Proceedings of the World Congress on Engineering 2013 Vol III,
WCE 2013, July 3 - 5, 2013, London, U.K.

Fire Detection Using Spatial-temporal Analysis

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***Abstract*—Fire detection is an important issue of modern security sensing system. In this paper, we propose a vision-based fire detection algorithm. The proposed approach integrates color, spatial and motion information to locate fire regions in video frames. Potential fire regions are detected by modeling the fire color with Gaussian mixture model. Based on some characteristics of burning flame, we combine spatial and temporal features to remove spurious fire-like regions. Finally, some missing fire regions are located using region growing method. Experimental results indicate that the proposed approach can be applied to a variety of conditions and outperform some existing technique.**

***Index Terms*—video content analysis, fire detection, image classification.**

I. Introduction

As fire accident makes great damage to our life and property, fire flame detection is an important issue of modern security sensing system. Most current fire detection systems are based on infrared sensors, optical sensors, or ion sensors that detect the presence of smoke, heat or radiation using ionization or photometry. However, alarm is not issued unless particles or heats actually reach the sensors to activate them. Thus, they can not be operated in open spaces and large covered areas. Besides, they usually are unable to provide additional information such as the location and size of the fire and the degree of burning. In contrast, vision-based fire detection system offers the following advantages: (1) The equipment cost is lower. Nowadays, closed circuit television (CCTV) systems are already installed in many public places for surveillance purposes. (2) The response time is faster as the camera does not need to wait for the smoke or heat to diffuse. (3) The CCTV system can monitor a large area to create a higher possibility of fire detection at early stage. (4) It directly senses the location of fire, not just radiation which comes from its general vicinity. Therefore, in this paper, we propose a new algorithm to detect fire event in surveillance video.

The next section of this paper briefly reviews some related works. Then, we describe the proposed flame detection algorithm in Section III. The performance evaluation of our approach is reported in Section IV. Finally, some concluding remark is given in Section V.

II. Related Works

Recently many works on visual fire flame detection have been proposed [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12]. Most of methods make use of various visual characteristics including color, motion and geometrical contour of flame regions. Healey et al. use color and motion information to classify the image frame into fire and non-fire regions[1]. This method requires that the camera be stationary, thus it is not very effective to detect fire in the moving recorded videos. Yamagishi and Yamaguchi present a flame detection algorithm based on the spatial-temporal fluctuation data of the frame contour[2]. A neural network is employed to determine fire from the Fourier transform of the fluctuation data. Their method only uses color information to extract flame pixels. However, we also observe that many non-fire objects have the same color distributions as fire. False extraction exists inevitably. Besides, the computational complexity of the algorithm is too high for practical application. Phillips et al. exploit both the color and temporal variation to detect fire[3]. They use the Gaussian-smoothed color histogram to generate a color lookup table of fire pixel and then take advantage of temporal variation of pixel values to determine whether it is a fire pixel or not. The method is insensitive to the motion of camera. But it requires a close proximity to the fire. Liu and Ahuja present spectral, spatial and temporal models of fire regions in video sequences[4]. They suggest that the shape of a fire region was represented in terms of spatial frequency content of the region contour using its Fourier coefficients and the temporal changes in these coefficients are used as the temporal signatures of the fire region. Their method can not detect flame in some situations, such as low burning power and relatively steady burning. Toreyin et al. integrate motion, flicker, edge blurring and color features for video flame detection[7]. Temporal and spatial wavelet transform are performed to extract the characteristics of flicker and edge blurring. Although they show good results for several test data, they use many heuristic thresholds. Celik et al. propose a real-time fire detector that combines foreground object information with color pixel statistics for fire[8]. The foreground information is extracted using an adaptive background subtraction algorithm, and then verified using a statistical fire color model. Although all the previous approaches achieve some level of success, they do not fully exploit the spatio-temporal information contained in video.

III. The Proposed Approach

To develop a robust fire detection system, it is necessary to understand the nature of flame. The flames usually display reddish colors, besides, the color of the flame will change with the increasing temperature. When the fire temperature is low, the color shows range from red to yellow, and it may become white when there is a higher temperature[5]. The shape of the flame also changes rapidly due to some environmental factors such as airflow and burning materials. Thus, the fire region exhibits a structure of nested rings of colors, changing from white at the core to yellow, orange and red in the periphery[4]. Based on these knowledge, the proposed flame detection algorithm is composed of the following four components:

Manuscript received February 4, 2013; revised March 1, 2013.

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ISBN: 978-988-19252-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

1) Fire-colored pixel detection
2) Moving pixel detection
3) Color image segmentation
4) Integration of spatial and temporal features

Each of these components is described in the following subsections.

A. Fire-colored Pixel Detection

To detect fire pixel, one of the easiest and often used methods is to define fire color cluster decision boundaries for different color space components. Single or multiple ranges of threshold values for each color space component are defined and the image pixel values that fall within these predefined ranges for all the chosen color components are detected as fire pixels. However, since this method requires a few empirical thresholds, it can fail when the environment or burning material is changed.

To capture the color variation of flame, we model the HSV color distribution of a fire pixel using the Gaussian mixture model. The probability density function of a Gaussian mixture model with k components for the feature vector $x \in R^d$ is defined as

$$p(x) = \sum_{j=1}^{k} \alpha_j p(x|j)$$

where α_j is the mixture weight and $p(x|j)$ is the Gaussian density model for the j'th component

$$p(x|j) = \frac{1}{(2\pi)^{d/2} |\sum j|^{1/2}} e^{-1/2(x-\mu_j)^T \sum j^{-1}(x-\mu_j)}$$

where μ_j is the mean vector and $\sum j$ is the covariance matrix for the j'th component, respectively. The model parameters α_j, μ_j and $\sum j$ can be estimated from a training data set using the EM algorithm[13]. The number of components in the mixture can be either supplied by the user or chosen using some optimization criteria[14]. For any pixel with color value $x = (h, s, v)$, if $p(x) > T_1$ (threshold), then it is declared as a candidate fire pixel. The advantage of this parametric model is that it can generalize well with less training data and also has very less storage requirements.

B. Moving Pixel Detection

Color is not the unique feature to identify fire. There are some non-fire objects with the same color with fire such as sun and red leaves. The main difference between fire and these non-fire objects is the nature of their motion. Because of airflow and burning materials, the size and shape of a flame are completely changeable. To detect such a significant fire movement, we analyze the difference between consecutive frames.

Consider a video sequence containing n frames, the average temporal variation is defined as

$$\Delta(x, y) = \frac{1}{n} \sum_{i=1}^{n-1} |f_i(x, y) - f_{i+1}(x, y)|$$

where $f_i(x, y)$ is the intensity at the pixel location (x, y) in the ith frame. If $\Delta(x, y) > T_2$ (threshold), then a moving pixel is detected at location (x, y).

C. Color Image Segmentation

To facilitate the subsequent processing, we divide the current image frame into homogeneous regions using the color information at each pixel. To perform this task, one classic method consists of finding clusters of points in the 3D color space and labeling each cluster as a different region[15], [16]. The main disadvantage of this method is the number of clusters (regions) is typically unknown for traditional data clustering algorithm such as k-means. Another problem with clustering is the spatial information is not taken into account. In this paper, we employ a new clustering algorithm called mean-shift [17] to determine the number of dominant colors automatically.

For each frame, dominant colors are first generated by the mean shift algorithm. Then, we explore the spatial relation of pixels to get the spatial segmentation result. All pixels are classified according to their distance to dominant colors in color space and spatial relationships within image domain. The Euclidean distance between two colors is calculated for clustering. For each pixel, we assign it to the class with the shortest distance if the distance is smaller than a threshold. Afterwards, the threshold is increased by a certain amount. For each unassigned pixel, we assign it to a certain class if its distance to the corresponding dominant color is smaller than the modified threshold and one of its neighboring pixels has been assigned to the same class. Finally, all remaining unassigned pixels are classified to its nearest neighboring region. It is noted that the dominant colors of the current frame can be used as the initial guess of dominant colors in the next frame. Due to the similarity of adjacent frames, the mean shift algorithm often converges in one or two iterations. Thus, the computational time is reduced significantly.

D. Integration of Spatial and Temporal Features

Each segmented region is declared as potential fire region if 50% of its pixels are fire-colored pixels. However, there are some false fire regions resulting from the following two factors[6]:

- Due to the reflection of the fire, some objects will change its appearance colors as well as its brightness to be similar to those of flame.
- Non-fire objects (such as sun) with similar fire-colors will be identified as fire region.

To remove spurious fire-like regions, the potential fire regions are classified into the following three types of regions.

1) Type I: true fire region with great temporal variation.
2) Type II: true fire region with little temporal variation.
3) Type III: false fire region.

The potential fire region is identified as type I region if 50% of its pixels are moving pixels. Any other potential fire region is identified as type II region if it is adjacent to type I region. Using region growing based method, type I and II regions are combined into true fire regions. The remaining potential fire regions are type III regions. Finally, if the true fire regions occupy 5% of an image frame then a fire event is detected in this frame.

IV. Experimental Results

The proposed algorithm is tested by four video sequences which consist of 35638 frames totally. The test videos include

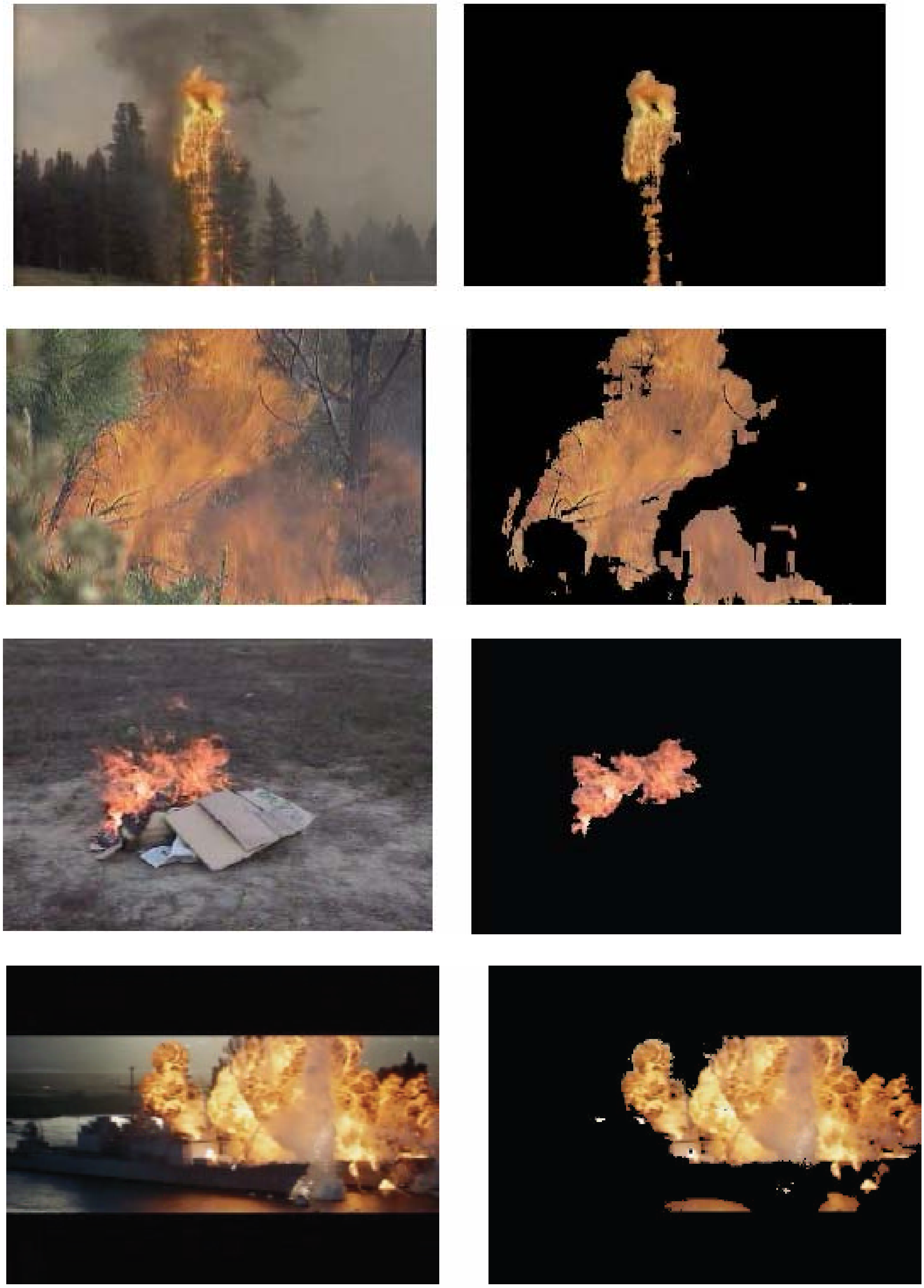

Fig.1. Some Test Images and The Detected Fire Regions

TABLE I
ACCURACY MEASURES FOR FOUR TEST VIDEOS

Video ID	No. of Frames with Fire	No. of Correct Detection	No. of Missed Detection	No. of False Detection
(1)	242	223	19	0
(2)	318	283	35	12
(3)	397	364	33	21
(4)	465	439	26	28

TABLE II
PERFORMANCE COMPARISON FOR FIRE DETECTION

Video ID	Our Approach		Toreyin's Approach	
	Recall	Precision	Recall	Precision
(1)	92.15%	100%	87.19%	100%
(2)	88.99%	95.93%	86.79%	94.20%
(3)	91.69%	94.55%	89.42%	91.03%
(4)	94.40%	94.00%	91.83%	93.03%

several fire events under a variety of conditions such as indoor, outdoor and explosion. Fig. 1 shows some test images and the detected fire regions. The experimental results are shown in Table I. The missed detections are due to two factors. One is that the size of flame is very small on the combustion such as small candles. The other is that the fire source is under control and lack of temporal variation such as blowtorch. The false detections are mainly caused by the fire-colored moving object such as a red parking car.

The performance of fire detection is usually measured by the following two metrics:

$$\text{Recall} = \frac{D}{D + MD} \qquad \text{Precision} = \frac{D}{D + FD}$$

where D is the number of fire event detected correctly, MD is the number of missed detection and FD is the number of false detection. For performance comparison, we also implement the well-known baseline algorithm proposed by Toreyin et al.[7]. To compare both approaches fairly, the parameters of each approach are tuned to achieve the best performance. As shown in Table II, our approach is, in overall, better than Toreyin's approach in term of recall and precision.

V. CONCLUSION

In this paper, we have analyzed the static and dynamic features of fire flame and proposed a flame detection algorithm based on the integration of spatio-temporal information in the video. Experimental results show that our flame detection algorithm can locate the position of flame accurately and can be applied to complex environment.The proposed technique can be incorporated with a fully automatic surveillance system monitoring open spaces of interest for early fire warning system. Finally, our future work will be the integration of other fire features such as smoke and flicker into current system to achieve more robust fire detection.

ACKNOWLEDGMENT

The authors would like to thank Shih-Yung Wu, Wen-Pang Chiang, Yu-Chieh Chen and Chih-Lin Lan for their assistance in preparing this manuscript.

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