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Forest smoke detection using CCD camera and spatial-temporal variation of smoke visual patterns

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Abstract

This paper proposes a new forest smoke detection method using spatial-temporal visual features extracted from camera images and a pattern classification technique. First, moving regions are detected by analyzing the frame difference between two consecutive key frames. Since smoke regions generally have a similar color, simple texture, and upward motion, the intensity, wavelet coefficients, and motion orientation are extracted as visual features. In addition, random forests are constructed using training data and then used for smoke verification process with four smoke classes. The proposed algorithm is successfully applied to various forest smoke videos and shows a better detection performance when compared with other methods.

Keywords: **forest smoke, spatial-temporal visual feature, key frame, random forest, ensemble trees**

1. Introduction

With the rapid increase in natural disasters caused by environmental disruption, new engineering solutions are needed for automatic warning and safety systems. In particular, the increasing occurrence of large-scale fires across the world has created an urgent need for research on automatic fire detection as an early warning system.

In general, since smoke appears before flames, sensors that can detect smoke are required for early fire warning systems. In the case of forest smoke, conventional sensors such as infrared sensors, optical sensors, or ion sensors cannot detect smoke due to the extended distance between the sensors and the burning point. Therefore, current studies [1-5] have investigated the use of CCD cameras to overcome the drawbacks of traditional sensors and provide dependable smoke detection results. Despite the clear importance of forest smoke detection, there have only been a few studies in this area, where the main smoke detection methods can be summarized as follows.

Töreyin et al.[1] used a Hidden Markov Model (HMM) to mimic the temporal behavior of smoke using the periodic behavior of smoke boundaries. In addition, the boundaries of smoke regions are represented in a wavelet domain, and the high frequency nature of the boundaries of smoke regions are used as a basis for modeling.

Yuan et al.[2] used motion information using the upward behavior of smoke. Thus, a candidate region is declared a smoke region if the ratio of the upward directions against other directions is over a pre-defined threshold.

Gubbi et al. [3] proposed outdoor smoke detection approach based on wavelets and support vector machine. Characterization of smoke was carried out by extracting wavelet features from approximate coefficients and three levels of detailed coefficients. Then binary support vector machine is used for smoke verification.

Gonzalez et al. [4] proposed outdoor smoke detection algorithm using a stationary wavelet transform (SWT) to remove high frequencies on horizontal, vertical, and diagonal details. The inverse SWT is then implemented and finally the image is compared to a non-smoke scene in order to determine the possible regions of interest (ROI).

Ham et al. [5] proposed a forest-fire smoke detection algorithm using Fuzzy Finite Automata (FFA) and spatial-temporal visual features. Using the key-frame difference and Gaussian Mixture Color Model, candidate smoke blocks are extracted more accurately. For smoke verification, three two-dimensional PDFs estimated from the average and entropy of the intensity, the average and skewness of wavelet, and motion information are then applied to the FFA.

The remainder of this paper is organized as follows. Section 2 describes the detection of candidate smoke blocks using the key-frame difference and spatial-temporal visual feature extraction is introduced in Section 3. The smoke-block verification using random forest is then introduced in Section 4. Section 5 evaluates

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the accuracy and applicability of the proposed smoke detection method based on experiments, and some final conclusions and areas for future work are presented in Section 6.

2. Detection of candidate smoke block

In this research, the images are divided into 32x24 blocks for real-time processing. Unlike indoor smoke, forest smoke has a relatively slow spreading speed, as the surveillance cameras for detecting smoke are installed at extended distances. Therefore, a general frame difference cannot detect moving regions in the case of a forest smoke. Thus, to overcome this problem, key-frames are selected from a video sequence whenever the frame differencing is over a certain threshold (θ_1).

$$\begin{aligned}&\mathit{if}\ (|\mathit{Kframe}[k] - \mathit{frame}[i]| > \theta_1)\\ &\mathit{Then}\quad \mathit{Kframe}[k+1] = \mathit{frame}[i];\\ &\qquad\qquad k++;\ i++;\\ &\mathit{Else}\quad i++;\end{aligned} \tag{1}$$

where θ_1 is an adjustable parameter according to the application. Using the new key-frame *Kframe* [k+1] and previous key-frame *Kframe* [k], a block (B_b) at position *b* in the current key-frame is declared as a moving block using the following formula:

$$B_b = \begin{cases} 1 & \sum_{(x,y)\in b} |\mathit{Kframe}[k](x,y) - \mathit{Kframe}[k+1](x,y)| > \theta_2 \\ 0 & \mathit{Otherwise} \end{cases} \tag{2}$$

$$(k \geq 1)$$

After detecting the candidate smoke blocks, the image is scanned to group the blocks into clusters based on block connectivity using morphological closing.

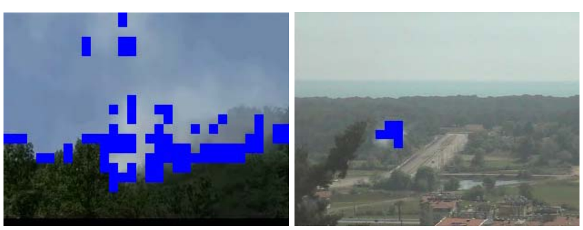


Figure 1. Candidate smoke blocks after moving block detection using key frames

3. Spatial-temporal visual feature extraction

Smoke regions generally have a higher intensity and frequency than the background as well as an upward motion with irregular fluctuation patterns in the time domain [6]. Thus, to consider the above characteristics over time, the variations in the intensity, wavelet energy, and motion orientation are used to generate random forests classifier.

First, since a smoke region has a relatively higher intensity value and little contrast, the average intensity value and skewness are estimated from the candidate block and its corresponding blocks in the 100 preceding frames to consider the feature variation and reduce the feature dimension.

Furthermore, as high frequency information is not sensitive to lighting changes or more prominent features, to discriminate a forest smoke from a smoke-colored object, the average of wavelet energy and skewness of the wavelet energy is computed from candidate smoke blocks using a linear combination of high frequency coefficients after a Daubechies wavelet transform.

Third, smoke tends to continuously move upward because of heat convection; hence, the motion orientation is estimated between the current and previous key frames. After estimating the motion for each block (*b*), the orientation of the motion is discretized into eight directions, and each discrete direction is coded as 1–8, respectively according to our previous study [6].

The final dimension of the feature vector for one block is 5. The final feature vector is normalized to unit length using the Gaussian normalisation method.

4. Smoke block verification using random forests

A random forest is a decision tree ensemble classifier with each tree grown using some type of randomization. Random forest has the capacity to process huge amounts of data with high training speeds based on a decision tree [7].

In the training procedure, the random forest starts by choosing a random subset I' from the training data I. At node *n*, the training data I_n is iteratively split into left and right subsets I_l and I_r by using the threshold and split function. After training of the random forest, the test candidate blocks are applied to the trained random forest. The final class distribution is generated by an ensemble of each distribution of all trees $L = (l_1, l_2, \ldots, l_T)$ using equation (3). In equation (3), *T* is the number of trees, and we choose c_i as the final class *f* of an input block if the average of $P(c_i \mid l_t)$ has the maximum value.

$$f = \max_{i=1\ to\ 4} \left\{ \frac{1}{T} \sum_{t=1}^{T} P(c_i \mid l_t) \right\} \tag{3}$$

In this paper, the four smoke classes are defined as **VH**, **H**, **L**, and **VL**, and these classes correspond to “very high,” “high,” “low,” and “very low,” respectively. These classes mean the possibility of fire smoke.

As shown in Figure 2, if the maximum value for smoke classes indicates class **VH** or **H** and it is over the predefined minimum threshold, the candidate block is declared a real fire-flame block.

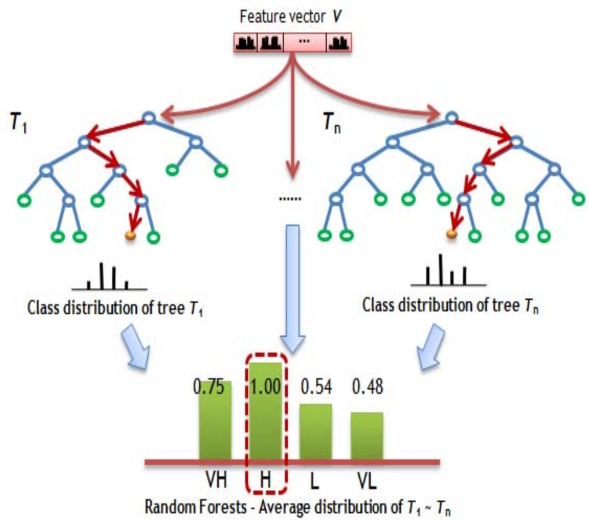


Figure 2. Classification process using feature vector with trained random forests. In this example, the test block is classified into the second class H because it has a maximum posterior probability of 1.0.

The decision trees of random forests are trained using candidate blocks extracted from training video sequences that included eight forest smoke and non smoke videos.

5. Experimental Results

The proposed forest smoke detection system was implemented using an Intel Core 2-Quad processor PC with an image size of 320 × 240 pixels. To evaluate the performance of the proposed algorithm, Töreyin's algorithm [1] and Ham's algorithm [5] which perform well among existing algorithms, are compared with the proposed method. The test is performed using five video sequences which used in Ham's experiment [5] as shown in Table 1.

Table 1. Properties of the test videos

Video Sequence	Number of frames	Description
Movie 1	457	Forest-smoke
Movie 2	735	
Movie 3	956	
Movie 4	781	
Movie 5	566	

Movie 1, 2, 3, 4 and 5 are general forest smoke videos. The comparative results are presented in Figure 3 where the true positive (TP) rate means correctly detected smoke, the false positive (FP) rate means recognizing a non-smoke region as a smoke region, and the missing rate (MR) means not recognizing a real smoke region. As seen in Figure 3, the proposed approach outperformed Töreyin's and Ham's method with an average true positive rate (ATPR) of 93.2% compared to 92.8% and 55.8%, and an average false positive rate (AFPR) of 2.2% compared to 7.2% and 11.8%. However, an average missing rate (AMR) of proposed method showed somewhat lower rate than Ham's method as 4.6% vs. 0% due to some errors of optical flow.

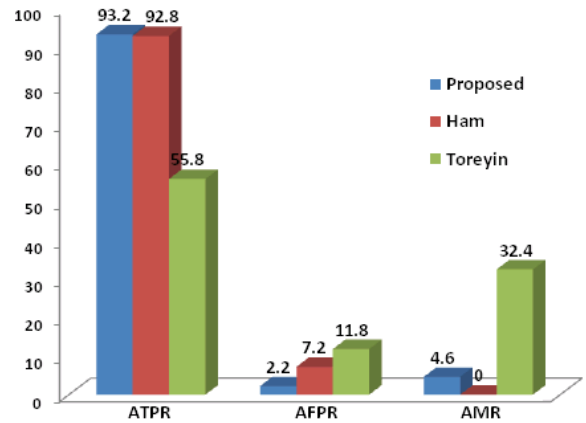


Figure 3. The performance test results between proposed method and two comparative methods.

In particular, Töreyin's method produced a higher MR, since it detected candidate smoke regions from every frame using the frame difference. However, since forest smoke moves very slowly, due to the extended distance between the camera and location of the smoke, many true smoke regions were missed.

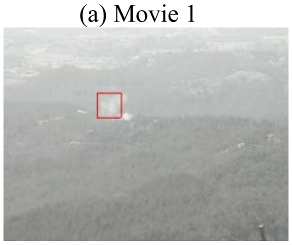
As shown in Figure 3, Töreyin and Ham's method showed a higher FP rate at 11.8% and 7.2%, where the main reason for the higher error was due to moving smoke-colored object being confused with a fire-smoke. However, the proposed algorithm was able to remove above false positives using the motion orientation and verify real smokes using the random forest classifiers.

Figure 4 shows the smoke detection results for the four smoke videos when using the proposed method.

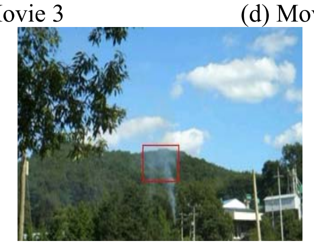
6. Conclusion

Since smoke appears before flames, smoke detection is particularly important for early fire detection systems. To consider the smoke characteristics over time, the spatial-temporal visual patterns of intensity, wavelet energy and motion orientation have been used for generating feature vector from 100 consecutive frames. For smoke verification, random forest was most effective method in a small number of training data and low feature dimension, with high computational performance and accuracy. The proposed algorithm was successfully applied to various forest smoke videos and showed a better detection performance.


(a) Movie 1 (b) Movie 2




(c) Movie 3 (d) Movie 4



(e) Movie 5

Figure 4. Smoke detection results using proposed algorithm

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