Fire Detection Using Computer Vision

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***Abstract*— This paper provides a computer vision based technique for detecting fire and identifying hazardous fire by processing the video data generated by an ordinary camera. While there are copious amount of publications in fire detection with images, distinguishing hazardous fire from non-hazardous is a problem that is still unsolved. The proposed technique uses the color and fluctuation characteristics of fire to detect it. Initially the algorithm locates regions of the video where there is motion; from these regions fire colored pixels are extracted and then wavelet transform is applied to confirm that the moving object is fire. The proposed technique tracks the rate of increment of fire region to distinguish between hazardous and controlled fire. Experimental results demonstrate that the proposed technique is effective in detecting the fire and classifying it as hazardous or controlled. The performance of the technique was observed in terms of true positive rate which was observed to be 85.57% while the average delay in detection of hazardous fire was 66.2 frames at a frame rate of 10 frames per second or 6.62 seconds.**

***Keywords*— Computer vision; fire detection;Video processing; wavelet transform; Real time; energy based detection.**

I. Introduction

Fire hazard can be disastrous to human property and lives, if it is not detected at the right stage [1], [2], [3]. The damage can be significantly reduced if fire is detected at an early stage. When the fire is of a smaller magnitude, less efforts are required to control it. In order to limit fire hazards, effective fire detection techniques are required. Automated fire detection systems can be used to detect fire. Such a system should be able to efficiently detect rapid fire development and alert relevant personnel as quickly as possible. If early detection is achieved, the system will be able to provide enough time for counter actions [4].

Traditional fire detection systems recognize fire by its physical properties such as smoke and temperature. These properties however, are hard to detect in early stages due to slow build up time. The smoke sensor uses chemical properties of the smoky air. These properties are then used to detect fire and raise an alarm. Many automatic fire detection systems utilize smoke sensors to identify fire [5], [6], [7], [8].

Temperature based sensors are also widely used in fire detection systems. Authors of [9] developed a fire detection system using thermistor, which was used to sense changes in temperature. It gives alert when the temperature becomes higher than a predefined threshold value. Similarly, in [10] the authors used temperature sensors, placed at the locations that are vulnerable to fire hazard. These sensors were programmed on a specific threshold temperature, above which the sensor would send an alarm. In [12] the authors created a wildfire observer network called Istria iForest Fire Net. Automatic fire detection was done using geographical information system (GIS). The system was a layered architecture having a sensor layer, a service layer and an application layer.

Sensors usually have short range of detection. This makes their response time inherently slow [11]. Smoke sensors are not applicable for open areas and in huge infrastructures for example, airplane holders, warehouses and forests. Innovation in camera and video processing techniques allow efficient fire detection through computer vision based systems.

As technology is advancing and electronic equipment are becoming common, there has been a significant increase in the use of security/surveillance cameras. The output of these devices can be used to build a fire detection system using computer vision technologies. Fire detection based on computer vision offers advantage over the traditional methods as the former is not restricted by surroundings hence covers a wider range . It will thus complement the existing devices and will be cost effective.

Fire detection using visual data is providing an effective and efficient way for preventing hazards at an early stage. The authors of [12] developed a method to identify fire using its color information. In light of the information that fire fluctuates with some range of frequency, two independent systems [13] and [14] examined variations of fire with respect to time for more accurate fire detection. In [15] the authors developed a system that used RGB color channel information. They created rules for identifying fire on the three channels using motion detection algorithm as a preprocessing step. The authors of [16] used pixel color values and their temporal variations, for the proposed detection system. Soe et al. [17] used the image properties of the light blue flame to detect fire. The fire-suspected regions, in an image, were defined by using the region of interest (ROI) technique. In [18] the authors proposed an algorithm for flame detection using a modified histogram back projection algorithm in YCbCr color space. The authors of [19] developed a method consisting of four steps: background subtraction, color feature detection, growth rate analysis and Lucas-Kanade optical flow algorithm to differentiate between non-fire objects. A.E. Gunawardena [20] proposed a method of detecting fire in an indoor environment by using temporal information and color. Authors of [21] used color and motion information obtained from video stream to trace fire. RGB color space was used by this system to model the fire. Toreyin et al. [22] used hidden Markov models (HMM) (2005) and the wavelet transform (2006) to extract spatial color variations to improve accuracy of detection and to decrease the false positives. Literature [23] proposed a video based fire detection technique which uses color, temporal and spatial information. The system divides the video into temporal and spatial blocks and characteristics of fire are extracted from these blocks for the detection of fire.

In this paper a video processing based fire detection engine will be provided. The contributions of this paper are detecting fire from live video streams, distinguishing between controlled and uncontrolled fires and generating alerts for uncontrolled fires. The proposed engine first substracts the background from the frames in order to detect movement in the frames. The resultant frame is subjected to the color detection module that identifies the region of fire. Once the region of fire is identified the energy of the fire signal is obtained through wavelet coefficients of the region. The analysis of the energy in these regions distinguishes between fire and non-fire regions. If the region with detected energy keeps increasing at a very high rate, then the fire is classified as hazardous. The details of the scheme are presented in the following section.

II. Methodology

The proposed algorithm detects fire by detecting three key properties. These are the motion of fire, its color and its energy. These properties are present in both controlled and hazardous fire. Therefore, to classify between controlled and hazardous fire the rate of increment of fire region is used.

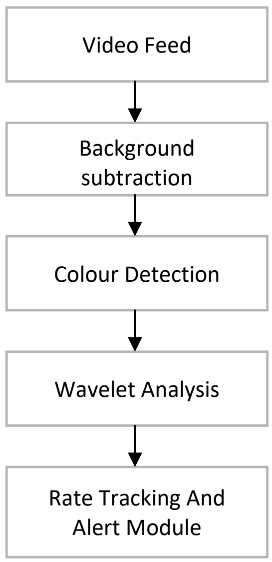

Fig 1: Block diagram of fire detection engine modules

Upon start up the proposed engine detects the moving objects in the video stream. Moving objects are detected by using background subtraction technique. Then color detection technique is applied to check whether the moving objects' color is similar to fire. After this wavelet transform is applied on the detected pixels to confirm other attributes of fire.

A. Background subtrction:

Identifying moving objects in video based fire detection is a primary task. A prior step of motion detection is background subtraction which distinguishes between foreground and back ground on the basis of changes in pixel values and positions. Motion detection identifies moving objects in subsequent video frames that differs considerably from the observed background. For detection of motion in video frames it is assumed that video camera is still and is not rotating about its axis. In order to extract moving pixels, background model is first developed and then this model is compared with the current frame. In this work Gaussian Mixture Model (GMM) [24] has been used for background subtraction. That model can deal with highly complex scenes such as moving cars, waving trees and bushes. One important feature of GMM is that it selects the suitable number of Gaussian distributions for each pixel. GMM easily adapts to illumination changes between frames. In this work, after subtracting the background, those pixel whose values change are identifies as moving objects.

B. Color Detection

Color in an important feature to detect fire. Its color is distinctive in both RGB and YCbCR color spaces.

a. RGB Color Space

The images obtained from video stream are in RGB color space and the intensity of these colors can classify fire colored pixels. In this color space there are three different elements of color in the pixel that are Red, Green and Blue. All of these components are needed to completely describe the color of the pixel. A fire pixel is described by the following relations.

$$R > G \text{ and } G > B \qquad (1)$$

In this work, RGB color space was used but the results were not satisfactory (fig. 2(b)) as RGB values cannot differentiate between chrominance and illumination. Therefore, therefore instead of RGB YCbCr color space was used.

b. YCbCr Color Space

Here Y is luminance component and Cb and Cr are chrominance blue and chrominance Red component respectively. YCbCr color space can effectively distinguish between luminance information and chrominance information. For a fire pixel;

$$Y > Cb \text{ and } Cr > Cb \qquad (2)$$

The results of YCbCr were better than RGB but not accurate as shown in fig 2(c). Traning an Artificial Neural Network (ANN) over YCbCr values showed great improvement, and is used as the color detection module of the proposed engine.

C. ANN structure and training

In this work a perceptron ANN is used in order to detect fire pixels using YCbCr values. This network consists of 3 layers, an input layer with 3 inputs, a hidden layer with 2 perceptron and an output layer with 1 perceptron. All input layer perceptron are connected to all hidden layer perceptrons, which are in turn connected to all output layer perceptron. The inputs of each layer are combined using weighted sum function. The ANN uses back propagation learning algorithm. The output function of each layer is a sigmoid symmetrical function.

The output of this ANN is a real number between 0 and 1. This output is compared to a threshold α to classify the pixel as fire colored or not. The value of α was determined through experimentation. The perceptron ANN is trained using pixel color data collected from various fire and non-fire images

D. Wavelet Analysis

From background subtraction and color detection, the regions that had motion and had fire like color are suspected fire regions. The wavelet analysis module distinguishes actual fire regions from the suspected regions, by calculating energy using wavelet transform.

Wavelet analysis is promising technique for determining energy of non-stationary signals. This transform gives improved frequency resolution for low frequency components and high temporal resolution for high frequency components. The wavelet transform

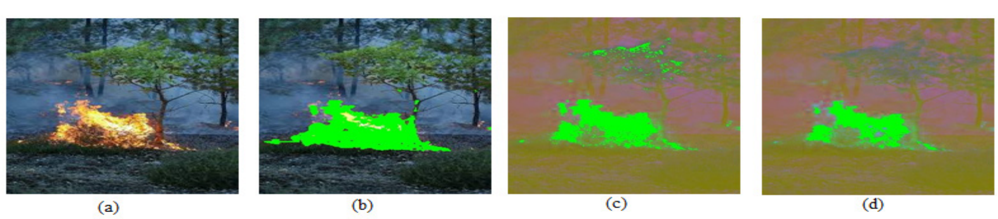

Fig 2 (a) Original image, (b) Detected using RGB, (c) Detected using YCbCr (d) Detected using ANN breaks the signal into smaller waves (wavelets) that are concentrated in both frequency and time around a point.

The areas where motion and color detection were positive are masked out. Wavelet analysis is used to give the High-High (x_{hh}), High-Low (x_{hl}) and Low-High (x_{lh}) sub signals of the areas, using the filter bank as mentioned in [22]. In order to obtain average energy of the region, eq.(3) is used where M*N is the number of pixels. Regions with energy higher then threshold β are classified as fire regions.

$$energy = \frac{1}{M \times N} \sum_{i,j} |x_{hh}^2| + |x_{hl}^2| + |x_{lh}^2| \quad (3)$$

E. Fire Rate Tracking

The engine proposed in the paper goes one step further from fire detection. The proposed engine classifies the frames into hazardous fire and non-hazardous fire. To distinguish a hazardous fire from a controlled fire (e.g. in a fireplace) the engine uses the rapid increment nature of a hazardous fire. Hazardous fire tends to grow quickly in magnitude, and indeed that is the very cause of its dangerous impact.

To track rate the area of each fire region is summed (the current area) and the increase from previous area is calculated. The previous area is the moving average of current areas.

$$rate = \frac{current\ area\ -\ previous\ area}{previous\ area} \quad (4)$$

The average rate of increase is calculated by summing all previous rates and dividing by the number of fire detected frames.

$$Average\ rate = \frac{\sum_n rate}{n} \quad (5)$$

Where n is the number of fire detected frames.

The average rate is than compared to a threshold γ. The value of γ as set in Table 1 was chosen after experimental results. If the average rate is lesser than threshold γ then a flag μ is reset. If the rate is above a γ then flag μ is set. This flag is used to determine whether the fire detected had high rate of increment in the previous frame. If the flag was not set in previous frame, then there was either no fire or the fire was not hazardous.

However, if the flag was set, this implies that the previous frame suspected a hazardous fire. The rate of the current frame is then compared to one-third of the value γ. If the rate is less than γ , the fire is detected to be controlled and the flag is reset. However, if the rate is greater than γ the fire is detected to be hazardous and an alert is generated. The value γ is chosen experimentally. This two-step threshold check is done to filter out the sudden surges in a controlled fire. The implementation and analysis of the result is presented in the next section.

III. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The fire detection program is tested with C++ using OpenCV libraries. Initial testing of this program was done on live video frames having only non-hazardous fire or no fire at all. However, in order to extensively test the proposed fire detection scheme, a set of 236 videos was used where each video was 30-45s long. The simulation parameters for fire detection algorithm have been listed and explained in Table1. The hazardous fire clips were selected such that the fire was ignited in the very first frame and its magnitude increased in subsequent frames. The non-hazardous and no-fire videos included clips from typical bakeries and restaurants as well as landscapes and animated videos. The performance of algorithm is measured in terms of true and false positive rates

True positive rate is defined as ratio of instances correctly detected as hazardous to the total number of actual hazardous fire instances. In this work true positive rate is calculated as the ratio of number of videos in which hazardous fire was correctly detected to the total number of videos. The results presented in Table 2 indicate the proposed engine has a high true positive rate of 85.57%.

False positive rate is defined as the ratio of instances incorrectly identified as hazardous fire to the total number instances with non-hazardous or no fire.

TABLE 1

SIMULATION PARAMETERS AND THEIR MEANING

Symbol	Meaning	Value
α	A threshold for ANN response, which is between 0 and 1, given a YCbCr pixel value.	0.35
β	Threshold for the energy calculated through wavelet transform.	2.5
γ	Threshold for average rate of increase of fire.	0.133
μ	A flag that is set or reset if hazardous fire was detected in the previous frame or not respectively.	0 or 1

TABLE 2

SIMULATION RESULTS

Parameters	Hazardous Fire	Non-hazardous or no fire
Average Number of frames/video processed for detection	226.5507	695.6667
Actual True cases	104	153
Correctly detected cases	89 (True positive)	70 (True Negative)
Wrongly detected cases	83 (False Positives)	15 (False negatives)
Average delay in detection of first frame	66.21693 frames (for True positives)	153.7737 frames (for false positives)
Frame Rate	10 fps	10 fps

Accuracy is defined as the ratio of correctly classified videos to the total number of videos. The proposed engine has an accuracy of 0.6186, as calculated from the experimental results shown in Table 2.

Precision is defined as the ratio of actual true cases to detected true cases. Precision of our engine is 0.5144.

Recall is the ratio of true positives to that of the sum of all cases that were positives, that is the sum of true positives and false negatives. This ratio shows how much of the positives are correctly identified. The recall for our engine is 0.85577 as per our results in Table 2.

The **F measure** is the harmonic mean of precision and recall. And is used to identify both precision and recall in one metric.

$$F\ measure = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} \quad (6)$$

From the above equation the F measure for our engine comes out to be 0.64.

IV. Conclusion

In this paper a computer vision based method for automatically detecting the fire by processing the video data generated by an ordinary camera is proposed. The engine used the color and fluctuation characteristics of fire to detect it. Experimental results proved that the proposed technique is effective in recognizing the fire. Such a solution is particularly useful in scenarios where sensors cannot be deployed or will not be affective. In this work a static camera was used to detect fire from only one direction. Detection results of multiple cameras when fused together, can provide more precise detection. Furthermore, a static threshold has been used in this work in order to distinguish between hazardous and non-hazardous fire. This threshold does not adapt to the screen ratios and nature and scale of fire. In our future research we will study the impact of adaptive thresholding on fire detection.

V. References

[1] F. Khan, "258 dead in Karachi garment factory fire," *THE EXPRESS TRIBUNE*, Sept 12, 2012.

[2] G. Karstens-Smith, "BC Wildfire Damage: 300 Buildings Gone So Far," Huffington post August 1, 2017.

[3] J. Ali, Imtiaz; Ghaffar, Abdul ; Feroze, "12 killed in fire at Karachi's Regent Plaza hotel," *DAWN*, December 5th 2016.

[4] Artim N. An introduction to fire detection, alarm, and automatic fire sprinklers. Northeast Document Conservation Center. 1999..

[5] Z. Nauman, S. Iqbal, M. I. Khan, and M. Tahir, "WSN-Based Fire Detection and Escape System with Multi-modal Feedback," in *Multimedia Communications, Services and Security: 4th International Conference, MCSS 2011, Krakow, Poland, June 2-3, 2011. Proceedings*, A. Dziech and A. Czyżewski, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 251–260.

[6] R. C. Luo and K. L. Su, "Autonomous Fire-Detection System Using Adaptive Sensory Fusion for Intelligent Security Robot," *IEEE/ASME Trans. Mechatronics*, vol. 12, no. 3, pp. 274–281, Jun. 2007.

[7] O. Asif, M. B. Hossain, M. Hasan, M. T. Rahman, and M. E. H. Chowdhury, "Fire-Detectors Review and Design of an Automated, Quick Responsive Fire-Alarm System Based on SMS," *Int. J. Commun. Netw. Syst. Sci.*, vol. 7, no. 9, p. 386, 2014.

[8] S. Mudunuru, V. Nayak, G. Rao, and K. Ravi, "Real time security control system for smoke and fire detection using ZigBee," *Int. J. Comp. Sci. Info. Techno*, vol. 2, no. 6, pp. 2531–2540, 2011.

[9] Rajput, Vikram, Aparna Bimal, K. Abishek, Utkarsh Sinha, and S. Raj Kumar. "Low Cost Fire Alarm System with Sprinkler." *International Journal of Advanced Research in Computer Science* 8, no. 5 (2017).

[10] Alkhatib, A.A., 2013. Smart and low cost technique for forest fire detection using wireless sensor network. *International Journal of Computer Applications*, *81*(11)..

[11] X. L. Zhou, F. X. Yu, Y. C. Wen, Z. M. Lu, and G. H. Song, "Early fire detection based on flame contours in video," *Inf. Technol. J.*, vol. 9, no. 5, pp. 899–908, 2010.

[12] G. Healey, D. Slater, T. Lin, B. Drda, and A. D. Goedeke, "A system for real-time fire detection," in *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, 1993, pp. 605–606.

[13] C.-B. Liu and N. Ahuja, "Vision based fire detection," in *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004.*, 2004, vol. 4, p. 134–137 Vol.4, 2004.

[14] G. Marbach, M. Loepfe, and T. Brupbacher, "An image processing technique for fire detection in video images," *Fire Saf. J.*, vol. 41, no. 4, pp. 285–289, 2006.

[15] T. C. Chen, P. Wu, and Y. Chiou, "An early fire-detection method based on image processing," *2004 Int. Conf. Image Process. 2004 ICIP 04*, vol. 3, pp. 1707–1710, 2004.

[16] W. Phillips, M. Shah, and N. Da Vitoria Lobo, "Flame recognition in video," *Proc. IEEE Work. Appl. Comput. Vis.*, pp. 224–229, 2000.

[17] X. Soe, Aung Kyaw; Zhang, "Fire Detection by Static Image Characteristics of the Light Blue Flame Using ROI-Based Color Intensity Composition Detection Algorithm," *ICIC Express Lett.*, vol. 5, no. 12, pp. 4479–4486, 2011.

[18] M. Wirth and R. Zaremba, "Flame region detection based on histogram backprojection," in *CRV 2010 - 7th Canadian Conference on Computer and Robot Vision*, 2010, pp. 167–174.

[19] S. Rinsurongkawong, M. Ekpanyapong, and M. N. Dailey, "Fire detection for early fire alarm based on optical flow video processing," in *2012 9th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, 2012, pp. 1–4.

[20] A. E. Gunawaardena, R. M. M. Ruwanthika, and A. G. B. P. Jayasekara, "Computer vision based fire alarming system," in *2016 Moratuwa Engineering Research Conference (MERCon)*, 2016, pp. 325–330.

[21] N. True, Y. Dedeoglu, U. Gudukbay, and A. Cetin, "Computer vision based fire detection," *San Diego Univ. Calif.*, 2009.

[22] B. U. Töreyin, Y. Dedeoğlu, U. Güdükbay, and A. E. Çetin, "Computer vision based method for real-time fire and flame detection," *Pattern Recognit. Lett.*, vol. 27, no. 1, pp. 49–58, 2006.

[23] Y. H. Habiboğlu, O. Günay, and A. E. Çetin, "Covariance matrix-based fire and flame detection method in video," *Mach. Vis. Appl.*, vol. 23, no. 6, pp. 1103–1113, 2012.

[24] "Background Subtraction." [Online]. Available: https://docs.opencv.org/3.0-beta/doc/py_tutorials/py_video/py_bg_subtraction/py_bg_subtraction.html.

[25] D. Stipani, M. Štula, D. Krstini, L. Šeri, T. Jakov, and M. Bugari, "Advanced automatic wildfire surveillance and monitoring network," in *VI International Conference on Forest Fire Research*, 2010, p. 15.