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Fast fire flame detection in surveillance video using logistic regression and temporal smoothing

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Real-time detection of fire flame in video scenes from a surveillance camera offers early warning to ensure prompt reaction to devastating fire hazards. Many existing fire detection methods based on computer vision technology have achieved high detection rates, but often with unacceptably high false-alarm rates. This paper presents a reliable visual analysis technique for fast fire flame detection in surveillance video using logistic regression and temporal smoothing. A candidate fire region is determined according to the color component ratio and motion cue of fire flame obtained by background subtraction. The candidate fire region is examined for genuine fire flame in terms of the proposed fire probability computed using logistic regression of prominent features of size, motion, and color information. Temporal smoothing is employed to reduce false alarm rates at a slight decrease in sensitivity. Experiments conducted on various benchmarking databases demonstrate that the proposed scheme successfully distinguishes fire flame from the background as well as moving fire-like objects in real-world indoor and outdoor video surveillance settings. The average time to fire detection was fastest among the state-of-the-art video-based fire flame detection techniques for comparison.

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1. Introduction

There exist various forms of natural disasters as well as man-made hazards that threat security and safety of the society. Among many such hazards, fire has been one of most devastating threats. Early detection of fire is extremely important more than anything else to minimize loss of lives and property damage. Various types of fire detectors such as smoke detectors and the sensors using temperature and photosensitive characteristics have been successfully exploited in fire detection. However, many such devices may not work properly in open or large spaces and outdoor environments. Automatic detection of fire based on computer vision has been an active research topic in fire detection [1,2]. Since light travels much faster than smoke or heat, visual analysis of the scene offers an effective means to detect fire flame in an early stage, which enables prompt reaction to fire accidents. Fast and accurate detection of fire flame will ensure a sufficient amount of time to dispatch fire engines to the fire site. Along with widespread deployment of affordable surveillance cameras, video-based fire flame detection techniques have become more and more significant in early detection of fire in both indoor and outdoor environments.

Many existing approaches to video-based fire flame detection consider the problem as a pattern recognition task. Various pattern classifiers including Bayesian classifiers [3], artificial neural networks [4], and Markov models [5,6] have been utilized to make a decision whether a video scene contains fire flame. Truong et al. [7] proposed a support vector machine (SVM) to classify multi-dimensional features extracted from a candidate fire region in the scene. Wang et al. [8] used the Wald–Wolfwitz randomness test algorithm to distinguish fire from non-fire events. This adaptive algorithm utilizes the characteristics of randomly fluctuating fire flame to detect fire, but with relatively low accuracy. Celik et al. [9] proposed a method based on a generic color model for classifying fire flame without using background subtraction to segment out moving blobs from the background. Both fire and non-fire images are trained to construct a chrominance model for flame pixel classification. The YCbCr color model has demonstrated advantageous at discriminating the luminance component from chrominance. A drawback can be high false alarm rates. Habiboglu et al. [10] proposed a method based on the covariance texture representation. This approach uses a moving camera to detect moving fire regions without background subtraction. They make simultaneous use of color and spatial and temporal domain information in feature vectors for each spatiotemporal block using region-based covariance descriptors. This method can only detect clearly visible fire flames in a close range, not the fire in the

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environments with poor visibility. Bosch et al. [11] introduced fire detection in infrared (IR) videos using combined spatial and temporal features. Candidate flame regions are detected by histogram-based image thresholding. Examining the intensity, signal, and orientation of the separated hot objects, one can distinguish fire from other non-fire hot objects. However, the number of publications on IR-based fire detection is still limited in the literature. Most video-based fire detection algorithms use a similar framework based on the motion and color information [12–14]. Video-based fire detection methods often consist of three parts: moving pixel detection, fire-color pixel detection, and classification. In some places, IR cameras are used to sense smoke and the temperature of the environment. However, IR cameras are not widely used because of their unsatisfactory response times and high cost.

This paper presents a fire flame detection scheme according to the fire probability using logistic regression and temporal smoothing. A candidate fire region (CFR) is extracted from a video scene by simultaneous application of color component ratio and the motion. The ratio of color components in the YCbCr color space gives a strong clue of fire flame and fire-like objects. Then we compute the fire probability, the probability of the CFR being genuine fire flame, using the logistic regression framework. In the decision stage, a CFR with fire probability exceeding a certain threshold is classified as fire. Frame-by-frame detection of fire flame according to the fire probability gives high sensitivity as well as high false alarm rates to fire flame detection. High false alarm rate is one of significant practical issues that many video-based fire detection approaches may encounter. High false alarm rates cause too frequent unnecessary fire warnings making video-based fire detection less useful in practice. Temporal smoothing helps reduce false alarm rates at a slight decrease in sensitivity. Logistic regression is easy to implement and computationally light, making the proposed scheme suitable for real-time video-based fire flame detection. Experiments with various benchmarking databases show that the average time to detection was as fast as 1.81 s after fire broke out, which is fastest among the state-of-the-art fire flame detection techniques. Comparisons with popular existing approaches, the proposed method was fast and reliable to provide early warning of fire with low false alarm rates.

2. Fire flame detection using logistic regression and temporal smoothing

2.1. Feature extraction

Fire appears in different colors depending on the temperature of the flame. The color of the center of a fire flame can be different from that of the edge. Fire-colored pixels are relatively easy to detect according to the specific range of the color spectrum. The colors of natural fire often belong to the red-to-yellow color range [15,16]. Since the fire color tends to be highly saturated in the red channel, red components of each fire pixel is greater than the others in the RGB color space. Since RGB color values are sensitive to variations of illumination, an RGB color is converted into the color space that can separate chrominance from luminance. The YCbCr color space describes the color with luma (Y) and chroma (Cb, Cr) components. In the fire region, Cb component tends to be smaller than Cr and therefore the ratio Cb/Cr is likely distributed in the range of [0, 1]. Fig. 1 shows normalized distribution of the ratio (Cb/Cr) of blue-difference and red-difference chroma of fire, fire-like object, and non-fire background regions. Fire-like objects include moving objects in fire colors such as a pedestrian in red shirts or red rear lights of a moving vehicle. The three types of regions were manually extracted from multiple video frames. Due

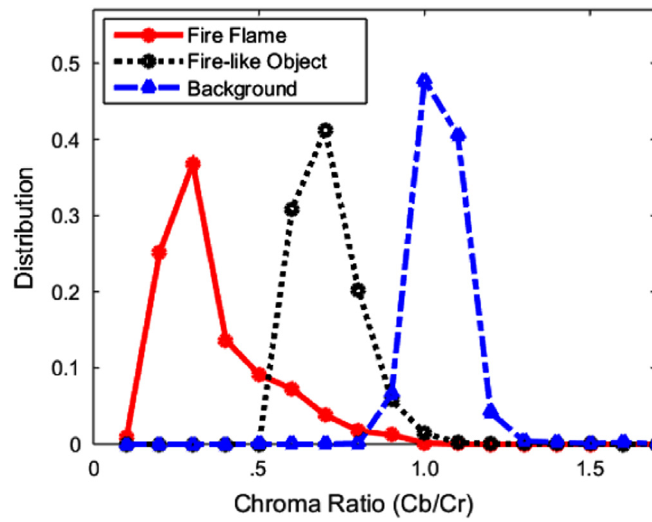

Fig. 1. Distribution of the chroma ratio (Cb/Cr) of fire flame, fire-like objects, and non-fire background regions. (For interpretation of the reference to color in this figure, the reader is referred to the web version of this article.)

to the similarity in color, fire flame and fire-like objects demonstrate similar shapes in terms of distribution, but with different average values in the chroma ratio axis. The background pixels show different shapes as well as different locations of the chroma ratio in the distribution.

Detecting fire flame directly in a surveillance video is not trivial since various fire-like objects may exist in the scene that can appear similar in appearance and in color to fire. Such objects include a person wearing a red shirt, red balloons, or red rear lights of moving vehicles. Fig. 2 shows color decomposition examples of an RGB color into the luma and chroma components of a real fire flame and a fire-like object in the scene. The chroma ratio shows a strong response to both fire-colored objects. This region can be rejected in the temporal smoothing step based on the assumption that fire-like objects are less consistent in motion and can appear often during a short period of time compared to fire flames.

Motion gives a fundamental clue of a moving object in a video stream. Background subtraction is a widely adopted scheme for detecting moving objects in a video stream captured by a fixed camera [17,18]. Background subtraction can also apply to fire flame detection in surveillance video [19–21]. Motion of an object in the scene can be found using the difference of the current video frame and the background image. Let $D_n(i,j)$ be the frame difference image by background subtraction:

$$D_n(i,j) = |I_n(i,j) - B_n(i,j)| \tag{1}$$

where $I_n(i,j)$ and $B_n(i,j)$ denote brightness intensity of a pixel located at (i,j) at n-th video frame in the original image and the background, respectively. Initially, $B_1(i,j)$ is set to $I_1(i,j)$. The background image is updated when the intensity of the input image is greater than the background to take temporal variations of the background into consideration. Fig. 3 shows examples of finding a CFR by background subtraction of neighboring video frames. Fig. 3(b) shows the pixels associated with the motion and Fig. 3(c) shows the determined CFR obtained by the multiplication operation of the Cb/Cr image and the frame difference image $D_n(i,j)$. A small fixed image blobs on top of the computer monitor of the color image in Fig. 3(a) is eliminated in the background subtraction procedure since no motion is involved and therefore regarded as the noise. Fig. 3(d)–(f) are the results applied to a video stream containing a fire-like object, a person wearing red shirt. A red vending machine in Fig. 3(d) was also filtered out. A small patch from the red-colored shirt region in Fig. 3(f) will be

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