the smoke recognition rate is as high as 96.94%.

The detection video used in this article is a hovering still shooting method. If it is used in actual detection, the early forest fire smoke detection of moving shots is more valuable, but also more complicated.

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