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Early smoke detection of forest fire video using CS Adaboost algorithm

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ABSTRACT

Smoke is an important indicator of forest fire video. However, many distractors such as heavy fog and smoke-like moving objects greatly degrade the recognition accuracy. This paper presents a novel smoke detection method of early forest fire video using CS Adaboost algorithm. First, motion regions are extracted from two adjacent frames by a proper background model which can avoid false positives of some static distractors, such as blue sky and gray leaves. Then, a CS Adaboost algorithm is used to recognize smoke regions using centroid movement by means of smoke flutter, image energy on the basis of the Wavelet Transform coefficients and color information between a reference smoke color and the input frame. Finally, the experimental results show that the proposed method can not only detect smoke image of early low thickness, but also more effectively distinguish dense fog from smoke.

1. Introduction

Forest fires can not only bring great harm to forests, but also to some extent destroy the ecological environment, thus the early warning of forest fire is particularly important. Due to effectively detect early forest fires, forest fire video surveillance has become one of research focuses in the field of forest fire prevention. Generally, methods for detecting fire in video can be categorized as flame detection and smoke detection. Because flame is very small and sheltered from trees during one early forest fire, smoke is a good indicator of forest fire.

Kopilovic et al. [1] computed the optical flow field using two adjacent images, and then used the entropy of the motion directions distribution as key feature to differentiate smoke motion from non-smoke motion. Vicente and Guillemant [2] extracted local motions from cluster analysis of points to use the velocity distribution histograms to discriminate between smoke and various natural phenomena such as clouds and wind-tossed trees. Similarly, Favorskaya and Levtin [3] tracked effectively a smoke propagation by a spatio-temporal clustering of moving regions with a turbulence parameter connecting with fractal properties of smoke. High-frequency analysis of moving pixels was conducted by wavelet transform for smoke flickering analysis and a measure of smoke turbulence as in [4,5]. Tian et al. [6] presented a new smoke detection scheme by background modeling where the estimation of the blending parameter and the actual smoke component were formulated as an optimization problem. Interesting work was presented by Wang et al. [7] who first detected motion regions from video frames, and then four flutter features of the motion regions are extracted over a sliding time window, including the flutter direction and three types of flutter intensities.

Although some achievements have been made for smoke video detection, the existing smoke detection algorithms are not suitable to forest fire video because sunlight reflexes and many moving leaves can cause false alarm, and there are relatively fixed objects such as trees and grass and not distractors such as smoke-like color vehicles and people clothes. This paper presents a novel early smoke detection method of forest fire video using CS Adaboost algorithm. First, motion regions are extracted from two adjacent frames by a proper background model which can avoid false positives of some static distractors, such as blue sky and gray leaves. Second, one image is divided into small regular blocks, in which three features are extracted, including moving direction of the block by means of smoke flutter, image energy on the basis of the Wavelet Transform coefficients, and color information between a reference smoke color and the input frame. Then, this paper proposes a novel smoke classifier using CS Adaboost algorithm. Finally, the experiments verified the efficacy and efficiency of the proposed methods.

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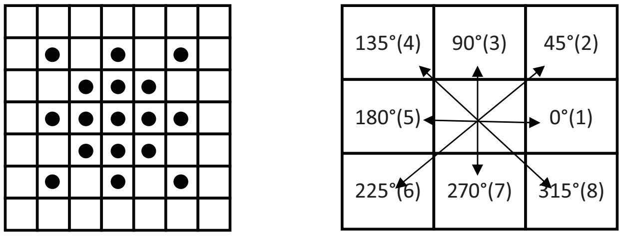


(a) Searching the optimal matching block (b) Encoding the orientation angles

Fig. 1. Discrete moving direction of one block.

2. Forest fire smoke feature extraction

Kalman Filtering is first used to update video background [8] in order to detect motion regions. And then three features of early smoke of forest fire are extracted in terms of flutter analysis, energy analysis and color analysis.

2.1. Flutter feature

As we know, there is massive heavy fog in the forest, so dense fog can easily cause false alarm. Fortunately, for early forest fire smoke has one characteristic that is different from heavy fog. Smoke moves from bottom to top because heat smoke has a lower density than air, which is significantly different from heavy fog. In this section, the motion direction of one block is estimated by the search of discrete motion orientation. The search method is shown in Fig. 1(a) [7]. The matching criterion between two blocks is to the sum of absolute error, that is, we search the optimal matching block that corresponds to the least sum of absolute error in 8 directions. Therefore, the direction components d_x and d_y can be determined by the following formula [7],

$$(d_x, d_y) = arg\min \left\{ \sum_{d_x=-1}^{1} \sum_{d_y=-1}^{1} S(d_x, d_y) \right\} \tag{1}$$

where $d_x(d_x = -1,\ 0,\ 1)$ and $d_y(d_y = -1,\ 0,\ 1)$ denotes horizontal component and vertical component of the search template, respectively. $S(d_x, d_y)$ is the sum of absolute errors that is computed as [7],

$$S(d_x, d_y) = \sum_{i=W_s}^{W_e} \sum_{j=H_s}^{H_e} \left| I(i, j, k) - I(i + d_x, j + d_y, k - 1) \right| \tag{2}$$

where $I(i, j, k)$ denotes the gray value of the pixel (i, j) of kth frame. W_s and W_e denote starting and end value of the block width, respectively, H_s and H_e denote starting and end value of the block height, respectively. The motion orientation angle of one block is encoded by a number. The coding method is shown in Fig. 1(b) and the coding number of motion orientation of the block b_m in the frame I_k is determined as follows,

$$\theta = \begin{cases} \arccos \dfrac{d_x}{\sqrt{d_x^2 + d_y^2}} & d_y = 1 \\ 2\pi - \arccos \dfrac{d_x}{\sqrt{d_x^2 + d_y^2}} & d_y = -1 \end{cases} \tag{3}$$

As shown in Fig. 1(b), the current block have 8 neighboring blocks whose orientation angles are 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315°, respectively.

The orientation code of the block b_m is defined by,

$$O_{\text{code}} = \frac{\theta}{45^\circ} + 1 \tag{4}$$

For example, the orientation angle 0° corresponds to $d_x = 1$, $d_y = 0$. According to the formula (4), the orientation angle 0° is encoded as 1. The orientation angle 45° corresponds to $d_x = 1$, $d_y = 1$, thus the orientation angle 45° is encoded as 2.

2.2. Energy analysis

When smoke diffuses in the scene, it covers part of the scene. Thus the edges are blurred and high frequency information slowly changes. On the contrary, the energy of the scenes that contain smoke-like objects significantly varies. In this section, image energy variation is evaluated by discrete Wavelet transform in order to exclude the smoke-color distractors.

The high frequency energy $E(b_m, I_k)$ of the block b_m in the frame I_k is calculated by using 2-d wavelet transform [9],

$$E(b_m, I_k) = \sum_{i,j \in b_m} \mathrm{LH}^2(i, j) + \mathrm{HL}^2(i, j) + \mathrm{HH}^2(i, j) \tag{5}$$

Let $E(b_m, BG_k)$ denotes the high frequency energy of corresponding background block with the block b_m, then relatively lower ratio of high frequency energy is computed as,

$$\mathrm{ELR}(b_m, I_k) = \frac{\left| E(b_m, I_k) - E(b_m, BG_k) \right|}{E(b_m, BG_k)} \tag{6}$$

2.3. Color feature

For one early forest fire, smoke color is light and partially transparent, which lowers color saturation of the covered scene region. On the contrary, smoke-like moving objects has little effect on color saturation of the scene [10]. In HSV color space, the saturation can be calculated using the following formula (7),

$$S(i, j, I_k) = \max\left[R(i, j), G(i, j), B(i, j)\right] - \min\left[R(i, j), G(i, j), B(i, j)\right] \tag{7}$$

In this section, the color feature extraction takes into account the case where the scene color and the smoke color are mixed together. Color feature $\mathrm{CF}(I_k, b_m)$ of the block b_m in the frame I_k is computed as,

$$\mathrm{CF}(b_m, I_k) = \frac{1}{M^2} \sum_{(i,j) \in b_m} \frac{S(i, j, I_k)}{S(i, j, \mathrm{BG}_k)} \tag{8}$$

where the size of the block b_m is $M \times M$.

3. A Cost-sensitive Adaboost approach for classification

3.1. Block-based statistic characteristics

One image is divided into regular blocks, b_m, of fixed size $M \times M$. Block-based statistic characteristics are computed as [11],

$$\mathrm{SC}_b^1 = \frac{1}{n} \sum_{k=1}^{n} C_b(i) \tag{9}$$

$$\mathrm{SC}_b^2 = \frac{\sum_{k=1}^{n} C_b(i)}{n} - \frac{\sum_{k=n+1}^{N} C_b(i)}{N - n} \tag{10}$$

Where N is the number of blocks and $1 \le n \le N$, and $C_b(i)$ represents moving direction O_{code} or energy lowering ratio ELR or color feature CF of the ith block.

3.2. Cost-sensitive Adaboost algorithm

Adaboost algorithm is effectively used for license plate detection and face recognition. Adaboost algorithm [12] promotes a group of weak classifiers into a strong classifier by updating weights of training samples. In a fire smoke detection method misjudgment cost of positive samples is higher than the one of negative samples, thus Cost-sensitive Adaboost approach is used to assign higher weight to positive sample by introducing cost factor c [13]. The weight of the ith sample x_i is initialized by the formula (11).

$$W_1(i) = \begin{cases} c/N_P & O_i = 1 \\ 1/N_N & O_i = 0 \end{cases} \tag{11}$$

where $O_i = 1$ represents positive sample, and $O_i = 0$ does negative sample. N_P and N_N are the number of positive samples and the number of negative samples, respectively. Then, the iterative formula is as follows,

$$W_{t+1}(i) = \begin{cases} W_t(x_i)\beta_t c & h_t(x_i) \neq O_i \\ W_t(x_i) & h_t(x_i) = O_i \end{cases} \tag{12}$$

where x_i represents a training sample. $\beta_t = \varepsilon_t/(1-\varepsilon_t)$, ε_t is the false rate of the weak classifier h_t. The weight of misjudging positive sample is c times that of misjudging negative sample if $c > 1$.

Each statistic feature corresponds to a weak classifier h_t. All the weak classifiers form a strong classifier using the following formula,

$$h(x_i) = \begin{cases} 1 & \sum_{t=1}^{r} \alpha_t h_t(x_i) \geq \frac{1}{2}\sum_{t=1}^{r}\alpha_t \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where $\alpha_t = \log \frac{1}{\beta_t}$.

4. Experimental results

The early smoke detection algorithm is performed with an image size of 320 × 240. Forest fire smoke video clips The proposed method is tested on 49 video clips of varying length, including 20 positive samples and 29 negative samples, are generally processed around 20fps.28 video clips are randomly chosen for training, the remaining 21 clips are used for testing. Part of the dataset is publicly available atwebsite http://imagelab.ing.unimore.it/visor

4.1. Cost factor

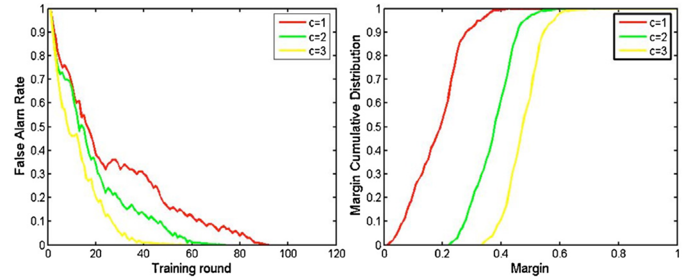
Iterative rounds and cumulative margin of samples are respectively used to evaluate convergence speed and generalization ability of smoke classifiers with different cost factor c. Detection rate is set as 100%, and iterative round is set as 120. Cumulative margin of samples is computed as [14],

$$M = \sum_{i=1}^{N_P} \left(2\frac{\sum_{t=1}^{r}\alpha_t h_t(x_i)}{\sum_{t=1}^{r}\alpha_t} - 1 \right) \times (2y_i - 1) \tag{14}$$

Higher cumulative margin represents better generalization ability. Fig. 2(a) and (b) shows iterative round and cumulative margin with different c, respectively. As shown in Fig. 2, higher cost factor c can improve convergence and generalization ability.

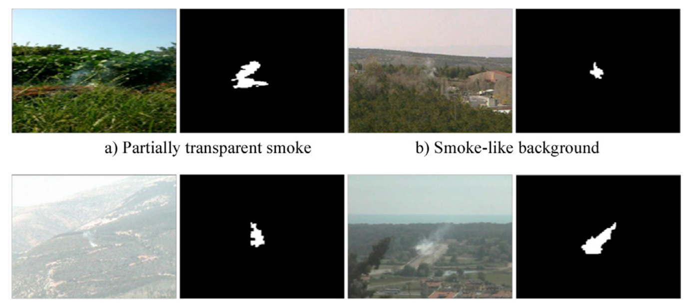
4.2. Early smoke detection of forest fire video

Smoke region is difficultly segmented in two cases. One reason is that background is partially covered, and another one is that some smoke-like objects such as dense fog is falsely recognized as smoke. Fig. 3 shows the detection results of four early smoke video clips.



a) False alarm rate with different c b) Cumulative margin with different c

Fig. 2. Convergence and generalization ability.



a) Partially transparent smoke b) Smoke-like background

c) Sunlight background d) Dense fog background

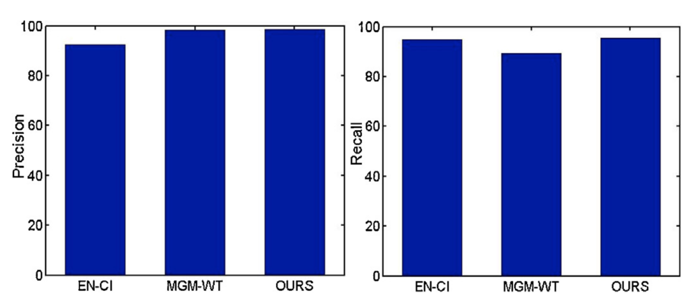
Fig. 3. Results of four early smoke video clips.

4.3. Performance of smoke detection Using CS Adaboost

A smoke strong classifier of four-layer cascaded architecture is established, in which the numbers of weak classifiers in each layer are 1, 26, 69 and 126. Cost factors of each layer are 60, 6, 4, 2, respectively. To validate the performance of our method, this section compares the proposed smoke detection method with other two methods: smoke detection using image energy and color information in [5] (EN-CI for short) and smoke detection method based on mixed Gaussian model and wavelet transformation in [10] (MGM-WT for short). Fig. 4 shows average precision and average recall of smoke detection using the three methods. Precision and recall are computed as:

$$\text{Precision} = \frac{N_{\text{Correct}}}{N_{\text{Correct}} + N_{\text{Error}}}, \quad \text{Rate} = \frac{N_{\text{Correct}}}{N_{\text{Correct}} + N_{\text{Miss}}} \tag{15}$$

It can be clearly seen from this figure that the proposed method outperforms the other two approaches in both precision and recall. Recall of EN-CI method are lower since EN-CI method falsely recognize more images of dense fog video clips as smoke than the proposed method. It indicates that flutter feature of smoke is an important feature for distinguishing dense fog from smoke.



a) b)

Fig. 4. Experimental results of different smoke detection methods in terms of average precision and average recall, respectively.

MGM-WT method extracts smoke features in terms of flutter analysis and diffusivity analysis, which is similar to our proposed method. Experimental results show that the proposed smoke detection method of forest fire using CS Adaboost has higher precision rate than MGM-WT method based on criteria fusion algorithm.

5. Conclusions

In this paper, a novel smoke detection scheme using CS Adaboost is proposed, which is inspired by the research results in the forest fire video. On the one hand, flutter feature of smoke video is expressed by defining moving direction of candidate smoke block, which is used to distinguish dense fog from smoke. On the other hand, smoke classifier of forest fire using CS Adaboost algorithm is proposed for effectively and efficiently recognize early smoke of forest fire. The experimental results demonstrate that the proposed method can significantly improve the performance of smoke detection. It is worth noting that there are several potential works for future development. One is to improve background model to effectively detect candidate smoke region in smoke-like scene, another is to extract more effective flutter features for completely excluding the interference of dense fog.

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