

VIDEO BASED FLAME DETECTION

Using Spatio-temporal Features and SVM Classification

Kosmas Dimitropoulos, Filareti Tsalakanidou and Nikos Grammalidis
Informatics and Telematics Institute, CERTH, 1st km Thermi-Panorama Rd., Thessaloniki, Greece

Keywords: Wildfires, Video Surveillance, Flame Detection, 2D Wavelet Analysis, Feature Fusion, SVM Classification.

Abstract: Video-based surveillance systems can be used for early fire detection and localization in order to minimize the damage and casualties caused by wildfires. However, reliability of these systems is an important issue and therefore early detection versus false alarm rate has to be considered. In this paper, we present a new algorithm for video based flame detection, which identifies spatio-temporal features of fire such as colour probability, contour irregularity, spatial energy, flickering and spatio-temporal energy. For each candidate region of an image a feature vector is generated and used as input to an SVM classifier, which discriminates between fire and fire-coloured regions. Experimental results show that the proposed methodology provides high fire detection rates with a reasonable false alarm ratio.

1 INTRODUCTION

Wildfires are considered one of the most dangerous natural disasters having serious ecological, economic and social impacts. Beyond taking precautionary measures to avoid a forest fire, early warning and immediate response to a fire breakout is the only way to minimize its consequences. Hence, the most important goal in fire surveillance is quick and reliable detection and localization of fire. Video-based forest surveillance is one of the most promising solutions for automatic forest fire detection, offering several advantages such as: low cost and short response time for fire and smoke detection, ability to monitor large areas and easy confirmation of the alarm by a human operator through the surveillance monitor (Ko, 2011). However, the main disadvantage of these optical based systems is increased false alarm rate due to atmospheric conditions (clouds, shadows, dust particles), light reflections etc (Stipanichev, 2006).

Video-based flame detection techniques have been widely investigated during the last decade. The main challenge that researchers have to face is the chaotic and complex nature of the fire phenomenon and the large variations of flame appearance in video. In (Toreyin, 2005), Toreyin et al. proposed an algorithm in which flame and fire flicker is detected by analyzing the video in the wavelet domain, while in (Toreyin, 2006) a hidden markov model was used

to mimic the temporal behavior of flame. Zhang et al (Zhang, 2008) proposed a contour based forest fire detection algorithms using FFT and Wavelet, whereas Celik and Demiral (Celik, 2009) presented a rule-based generic color model for fire-flame pixel classification. More recently, Ko et al (Ko, 2010) used hierarchical Bayesian networks for fire-flame detection and a fire-flame detection method using fuzzy finite automata (Ko, 2011).

Despite of extensive research results listed in literature, video flame detection remains an open issue. This is due to the fact that many natural objects have similar colours as those of the fire (including the sun, various artificial lights or reflections of them on various surfaces) and can often be mistakenly detected as flames. In this paper, we present a new algorithm for video based flame detection, which identifies spatio-temporal features of fire such as color probability, countour irregularity, spatial energy, flickering and spatio-temporal energy. More specifically, we propose a new colour analysis approach using non-parametric modelling and we apply a 2D wavelet analysis only on the red channel of image to estimate the spatial energy. In addition to the detection of flickering effect, we introduce a new feature concerning the variance of spatial energy in a region of the image within a temporal window in order to further reduce the false alarm rate. Finally, a Support Vector Machine (SVM) classifier is applied for the

discrimination between fire and non-fire regions of an image.

2 METHODOLOGY

The proposed algorithm initially applies background subtraction and colour analysis processing to identify candidate flame regions on the image and subsequently distinguishes between fire and non-fire objects based on a set of extracted features as shown in Figure 1. The different processing steps of the proposed algorithm are described in detail in the following sections.

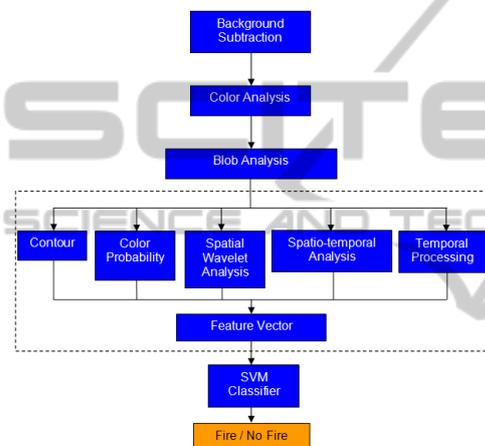


Figure 1: The proposed methodology.

In the first processing step moving pixels are detected using a simple median average background subtraction algorithm (McFarlane, 1995). The second processing step aims to filter out non-fire coloured moving pixels. Only the remaining pixels are considered for blob analysis, thus reducing the required computational time. To filter out non-fire moving pixels, we compare their values with a predefined RGB colour distribution created by a number of pixel-samples from video sequences containing real fires.

Let x_1, x_2, \dots, x_N be the fire-coloured samples of the predefined distribution. Using these samples, the probability density function of a moving pixel x_i can be non-parametrically estimated using the kernel K_h (Elgammal, 2000) as:

$$\Pr(x_i) = \frac{1}{N} \sum_{i=1}^N K_h(x_i - x_i)$$

If we choose our kernel estimator function, K_h , to be a Gaussian kernel, $K_h = N(0, S)$, where S represents the kernel function bandwidth, and we assume

diagonal correlation matrix S with a different kernel bandwidths σ_j for the j^{th} colour channel, then the density can be estimated as:

$$\Pr(x_i) = \frac{1}{N} \sum_{i=1}^N \prod_{j=1}^d \frac{1}{\sqrt{2\pi\sigma_j^2}} e^{-\frac{(x_{ij} - x_{ij})^2}{\sigma_j^2}}$$

Using this probability estimation, the pixel is considered as a fire-coloured pixel if $P_r(x_i) < th$, where the threshold th is a global threshold for all samples of the predefined distribution and can be adjusted to achieve a desired percentage of false positives. Hence, if the pixel has an RGB value, which belongs to the distribution of Figure 2(b), then it is considered as a fire-coloured pixel. After the blob analysis step, the colour probability of each candidate blob is estimated by summing the colour probabilities of all pixels in the blob.

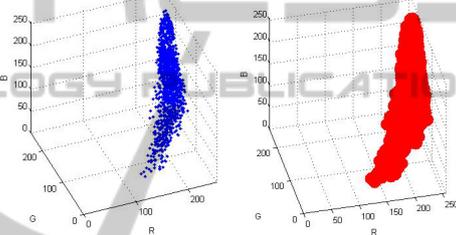


Figure 2: (a) RGB color distribution and (b) flame color distribution with a global threshold around each sample.

The next processing step concerns the contour of the blob. In general, shapes of flame objects are often irregular, so high irregularity/variability of the blob contour is also considered as a flame indicator. This irregularity is identified by tracing the object contour, starting from any pixel on it. Thus a direction arrow is defined for each pixel on the contour, which can be specified by a label L , where $0 \leq L \leq 8$, assuming 8-connected pixels, as shown in the figure below.

The variability of the contour for each contour pixel can be measured by calculating the difference (distance) between two consecutive directions (from and to the specific pixel) using the following formula returning a distance between 0 and 4 for each pixel:

$$d = \begin{cases} d_{\max} - d_{\min} & \text{if } d_{\max} - d_{\min} \leq 4 \\ 8 + d_{\min} - d_{\max} & \text{otherwise} \end{cases}$$

Where $d_{\min} = \min(d_1, d_2)$, $d_{\max} = \max(d_1, d_2)$ and d_1, d_2 are the codes of two consecutive directions.

The average value of this distance function can be used as a measure of the irregularity of the

contour and is used as the second extracted feature in the proposed approach.

The third feature concerns the spatial variation in a blob. Usually, there is higher spatial variation in regions containing fire compared to fire-coloured objects. To this end, a two-dimensional wavelet is applied on the red channel of the image, and the final mask is obtained by adding low-high, high-low and high-high wavelet sub-images. For each blob, spatial wavelet energy is estimated by summing the individual energy of each pixel. However, the spatial energy within a blob region changes, since the shape of fire changes irregularly due to the airflow caused by wind or the type of burning material. For this reason, another (fourth) feature is extracted considering the spatial variation in a blob within a temporal window of N frames.

The final feature concerns the detection of flickering within a region of a frame. In our approach, we use a temporal window of N frames (N equals 50 in our experiments), yielding an 1-D temporal sequence of N binary values for each pixel position. Each binary value is set to 0 or 1 if the pixel was labeled as “no flame candidate” or “flame candidate” respectively after the background extraction and color analysis steps. To quantify the effect of flickering, we traverse this temporal sequence for each “flame candidate” pixel and measure the number of transitions between “flame candidate” and “no flame candidate” (0->1). The number of transitions can directly be used as a flame flickering feature, with flame regions characterized by a sufficiently large value of flame flickering.

For the classification of the 5-dimensional feature vectors, we employed a Support Vector Machines (SVM) classifier using RBF kernel. The training of the SVM classifier was based on approximately 500 feature vectors extracted from 500 frames of fire and non-fire video sequences.

3 EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, videos containing fire or fire-colored objects were used. Figure 3(a) shows the detection of flame along with the intermediate feature masks (background, color, spatial wavelet, spatiotemporal and temporal map), while in Figure 3(b), an example with a video containing a moving fire-coloured object is presented. As can be clearly seen from the intermediate masks, feature values are higher in case of flame detection due to the random behavior of fire.



Figure 3: (a) True detection of fire and (b) True rejection of a fire-colored object (First row: Frame along with the detected fire region, background subtraction mask, colour analysis mask. Second row: Spatial wavelet analysis, spatio-temporal mask and flickering mask).

Table 1: Test videos used for the evaluation of the proposed algorithm.

Fire Video 1		Non Fire Video 1	
Fire Video 2		Non Fire Video 2	
Fire Video 3		Non Fire Video 3	
Fire Video 4		Non Fire Video 4	
Fire Video 5		Non Fire Video 5	
Fire Video 6		Non Fire Video 6	
Fire Video 7		Non Fire Video 7	

Fourteen test videos were used for the evaluation of the algorithm. The first seven videos contain actual fires, while the remaining seven contain fire colored moving objects e.g. car lights, sun

reflections, etc. Screenshots from these videos are presented in Table 1 (the first column presents flame detection results in real fire scenes, while the second column contains screenshots from videos with fire colored moving objects). Results are summarized in Table 2 and Table 3 in terms of the true positive, false negative, true negative and false positive ratios, respectively.

Experimental results show that the proposed method provides high detection rates in all videos containing fire, with a reasonable false alarm ratio in videos without fire. The high false positive rate in "Non_fire_video3" is due to the continuous reflections of car lights on the road, however, we believe that the results may be improved in the future with a better training of the SVM classifier. The proposed method runs at 9 fps when the size of the video sequences is 320x240. The experiments were performed with a PC that has a Core 2 Quad 2.4 GHz processor with 3GB RAM. In the future, the speed of the algorithm can be further improved by dividing the image in blocks instead of using blob analysis, which increases the processing time.

Table 2: Experimental results with videos containing fires.

Video Name	True Positive (%)	False Negative (%)
Fire Video 1	98.89	1.11
Fire Video 2	93.46	6.54
Fire Video 3	99.59	0.41
Fire Video 4	99.03	0.97
Fire Video 5	90.00	10.0
Fire Video 6	99.50	0.50
Fire Video 7	99.59	0.41
Total	97.65	2.35

Table 3: Experimental results with videos containing fire coloured objects.

Video Name	True Negative (%)	False Positive (%)
Non Fire Video 1	100.00	0.00
Non Fire Video 2	97.41	2.59
Non Fire Video 3	74.37	25.63
Non Fire Video 4	100.00	0.00
Non Fire Video 5	99.68	0.32
Non Fire Video 6	100.00	0.00
Non Fire Video 7	97.96	2.04
Total	98.01	1.99

4 CONCLUSIONS

Early detection of fire is crucial for the suppression of wildfires and minimization of its effects. Video based surveillance systems for automatic forest fire detection is a promising technology that can provide

real-time detection and high accuracy. In this paper, we presented a flame detection algorithm, which identifies spatio-temporal features of fire such as color probability, countour irregularity, spatial energy, flickering and spatio-temporal energy. The final decision is made by an SVM classifier, which classifies candidate image regions as fire or non-fire. The proposed technique was evaluated in a database of 14 video sequences and demonstrated increased detection accuracy.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7-ENV-2009-1) under grant agreement no FP7-ENV-244088 "FIRESENSE". We would like to thank all project partners for their fruitful cooperation within FIRESENSE project.

REFERENCES

- Ko, B. C., Ham, S. J., Nam, J. Y., Modeling and Formalization of Fuzzy Finite Automata for Detection of Irregular Fire Flames, *IEEE Transactions on Circuits and Systems for Video Technology*, May 2011.
- Stipaničev, D., Vuko, T., Krstinić, D., Štula, M., Bodrožić, Lj., Forest Fire Protection by Advanced Video Detection System - Croatian Experiences, *Third TIEMS Workshop – Improvement of Disaster Management System*, Trogir, 26-27 September, 2006
- Töreyn, B., Dedeoglu, Y., Gudukbay, U., Cetin, A., "Flame detection in video using hidden markov models," *IEEE Int. Conf. on Image Processing*, pp. 1230-1233, 2005.
- Toreyin, B.U., Dedeoglu, Y., Gudukbay, U. Cetin, A.E., Computer vision based method for real-time fire and flame detection, *Pattern Recognition Letters*, 27, pp. 49–58, 2006.
- Zhang, Z., Zhao, J., Zhang, D., Qu, C., Ke, Y., and Cai, B. "Contour Based Forest Fire Detection Using FFT and Wavelet", In *Proceedings of CSSE (1)*. 2008, 760-763.
- Celik, T., Demirel, H., "Fire detection in video sequences using a generic color model," *Fire Safety Journal*, Vol. 44, pp. 147-158, 2009.
- Ko, B., Cheong, K., Nam, J., "Early fire detection algorithm based on irregular patterns of flames and hierarchical Bayesian Networks," *Fire Safety Journal*, Vol 45, Issue 4, pp. 262-270, 2010.
- Elgammal, A. Harwood, D., Davis L. "Non-parametric model for background subtraction" *6th European Conference on Computer Vision*, Vol. 1843, pp. 751-767, Dublin, Ireland, 2000.