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Fire flame detection in video sequences using multi-stage pattern recognition techniques

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ABSTRACT

In this paper, we propose an effective technique that is used to automatically detect fire in video images. The proposed algorithm is composed of four stages: (1) an adaptive Gaussian mixture model to detect moving regions, (2) a fuzzy c-means (FCM) algorithm to segment the candidate fire regions from these moving regions based on the color of fire, (3) special parameters extracted based on the tempo-spatial characteristics of fire regions, and (4) a support vector machine (SVM) algorithm using these special parameters to distinguish between fire and non-fire. Experimental results indicate that the proposed method outperforms other fire detection algorithms, providing high reliability and a low false alarm rate.

1. Introduction

Fire detection has become very appealing for both personal security and commercial applications, and several conventional methods have been proposed to detect fire. However, most of these methods require a close proximity to the source of the fire and are based on particle sensors (Jones, 2004). Therefore, they cannot detect fire in open or large spaces and cannot provide additional information regarding the burning process. To overcome these weaknesses, video fire detection is a suitable candidate.

Several video-based fire detection algorithms have been proposed (Chen et al., 2004; Toreyin and Centin, 2007; Celik and Demirel, 2009; Ko et al., 2009; Toreyin et al., 2006; Borges and Izquierdo, 2010; Han and Lee, 2006; Celik et al., 2007). Most of these algorithms are based on color pixel recognition, motion detection, or both. In (Chen et al., 2004), a dynamic analysis of flames using an RGB/HIS color model was used to determine the existence of fire. However, the decision rule of this method is not good at distinguishing real fire regions from regions of movement or noise since the flame difference is measured only between two consecutive frames. In (Toreyin and Centin, 2007; Toreyin et al., 2006), the boundary of the flames was represented in the wavelet domain, and the high frequency natures of the boundaries of fire regions were used to spatially model flame flicker, yielding good results. In (Celik and Demirel, 2009), a new method of flame detection that used flame pixel color properties was proposed. This method used the YCbCr color space because the RGB color space has illumination dependence disadvantages. This means that if the illumination in the image changes, the fire pixel classification rules will not perform well. In (Ko et al., 2009), fire detection based on vision sensors and support vector machines was proposed. In the study, a non-linear classification method using support vector machines and luminescence maps was proposed, showing robust results for flame detection. In (Borges and Izquierdo, 2010), a probabilistic model for color-based fire detection was utilized to extract candidate fire regions. In addition, four parameters were extracted from the features of candidate fire regions, such as area size, surface coarseness, boundary roughness, and skewness. Moreover, a Bayes classifier was used to distinguish between fire and non-fire. In (Han and Lee, 2006), the authors proposed the fire and smoke detection system in the tunnel environment. This algorithm detects the fire by comparing image of normal state with input image using color information. In addition, it automatically detects smoke using motion direction, edge detection, and comparison of color information of input images. However, this algorithm uses many ad-hoc parameters, prohibiting for applying to dynamic fire situations. A real-time fire detection method using the statistical color model and foreground object information was proposed in (Celik et al., 2007). The authors introduced the statistic color model for generic fire model. Some of the above algorithms were applied to real systems with considerable success. However, each of these methods still had limited application and lacked enough robustness. In order to enhance the performance of fire detection, we propose an efficient four-stage fire detection approach. In the first stage, movement-containing regions are detected using an adaptive Gaussian mixture model. In the second stage, fire and non-fire regions are segmented using fuzzy c-means (FCM) clustering. In the third stage, additional features are extracted from

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the tempo-spatial characteristics of fire regions. In the final stage, fire is classified using support vector machines (SVM). Experimental results indicate that the proposed approach outperforms existing fire detection algorithms in terms of accuracy of fire detection, providing a low false alarm rate and high reliability in both indoor and outdoor test videos.

The rest of this paper is organized as follows. Section 2 introduces the features of fire. Section 3 describes the proposed four-stage fire detection algorithm. Section 4 discusses experimental results of the proposed method and compares the performance of the proposed method with those of other fire detection algorithms, and Section 5 presents conclusions of the study.

2. Features of fire

The features of fire play an important role in the development of fire detection systems since these features are used to distinguish between fire and non-fire. In this study, important characteristics of fire such as color, region, time, and space were analyzed. In practice, most fuels will burn under appropriate conditions, reacting with oxygen from the air, generating combustion products, emitting light, and releasing heat. When fire is produced, it usually arises from a stable location, drifting upward in a diffuse manner. The color usually ranges from red to yellow and may turn white when the temperature is very high. The size, area, shape and number of fire regions in an image vary from frame to frame. The surfaces and contours of fire regions are usually rough.

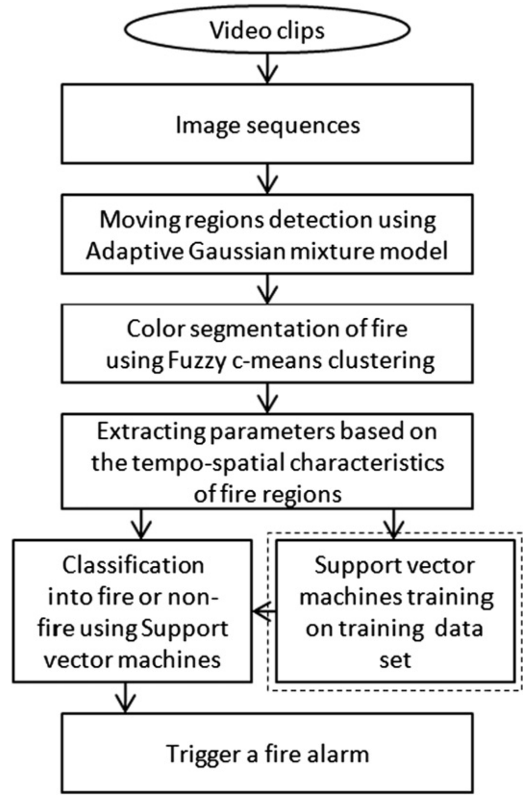

Fig. 1. A flowchart of the proposed video-based fire detection approach.

3. The proposed fire detection algorithm

A flowchart of the proposed fire detection approach is depicted in Fig. 1. The proposed algorithm is comprised of four stages: (1) moving region detection using an adaptive mixture Gaussian model, (2) fire color segmentation using FCM clustering, (3) parameter extraction from the tempo-spatial characteristics of fire regions and (4) fire identification using support vector machines. The approach is also composed of the two phases of training and classification. In the training phase, the training data sets are extracted from the training videos and used to train the SVM. In the classification phase, the trained SVM is utilized to distinguish between fire and non-fire. In the following sections, the proposed fire detection algorithm is analyzed in detail.

3.1. Moving region detection

The detection of moving regions is a fundamental key in video fire detection, which is the first stage of the proposed method. Several methods have been proposed to detect moving regions, with background subtraction being the most typical. As the name suggests, background subtraction is the process of separating out foreground objects from the background in a sequence of video frames. Many different techniques have been proposed with different strengths and weaknesses in terms of performance and computational requirements (Piccardi, 2004). Among these methods, the Gaussian mixture model (GMM) that was first introduced by Stuaffer and Grimson in 1999 is the most widely used method for background subtraction due to its speed, simplicity and ease of implementation (Stauffer and Grimson, 1999; Stauffer and Grimson, 2000). In this method, each pixel is modeled as a mixture of Gaussian distributions, and any pixel intensity value that does not fit into one of the modeled Gaussian distributions is marked as a foreground pixel. In order to achieve high performance, we utilize an adaptive Gaussian mixture model (KaewTraKulPong and Bowden, 2002) because it can successfully manage illumination changes and reduces the effects of small repetitive motions such as moving vegetation and small camera displacement.

In GMM, each pixel location in RGB color space is modeled with a set of K Gaussian distributions. The probability of observing the current pixel value X_t at the time t is defined as follows:

$$P(X_t) = \sum_{k=1}^{K} \omega_{k,t}\eta\left(X_t,\mu_{k,t},\sum\nolimits_{k,t}\right), \tag{1}$$

where K is the number of Gaussian components per pixel, $\omega_{k,t}$ is the estimate of the weight parameter of the kth Gaussian component at the time t, $\mu_{k,t}$ and $\sum_{k,t}$ are the mean and the covariance matrix of the kth Gaussian component in the mixture at time t, and $\eta(X_t,\mu_{k,t},\sum_{k,t})$ is the Gaussian probability density function which is defined as follows:

$$\eta(X_t,\mu,\Sigma) = \frac{1}{(2\pi)^{d/2}\left|\sum\right|^{1/2}} e^{-(1/2)(X_t-\mu_t)^T\Sigma^{-1}(X_t-\mu_t)}, \tag{2}$$

where $d=3$ because X_t is in the RGB color space, and $\sum_{k,t} = \sigma_k^2 I$. This assumes that the red, green and blue pixel values in RGB color space are independent and have the same variances.

The mixture of Gaussians actually models both foreground pixels and background pixels without distinction; that is, some mixture components model foreground pixels, while others model background pixels. In order to identify the foreground pixels, the background pixels are determined as follows: K distributions are sorted based on the fitness value ω_k/σ_k, and then the first B Gaussian distributions are used as a model of the image background, where B is estimated as follows:

$$B = \arg\min_b\left(\sum_{j=1}^{b}\omega_j > T\right), \tag{3}$$