Kerbala Journal for Engineering Science

https://kjes.uokerbala.edu.iq/

An Automatic System for Smoke Detection in Outdoor Areas

Zahraa Shihab AL Hakeem [a]*, Haider Ismael Shahadi [a], Hawraa Hasan Abbas[a]

[a] Electrical and Electronic department, Collage of Engineering, University of Kerbala, Kerbala, Iraq
* Corresponding author, Email: zahraa.shihab@s.uokerbala.edu.iq

Received: 12 November 2023; Revised: 20 February 2023; Accepted: 08 March 2023, Published: 31 March 2023

Abstract

Early detection of fires plays a crucial role in minimizing their impact and preventing them from spreading. Every year, the repetition of fires results in the loss of human life, animal life, and plant life. Fire detection has become increasingly desirable and significant in surveillance systems, where traditional methods of detecting smoke relied on smoke sensors. Therefore, this method is ineffective in open and large buildings, and outdoor areas. As a result, this study suggests using computer vision systems to detect smoke in open spaces by using a static camera. To reduce the data size while preserving important details, the input video is framed and decomposed using the Integer Haar Lifting Wavelet Transform (IHLWT). Then, for smoke color detection, a new method called the multi-threshold International Commission on Illumina (CIE) Lab color space is used, which took into account the smoke colors' change from whitish gray to blackish gray. In addition, the Frame Differences (FD) technique is used to detect motion and thus reduce false alarms. The smoke color detection is combined with frame difference techniques. The small pixels are removed via a morphological operation that represents noise. According to the experimental findings, the approach precision for offline videos is greater than 94.7% for eleven videos, while the average detection reaches 92.8% for online (real time) videos. It also reduces false alarms significantly. According to the trials and comparisons, the suggested smoke detection algorithm performs better than the traditional algorithms in many scenarios. It is also simple, efficient, and low in complexity.

Keywords: wavelet transform, CIE Lab color space, frame differences.

1. Introduction

Fires bring societal, economic, and environmental harm. Because fires result in the loss of human life, fire detection has become increasingly desirable and significant in surveillance systems. To build automated fire alarm systems, several conventional techniques have been offered. Existing approaches rely on relative humidity sampling, light sampling, temperature sampling, air transparency testing, and fire color analysis [1]. Smoke is the main sign of fire. The smoke detection in early fire alarm systems is very appealing for personal safety and business applications. However, most of these solutions require close contact with the source of the smoke or fire and rely on sensors to detect fire characteristics [2]. As a result, they fail to detect smoke in open or large spaces. It also cannot provide additional information about the burning process. To address these issues, video-based smoke detection has had more attention lately. In open or large places, video-based smoke detection is an effective and low-cost technology.

This paper proposes an automated approach for smoke detection based on a camera. The proposed method is suited for both closed and open places (indoor and outdoor areas). It is based on automatic detection of smoke from a fire with the novel method of multi threshold for International Commission on Illumina (CIE) Lab color space compound with frame difference. The Integer Haar Lifting Wavelet Transform (IHLWT) is used during the pre-processing stage to minimize processed data size and obtain better features. Figure 1 shows the block diagram of the proposed framework.

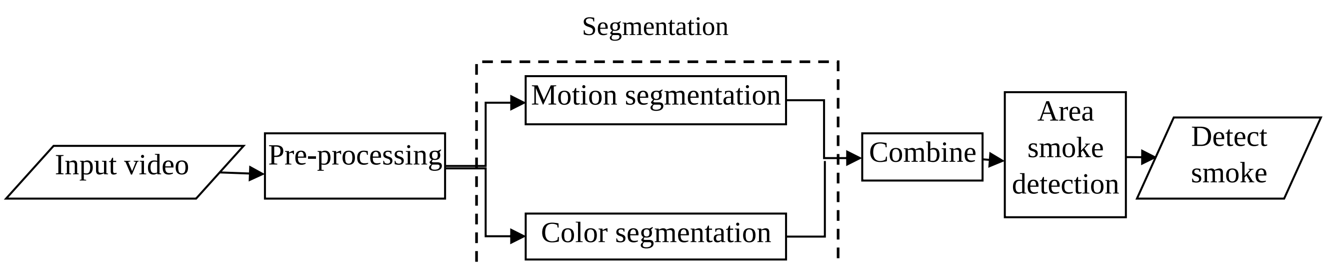


Figure 1 The block diagram of the proposed framework.

In this paper, Section 2 presents a review of the literature on some literature that presented various methods for smoke detection. The proposed system for detection system is introduced in Section 3, including frame differences and color detection. The experiment results and comparison with other research results are presented in Section 4. Finally, conclusions are drawn in the last section.

2. The related work

Since cameras and artificial intelligence have developed, studies on fire detection based on video and image processing have proliferated.

Smoke feature recognition is the core component of many smoke detection techniques, which are subsequently complemented by additional filtering algorithms. Potential smoke areas are divided in YUV color space by Prema et al. [3], who also examine the dynamic texture, spatial, and temporal properties of the candidate smoke regions. Then, additionally, extract the spatial and temporal characteristics of the smoke. This method provides acceptable results; however, it was tested by recording video and not in real time. Color, shape and dynamic properties were employed by Wang et al. [4] to identify smoke. Their technique for extracting potential smoke locations is based on the fact that smoke plumes typically have a conical form. The paper presented a texture filtering-based sub algorithm. The created algorithm has been evaluated on a small sample of video clips, which is a disadvantage.

Wang et. al [5] presented a new method to detect early fire smoke and resolve the issue of false positives brought on by moving objects that aren't smoke, including vehicles and pedestrians. The suggested approach took into account the color and diffusion properties of smoke, in addition to counting the number of pixels in each potential smoke location. To match a linear change rate of smoke per 10 frames, a time window of 30 consecutive frames is established. Through the smoke slope relation, the smoke discrimination criteria are supplied. However, this algorithm had a tendency to trigger false positives because similar changes in pixel size were generated by adjustments in moving clouds and fog concentration.

Jesus et al. [6] suggested a technique for early smoke detection that relies on estimating the motion, color, and texture attributes in a cascade to define the prospective smoke zone. The texture is then examined using the Local Binary Pattern (LBP) and Local Binary Pattern Variance (LBPV) operators. Finally, the existence of smoke is determined if the candidate regions continue to expand upward. According to the evaluation's findings, the suggested system had a high rate of smoke detection. The biggest disadvantage, however, is the spacing between the camera and smoke, since if the fire event occurs far from the camera, the suggested approach can not accurately identify it. Hence this method is inapplicable in a forest fire. While the algorithm produces good results in the aforementioned circumstances, it's effectiveness in the presence of dust or aerosols and under different illumination conditions, particularly at night is not established.

Islam et. al [7] proposed that the moving smoke only object is segmented from the complex backdrop and other moving objects using a mix of Gaussian mixture model (GMM) based adaptive moving object recognition and HSV color segmentation as the preprocessing step. The suggested frame block segmentation-based smoke growth analysis is used to extract the smoke growth characteristics following preprocessing with other operation. In addition to the advantages of accurate smoke detection, this suggested approach may not be appropriate for a smoke accident that occurs away from the camera.

Despite the great success rates and precision of the prior methods, some of them cannot be utilized in real time, while others take a lengthy time to detect fire.

Deep learning is an important topic due to its high recognition accuracy across a variety of applications. High accuracy was attained using a deep learning algorithm in the research for smoke detection. Using deep learning technology, issues with the fire detection process might be resolved. There are certain restrictions, though. For instance, deep learning can improve the accuracy when working with large amounts of information [8]. Stronger tools and extensive training are needed for deep learning. As an example, 800 photos contribute to the Alves et al. [9] fire dataset. Alves [9] used a deep convolutional neural network (DCNN) to detect fire in the forest at night and during the day. The accuracy during the day was 94.1%, while it was 94.8% at night. However, false alarms occurred when the system was used to detect fire in foggy weather conditions during the day and artificial illumination lights at night.

As was previously discussed, multi-domain technology has been used to overcome the limitations of existing systems while still having certain drawbacks in the field of fire detection video research and development.

3. Methodology

In this section, the proposed block diagram will be described in detail. As shown in Figure 1, the suggested method comprises mostly of three key steps: preprocessing technique, segmentation and area smoke detection. All work was done using the MATLAB, version R2021b, and on a PC with Intel Core i7 2.70GHz CPU,16GB of RAM, and Windows 10 operating system.

3.1. Pre-Processing Stage

The process of preparing an image for further analysis or processing is referred to as preprocessing. It entails a series of operations that are carried out on the image to enhance its suitability for a specific use or task. The input video is either captured from an online camera or imported from the database, as described in references [10] and [11]. The pre-processing in this paper uses one of the wavelet transform types, as seen in Figure 2.

3.1.1. Wavelet Transform

Wavelets are non-linear basis sets. The wavelet basis functions are chosen per function and are approximated when approximating a function in terms of wavelets. Wavelets rely on a dynamic collection of basic functions to better portray the input function. One of the most popular types of wavelets is the discrete wavelet transform (DWT), a mathematical technique used to break down a signal or image into wavelets, which are localized functions in both time and frequency [12]. The integer lifting wavelet transform (ILWT), which is a method that allows the DWT to be implemented using only integer arithmetic. Decomposing a wavelet transforms it into a collection of elements, is done using a lifting scheme. The Haar wavelet is a simple example of a lifting scheme. Haar dilates and shifts the wavelets in order to transform them [13].

The average of each adjacent sample of the input signal is used to construct the approximation coefficients in (IHLWT). The detailed coefficients are calculated by computing the difference between the input signal's surrounding samples. Due to the strong correlation between neighboring input signal samples, the approximation coefficients are fairly similar to the actual input samples. And for the same reason as above, the coefficients of the detail signal have low power relative to the original coefficients. In the integer-to-integer lifting scheme based on Haar DWT, Sj is the input sample and has an integer value, therefore the prediction {Sj(e)} = Sj(e) is true. Where Sj is integer, thus, floor (Sj(e)) = Sj(e). Consequently, the prediction of odd can be easily calculated to obtain the detailed coefficients shown in Eq. 1:

$$\text{IHLWT prediction: } dj - 1 = Sj(o) - Sj(e) \qquad (1)$$

Sj(o) and Sj(e) indicate the signal input is odd and even, respectively [14]. The frame is divided into four parts (LL, HL, LH, HH). The low-level band frequency (LL) is used as a source of information for the detection system, where the input data size can be decreased to 75% using the integer Haar lifting wavelet transform (IHLWT).

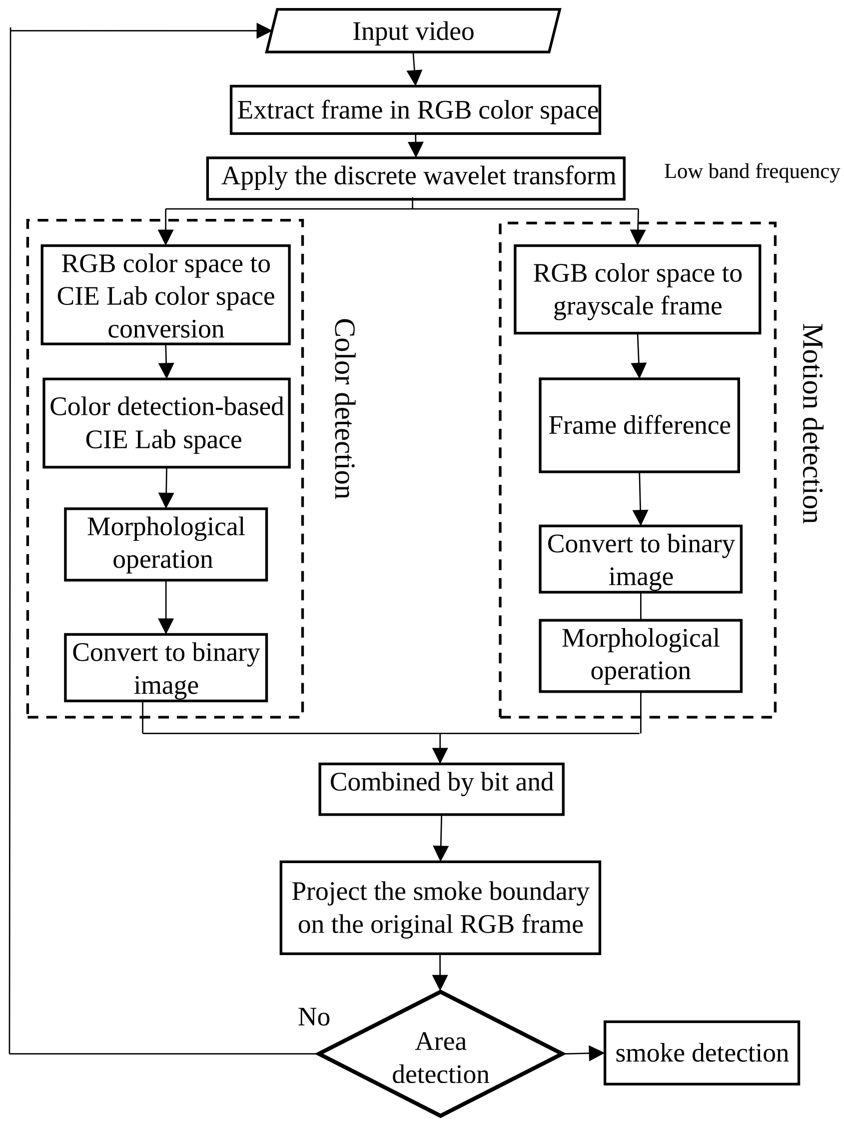


Figure 2 The proposed system of smoke detection.

3.2. Segmentation

Image segmentation is an important aspect of image analysis and computer vision since it enables the identification and separation of individual objects or regions within an image for further analysis [15]. The pre-processed input frames are further processed to segment the motion and color of smoke from the image; all details are in Figure 2.

3.2.1. The Frame Differences

One of the most distinguishing aspects of smoke is the random diffusion of its form as a result of heat convection or wind driven airflow. Therefore, potential smoke zones are first identified using a different frame. This procedure is necessary for improving smoke detection performance and decreasing detection time [16].

Since wildfire smoke spreads slower than interior smoke or smoke from moving objects, A generic frame difference (FD) is ineffective in detecting moving smoke zones. The difference between the frames is not sequential. Specifically, a gray frame and a static camera are employed every 8 frames to enhance the detection of pixel changes associated with smoke motion. The absolute differential frames are defined as follows [17]:

$$I_{d(k,k+8)} = |I_{(k+8)} - I_k| \tag{2}$$

In video, I_k is meant to be the value of the k^{th} frame. The value of the $(k+8)^{th}$ frame in video is $I_{(k+8)}$. The motion detection frame must be binarized and morphological operation to remove small pixel before the next phase, which is color detection [18].

3.2.2 The Color Detection

Smoke displays strong, albeit not unique, color features. The color of smoke can range from whiteish gray to blackish gray. Color remains one of the most obvious elements of smoke, despite the considerable inter-class and intra-class color differences. Frames are often taken in RGB format. Figure 3 provides a depiction of an RGB aerial frame in each of the three channels. One downside of adopting this color space for flame and smoke detection is seen in Figure 3. Both the R and G channels show that the sky in the backdrop and the flame pixels are saturated. This is due to the fact that luminance and chrominance are not separated in RGB color space.

Converting the frame into International Commission on Illumination (CIE) Lab color spaces is an improved method to solve this problem. Figure 4 depicts the L, a, and b color channels of the original RGB color space image from Figure 3. It can be seen that the color information of smoke and flame is significant in a and b color spaces, but the luminance of flame is prominent in L color spaces. The CIE Lab color space is modeled around how the human eye perceives color. L stands for luminance, value [0,100], a stand for colors ranging from red to green; values commonly fall in the range [-100, 100] or

[-128, 127], and b stands for colors ranging from yellow to blue; values commonly fall in the range [-100, 100] or [-128, 127] in the CIE Lab color space. The following are the mathematical formulas for CIE Lab color space conversion [19]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} M_{11} & M_{12} & M_{13} & M_{14} \\ M_{21} & M_{22} & M_{23} & M_{24} \\ M_{31} & M_{32} & M_{33} & M_{34} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \\ 1 \end{bmatrix} \tag{3}$$

where Mij is a linear transformation matrix between the spaces RGB and XYZ, and Xn, Yn, and Zn are the values of the reference blank.

$$L = \begin{cases} 116 \times \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16, & if \left(\frac{Y}{Y_n}\right) > 0.008856 \\ 116 \times \left(\frac{Y}{Y_n}\right), & if \left(\frac{Y}{Y_n}\right) \leq 0.008856 \end{cases} \tag{4}$$

$$a = 500 \times \left\{ \left(\frac{X}{X_n}\right)^{\frac{1}{3}} - \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} \right\} \tag{5}$$

$$b = 500 \times \left\{ \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - \left(\frac{Z}{Z_n}\right)^{\frac{1}{3}} \right\} \tag{6}$$

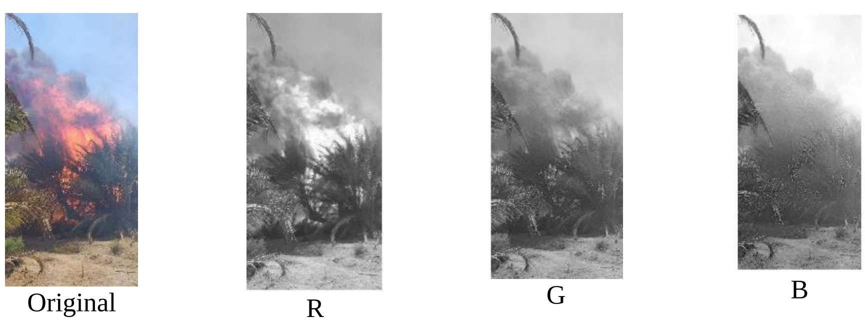


Figure 3 The original flame and smoke image RGB split to each channel R-G-B.

L a b

Figure 4 L, a and b color channel representation of Figure 2 original image. L is lightness; a and b are chrominance.

Table 1 includes the value of the multi-thresholds of the CIE Lab color space; these thresholds represent the smoke color gradation from whitish gray to blackish gray. The thresholds segment the frame to the foreground, which represents the color of smoke in CIE Lab color space, while the background represents non-color smoke.

Table 1. The multi threshold of CIE Lab color space to detect smoke color

Thresholds / The rules	The ranging of threshold 1	The ranging of threshold 2	The ranging of threshold 3
$\boldsymbol{Rule}$ **1 : L**	$(0.058\sim98.32)$	$(87.955\sim100)$	$(8.876\sim3.748)$
$\boldsymbol{Rule}$ **2 : a**	$(-8.067\sim4.853)$	$(-2.211\sim5.546)$	$(-2.377\sim2.773)$
$\boldsymbol{Rule}$ **3 : b**	$(-24.653\sim-9.788)$	$(-9.359\sim3.12)$	$(-10.399\sim4.065)$

The region of smoke color R_{color} is represented in the following formula:

$$R_{color} = \text{threshold } 1 \cup \text{ threshold } 2 \cup \text{ threshold } 3 \qquad (7)$$

The morphological approach is used to remove extra small pixels that did not extend into the smoke in any way, leading to better results [18]. Figure 5 shows the steps of the smoke color detection-based CIE Lab color space. N represents the new value of L, a, and b, where some values were selected from the overall value after applying the thresholds.

3.3. Area smoke detection

The extensive examination of the frame difference and color feature of smoke discussed above leads to the conclusion that employing frame difference or color detection alone to identify smoke results in a significant percentage of false alarms. As a result, in order to fully leverage their properties and acquire the precise smoke region, we must do extra operations that integrate the findings of the two approaches.

$$R_{smoke}(i,j,n) = R_{color}(i,j,n) \cap I_d(i,j,n) \quad (8)$$

The smoke must then be bound in binary by defining its region and inserting the red bounding box. Also, the area of the bounded region is determined, which is calculated by subtracting the original frame from the boundary frame. When the value is greater than the threshold, the results of this area take it into account as a smoke. The threshold for the area is not less than 85.

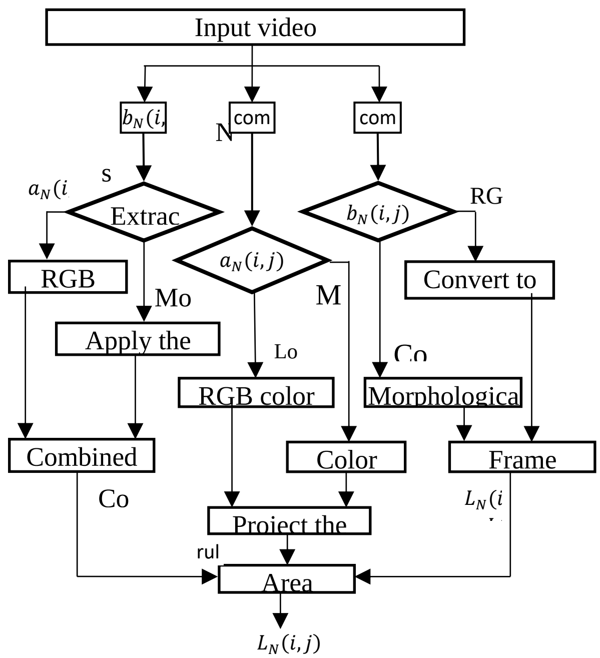
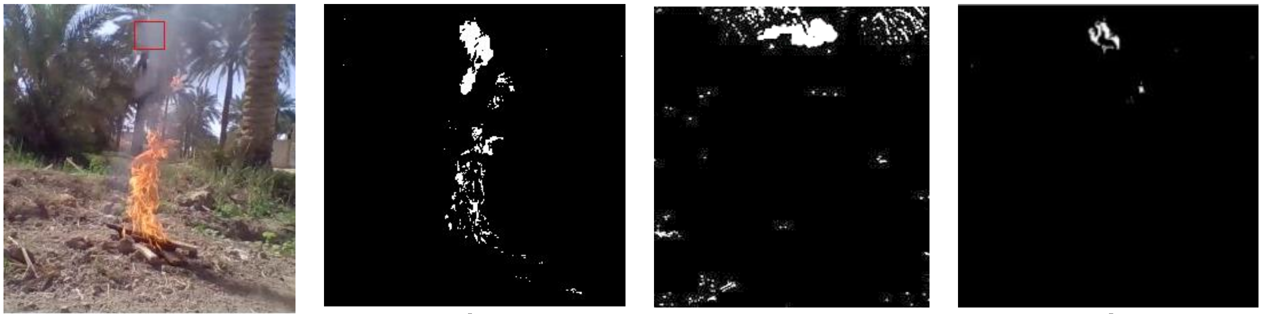


Figure 5 The smoke color detection on based CIE Lab color space.

4. The experimental results

The test video database is compiled offline a variety of scenarios, including varying backgrounds and environmental conditions, from Jiangxi University of Finance and Economics' Yuan Feiniu Laboratory [10] and other databases [11]. The real-time smoke detection was also tested with different colors of smoke using the static camera. The results of smoke detection come basically from the combination of the color and motion of the smoke. The result of the combination is depicted in Figure 6.



a b c d

Figure 6 Results of combination. (a) Results detection on original frame. (b) Result of motion detection. (c) Result of color detection. (d) Result of combination of b and c.

The real time smoke detected in the outdoors is shown in Figure 7 with four different smoke video scenarios (S25, S01, S04, F61). This video contains many colors of smoke gradient from gray to white where the proposed system can detect the color of smoke depending on using the three ranging thresholds of CIE Lab color space. Table 2 provides an explanation of the experiment's real-time findings, where N_n stands for both the number of video frames and the number of smoke-filled frames. N_{TP} is the number of frames where the algorithm has identified fire smoke. The rate of smoke detection in a video is R_D.

$$R_D = N_{TP}/N_n \qquad (9)$$

On the real-time video, the average detection rate may be higher than 92.8%.

S25

S01

S04

F61

Figure 7 Results of smoke detection in the real time.

Table 2 Results of smoke detection in the real time.

Video	Nn	N_{TP}	R_D
S25	25	25	1.000
S01	70	65	0.929
S04	24	22	0.917
F61	21	18	0.857
Total	140	130	**92.8%**

The recording video in Figure 8 shows the testing outcomes in several different contexts extracted from the database. Smoke detection was not restricted to the database videos but in addition, it included footage recorded from Iraqi forests, as shown in Figure 8 (e), in order to cover as many expected episodes of forest fires as possible and assess the effectiveness of the suggested approach.

a b c d e

Figure 8 Results of offline smoke detection.

The suggested method is compared with previous smoke detection systems based on color and other characteristics. The first part, compared with the Yang et al. [20] method, which depends on using CIE Lab color space, optical flow and other characteristics where the precision equals 93% for eleven video databases from [11-21] as shown in Table 3. The proposed method's precision reaches up to 94.7% as shown in Table 4. The higher precision means a lower false alarm.

$$\text{precision} = \frac{True\ Positive\ (\mathrm{N}_{TP})}{True\ Positive(\mathrm{N}_{TP}) + False\ Positive\ (\mathrm{N}_{FP})} \qquad (10)$$

N_{TP} is the number of frames where the algorithm has identified fire smoke.
N_{FP} is the number of frames where there are no signs of smoke yet some have been mistakenly recognized by the algorithm.

As a result of the poor video quality, videos 6 and 7 had lower precision. The precision of the forest videos is nearly 99% in videos 9, 10, and 11 for both methods (this papers and Yang's method).

Table 3 The description of videos.

No.	Description
Video1	Smoke spread quickly across the field.
Video2	Short distance indoor rapid spread of cotton smoke.
Video3	Smoke spreads quickly across a field while a person is walking.
Video4	At a relatively short distance, indoor smoke diffuses slowly.
Video5	Smoke from a pretty near distance
Video6	There is smoke in the sky not very far away.
Video7	Indoor leaf smoke quickly dissipates over a small area.
Video8	rapid outdoor smoke dispersal at close range.
Video9	rapid smoke dispersion over a distant low hill.
Video10	rapid smoke dispersion over a distant low hill.
Video11	Long distances slow smoke dispersion on low hills.

Table 4 Precision of the proposed method

Video	No. frames	N_{TP}	N_{FP}	precision
Video1	80	40	2	0.95
Video2	1446	250	10	0.96
Video3	2875	1167	94	0.93
Video4	480	341	12	0.97
Video5	896	700	66	0.91
Video6	3176	2051	240	0.90
Video7	624	490	60	0.89
Video8	6084	4200	366	0.91
Video9	2328	2180	22	0.99
Video10	7624	5817	76	0.99
Video11	2888	1988	39	0.98
Total	28501	19226	987	94.7%

The second part included the performance of the suggested approach is contrasted with that of the method employed by Wang et al. [22] and Yu et al. [23]. The phrase "detection at frame n" in Table 5 denotes the fact that smoke is detected at frame n after starting at frame 0. The database that used from [21], [24]. The proposed technique in the current study performs better than that of [22] and [23], as demonstrated in Table 5. As [23] method's optical flow algorithm is sensitive to motion regions where the gray levels vary dramatically, the gradual shift in gray levels in Movies (a), (b), and (c) led to a later smoke warning than the other two techniques.

A subsequent smoke warning in Movie (c) resulted from Wang et al method's excessive texture filter limitations. Consequently, the new method of the current study is more suited to early detection than the other two methods. The three approaches' false alarm rates were tested using a few non-smoking movies. The number of false alerts in Table 6 refers to the number of false alarms discovered after evaluating each frame of a video. The suggested technique had a lower false alarm rate than the other two methods, except that [22] method achieved better results regarding movie f, as demonstrated in Table 6, which compares the three methods. This demonstrates that the suggested approach for detecting smoke is more accurate than the other two methods since it makes use of color and motion information.

Table 5 Smoke detection performance comparison

Video	No. frames	Detection at frame n			Description
		proposed method	[22] method	[23] method	
Movie a	2201	2	5	69	Cotton smoke
Movie b	2250	14	16	86	Smoke near an ash bin
Movie c	244	30	87	121	Smoke near a window

Table 6 False alarm performance comparison

Video	No. frames	Number of false alarms			Description
		proposed method	[22] method	[23] method	
Movie d	895	0	0	0	Waving leaves
Movie e	1132	0	3	3	Moving light
Movie f	1	2	1	2	Vehicles in a road

5. Conclusion

This study provided an autonomous method for video stream smoke detection. This approach has four major steps: The integer Haar lifting wavelet transformations are used for pre-processing to frame the input video and reduce the data size without losing significant data. Frame differences are used to detect smoke motion. Smoke color recognition based on CIE Lab color space models as a new method to identify possible smoke locations and the method uses multiple thresholds. Combining the outcomes is necessary to determine the smoke zones. This method was tested using various video feeds. The findings of the tests show that the method can achieve a precision of around 94.7% in video recording and an average detection rate that exceeds 92.8% in real-time. Although the proposed method is quick, effective, and minimal in complexity.

References

[1] X. F. Han, J. S. Jin, M. J. Wang, W. Jiang, L. Gao, and L. P. Xiao, “Video fire detection based on Gaussian Mixture Model and multi-color features,” *Signal, Image Video Process.*, vol. 11, no. 8, pp. 1419–1425, Nov. 2017, doi: 10.1007/s11760-017-1102-y.

[2] S. J. Chen, D. C. Hovde, K. A. Peterson, and A. W. Marshall, “Fire detection using smoke and

gas sensors," *Fire Saf. J.*, vol. 42, no. 8, pp. 507–515, 2007, doi: 10.1016/j.firesaf.2007.01.006.

[3] C. Emmy Prema, S. S. Vinsley, and S. Suresh, "Multi Feature Analysis of Smoke in YUV Color Space for Early Forest Fire Detection," *Fire Technol.*, vol. 52, no. 5, pp. 1319–1342, 2016, doi: 10.1007/s10694-016-0580-8.

[4] S. Wang, Y. He, H. Yang, K. Wang, and J. Wang, "Video smoke detection using shape , color and dynamic features," *J. Intell. Fuzzy Syst.*, vol. 33, no. 1, pp. 305–313, 2017, doi: 10.3233/JIFS-161605.

[5] H. Wang, Y. Zhang, and X. Fan, "Rapid Early Fire Smoke Detection System Using Slope Fitting in Video Image Histogram," *Fire Technol.*, vol. 56, no. 2, pp. 695–714, 2019, doi: 10.1007/s10694-019-00899-5.

[6] J. Olivares-mercado *et al.*, "Early Fire Detection on Video Using LBP and Spread Ascending of Smoke," *Sustainability*, vol. 11, no. 12, pp. 1–16, 2019, doi: 10.3390/su11123261.

[7] M. R. Islam, M. Amiruzzaman, S. Nasim, and J. Shin, "Smoke object segmentation and the dynamic growth feature model for video-based smoke detection systems," *Symmetry (Basel).*, vol. 12, no. 7, pp. 1–18, 2020, doi: 10.3390/SYM12071075.

[8] F. Gong *et al.*, "A real-time fire detection method from video with multifeature fusion," *Comput. Intell. Neurosci.*, vol. 2019, p. 18, 2019, doi: 10.1155/2019/1939171.

[9] J. Alves, C. Soares, J. M. Torres, P. Sobral, and R. S. Moreira, "Automatic Forest Fire Detection Based on a Machine Learning and Image Analysis Pipeline," in *World Conference on Information Systems and Technologies.*, 2019, pp. 240–251, doi: 10.1007/978-3-030-16184-2_24.

[10] "Video smoke detection," 2022. http://staff.ustc.edu.cn/~yfn/vsd.html (accessed Dec. 20, 2022).

[11] "Sample Fire and Smoke Video Clips," 2013. http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SampleClips.html (accessed Dec. 20, 2022).

[12] Z. Váňa, S. Prívara, J. Cigler, and H. A. Preisig, "System identification using wavelet analysis," *Eur. Symp. Comput. Aided Process Eng.*, vol. 29, pp. 763–767, 2011, doi: 10.1016/B978-0-444-53711-9.50153-X.

[13] M. Ramalingam and N. A. M. Isa, "Video steganography based on integer Haar wavelet transforms for secured data transfer," *Indian J. Sci. Technol.*, vol. 7, no. 7, pp. 897–904, 2014, doi: 10.17485/ijst/2014/v7i7.4.

[14] H. I. Shahadi, R. Jidin, and W. H. Way, “High Performance FPGA Architecture for Dual Mode Processor of Integer Haar Lifting-Based Wavelet Transform,” *Int. Rev. Comput. Softw.*, vol. 8, no. 9, pp. 2058–2067, 2013.

[15] R. M. Haralick and L. G. Shapiro, “Image segmentation techniques.,” *Comput. Vision, Graph. Image Process.*, vol. 29, no. 1, pp. 100–132, 1985, doi: 10.1016/S0734-189X(85)90153-7.

[16] B. Ko, J. Park, and J. yeal Nam, “Spatiotemporal bag-of-features for early wild fi re smoke detection ☆,” *IMAVIS*, vol. 31, no. 10, pp. 786–795, 2013, doi: 10.1016/j.imavis.2013.08.001.

[17] N. Singla, “Motion Detection Based on Frame Difference Method,” *Int. J. Inf. Comput. Technol.*, vol. 4, no. 15, pp. 1559–1565, 2014, [Online]. Available: http://www.ripublication.com/irph/ijict_spl/ijictv4n15spl_10.pdf.

[18] G. F. Shidik, F. N. Adnan, C. Supriyanto, R. A. Pramunendar, and P. N. Andono, “Multi color feature, background subtraction and time frame selection for fire detection,” in *Proceedings of 2013 International Conference on Robotics, Biomimetics, Intelligent Computational Systems, ROBIONETICS 2013*, 2013, pp. 115–120, doi: 10.1109/ROBIONETICS.2013.6743589.

[19] K. León, D. Mery, F. Pedreschi, and J. León, “Color measurement in L*a*b* units from RGB digital images,” *Food Res. Int.*, vol. 39, no. 10, pp. 1084–1091, 2006, doi: 10.1016/j.foodres.2006.03.006.

[20] Y. Jia, J. Yuan, J. Wang, J. Fang, Q. Zhang, and Y. Zhang, “A Saliency-Based Method for Early Smoke Detection in Video Sequences,” *Fire Technol.*, vol. 52, no. 5, pp. 1271–1292, 2016, doi: 10.1007/s10694-014-0453-y.

[21] “State Key Laboratory of Fire Science,” 2022. https://en.sklfs.ustc.edu.cn/main.htm (accessed Dec. 20, 2022).

[22] S. Wang, Y. He, J. J. Zou, D. Zhou, and J. Wang, “Early smoke detection in video using swaying and diffusion feature,” *J. Intell. Fuzzy Syst.*, vol. 26, no. 1, pp. 267–275, 2014, doi: 10.3233/IFS-120735.

[23] Y. Chunyu, F. Jun, W. Jinjun, and Z. Yongming, “Video fire smoke detection using motion and color features,” *Fire Technol.*, vol. 46, no. 3, pp. 651–663, 2010, doi: 10.1007/s10694-009-0110-z.

[24] “University of Science and Technology of China,” 2022. https://en.ustc.edu.cn/ (accessed Dec.

23, 2022).

نظام أوتوماتيكي لاكتشاف الدخان في المناطق الخارجية

الخلاصة: *يلعب اكتشاف الحرائق في مرحلة مبكرة دورًا مهمًا في الحد من كارثتها ووقف انتشارها. في كل عام ، يؤدي تكرار الحرائق إلى فقدان الأرواح البشرية والحيوانية والحياة النباتية. أصبح اكتشاف الحرائق مرغوبًا بشكل متزايد وهامًا في أنظمة المراقبة ، حيث كان الاكتشاف التقليدي للدخان يعتمد على أجهزة استشعار الدخان. لذلك ، هذه الطريقة غير فعالة في المباني المفتوحة والكبيرة ، والمناطق الخارجية. نتيجة لذلك ، تقترح هذه الدراسة استخدام أنظمة رؤية الكمبيوتر للكشف عن الدخان في الأماكن المفتوحة باستخدام كاميرا ثابتة. لتقليل حجم البيانات دون فقد التفاصيل المهمة ، يتم تأطير الفيديو المُدخل وتحلله باستخدام العدد الصحيح لتحويل مويجات رفع (The integer Haar lifting wavelet transform) بعد ذلك ، بالنسبة لاكتشاف لون الدخان ، استخدمت طريقة جديدة مساحة (International Commission on Illumina (CIE) Lab) متعددة العتبات ، والتي أخذت في الاعتبار تغيير ألوان الدخان من الرمادي الأبيض إلى الرمادي الأسود. بالإضافة إلى ذلك ، يتم استخدام طريقة فروق الإطارات (Frame differences) لاكتشاف الحركة وبالتالي تقليل الإنذارات الكاذبة. يتم الجمع بين اكتشاف لون الدخان وتقنيات اختلاف الإطار. تتم إزالة وحدات البكسل الصغيرة من خلال عملية مورفولوجية (Morphological operation) تمثل التشويش. وفقًا للنتائج التجريبية ، فإن دقة النهج لمقاطع الفيديو غير المتصلة بالإنترنت (Off-line) تزيد عن 94.7٪ لأحد عشر مقطع فيديو ، بينما يصل متوسط الاكتشاف إلى 92٪ لمقاطع الفيديو عبر الإنترنت (في الوقت الفعلي) (Real time). كما أنه يقلل بشكل كبير من الإنذارات الكاذبة. وفقًا للتجارب والمقارنات ، فإن خوارزمية الكشف عن الدخان المقترحة تعمل بشكل أفضل من الخوارزميات التقليدية في العديد من السيناريوهات. كما أنها بسيطة وفعالة ومنخفضة التعقيد وقليلة الكلفة.*