An automatic flame detection system for outdoor areas

Zahraa Shihab Al Hakeem, Haider Ismael Shahadi, Hawraa Hassan Abass
Department of Electrical and Electronics, Collage of Engineering, University of Kerbala, Karbala, Iraq

Article Info

Article history:

Received Aug 10, 2022
Revised Nov 16, 2022
Accepted Feb 16, 2023

Keywords:

Area detection
Frame differences
HSV/YCbCr color space
Image processing
Otsu's algorithm
Wavelet transforms

ABSTRACT

Traditional fire detection depends on smoke sensors. This strategy, however, is unsuited for big and open buildings, as well as outdoor regions. As a result, based on computer vision systems, this research proposes an effective method for recognizing flames in open areas. To minimize data size without losing important information, integer Haar lifting wavelet transform is used to frame and analyze the input video. Then, three color spaces (binary, hue, saturation, value (HSV), and YCbC) are used in simultaneous color detection. In binary space, Otsu's approach is utilized to determine automated intensity pixels. Additionally, using frame differences to reduce false alarms. According to the experimental results, the approach achieves 99% accuracy for offline videos and surpasses 93% accuracy for real-time videos while maintaining a lower level of complexity.

Corresponding Author:

Zahraa Shihab Al Hakeem
Department of Electrical and Electronic, Collage of Engineering, University of Kerbala
Karbala, Iraq
Email: zahraa.shihab@s.uokerbala.edu.iq

1. INTRODUCTION

The rapid expansion of the economy has resulted in considerable challenges in fire management due to the increased scale and intricacy of projects. Detecting fires early and accurately is crucial in minimizing fire-related damages. Therefore, having reliable fire detection and alarm systems that possess high sensitivity and precision is essential. Traditional fire detection systems [1], [2], such as those that rely on heat and smoke detectors, may find them inadequate in larger spaces in complex buildings or environments with multiple sources of interference. The limitations of these methods can lead to missed detections. False alarms, delays in recognizing real fires, and other challenges make it difficult to provide timely fire warnings. Fire detection has recently become a popular research topic as it offers several benefits, including early fire detection, high accuracy, and the ability to identify fires in large areas and complex building systems [3].

Studies on fire detection based on video and image processing have appeared widely after the development of cameras and artificial intelligence. For identifying motion pixels in the video, Töreyin *et al.* [4] presented a Gaussian mixture background estimation approach. This approach uses a color model to identify possible fire locations, then uses wavelet analysis in the spatial and temporal dimensions to assess high frequency activity in the area. In practice, this approach, like the prior problem, has high computational complexity.

Han *et al.* [5] successfully detected motion in the lab using a multicolor model and a Gaussian mixture model, but these methods cannot be used in real-world applications thus, they take a large amount of processing time. Khan *et al.* [6] proposed a video-based approach that employs fire dynamics and static indoor fire identification based on the color, area, roundness, and perimeter of the fire. A small amount of fire, like in a candle, is used as a supplementary component of their technique. Because it eliminates and then uses flame development aspects to analyze, this technique may have a significant fault in the early detection of fire.

Khalil *et al.* [7] introduced a novel fire detection approach based on Commission Internationale de l'Eclairage (CIE) L*a*b* and red, green and blue (RGB) color spaces by combining motion detection with flame object monitoring and calculating the rate of flame growth in the video. This method enhances fire detection accuracy and produces decent results, but it has a significant frequency of false positive alerts and is unstable for complex words.

Deep learning is currently a popular area of research due to its remarkable accuracy in recognizing patterns across a diverse set of applications. For fire detection, the researchers employed a deep learning algorithm [8], [9], and excellent accuracy was achieved. The utilization of deep learning technology could potentially address issues encountered in the fire detection process. But there are certain limitations. Deep learning, for example, when dealing with large volumes of data, can improve accuracy. Despite this, the camera collects fewer instances of flames and actual flame samples. Training for deep learning demands powerful equipment and consumes a significant amount of time. As an illustration, the flame dataset from Alves *et al.* [10] includes 800 images.

This research addresses the challenges that still exist in fire detection video technology by proposing a camera-based automatic fire detection approach. The proposed method is applicable to both enclosed and open spaces and employs multi-domain technology to surpass the current limitations of the system. The proposed method involves recognizing the flame of the fire in YCbCr and hue, saturation, value (HSV), color space using frame difference and Otsu's method. Additionally, a new method is introduced during the preprocessing step that involves the integer Haar lifting wavelet transform to not only decrease the size of the processed data but also produce more effective features.

2. METHOD

A five-step approach is proposed for fire detection: 1) preprocess input data with a wavelet transform; 2) use Otsu's technique to classify fire pixels; 3) detect fire motion with frame differences; 4) fire and non-fire objects can be distinguished using a two-color space model; and 5) compute flame area. See Figure 1 for a detailed explanation of each step. The video is framed to enable fire detection functions.

2.1. Pre-processing (wavelet transforms)

The integer Haar lifting wavelet transform (Int-to-Int-HLWT) is a method used in this study to reduce processing time. The wavelet transform differs from the Fourier transform by using infinite basic functions to represent a signal. The wavelet transform analyzes signals across time and frequency domains, where the longer duration of low-frequency signals provides better resolution for higher-frequency signals [11].

Each frame is separated into four parts: high-high (HH), low-high (LH), high-low (HL), and low-low (LL) in the Int-to-Int-HLWT technique, and the low-band frequency (LL) is utilized for processing. The Haar filter, which is commonly used in conjunction with the discrete wavelet transform, is used to compute the approximation and detailed coefficients [12]. The overarching objective of the Int-to-Int-HLWT technique is to curtail the extent of data storage capacity by a staggering 75%, thereby facilitating expedited processing time while simultaneously safeguarding crucial data.

2.2. Otsu's algorithm

Otsu's threshold selection method is a simple and effective technique for processing grayscale color frames, as proposed by Nobuyuki Otsu in 1979 [13]. Figure 1 illustrates the classic Otsu algorithm for establishing a threshold value. After successful segmentation of the fire frame, the color distribution becomes restricted to black (0) and white (1). The flame is denoted by white (1) and the background by black (0). To improve the results, a morphological approach was used to remove small pixels that were unrelated to the fire [14].

2.3. Frame difference method for motion detection

The flame's form is uneven and varies frequently due to the dynamic properties of fire. When fire is employed as a prominent characteristic in motion identification, common detection methods involve continuous frame changes [15], mixed Gaussian background modeling [16], and background subtraction [17]. Due to the significant day and night difference, background subtraction must establish the backdrop appropriately. It's challenging to have a constant background, and parameters must be defined, which is more intricate than a static background. Preprocessing is required to determine the history frame, Gaussian mixture number, background update rate, and noise in the mixed Gaussian model, which is excessively complicated.

The frame difference method is easy to use, doesn't require a lot of programming, isn't affected by changes in the scene like lighting, and can quickly adjust to changing circumstances. However, it doesn't detect motion in consecutive frames. Therefore, this research uses an enhanced frame difference approach that employs a new method due to continual shifts in flame pixels caused by airflow and combustion qualities [18]. The enhanced frame difference method involves transforming the video stream into a frame image, grayscale processing to combine RGB channels, and subtracting after eight frames where the pixel's flame has changed the most.

$$I_{d(k,k+8)} = |I_{(k+8)} - I_k| \quad (1)$$

In video, I_k is represented to be the value of the k^{th} frame. The value of the $(k+8)^{th}$ frame in the video is $I_{(k+8)}$. The motion detection frame must be binarized before proceeding to the color detection step, also using morphological operations to neglect the small white pixels [14].

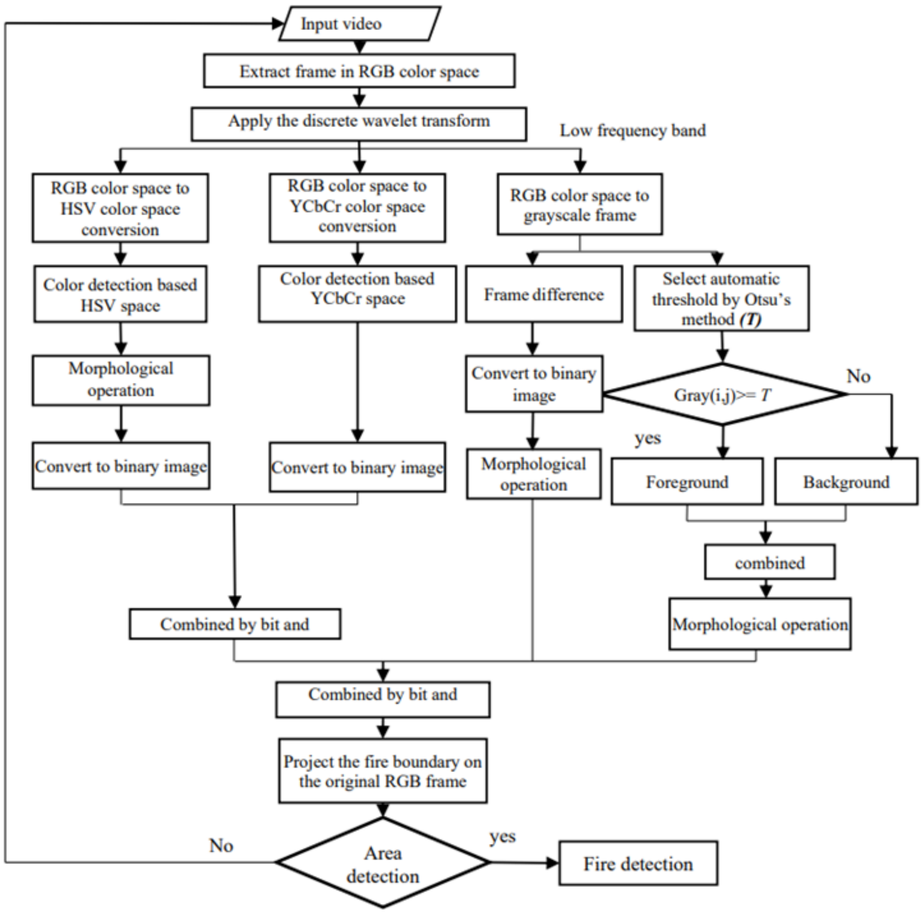


Figure 1. The suggested flame detection system

2.4. The two-color detection

The color of a flame is frequently identified as its most striking attribute. It is widely used to distinguish fire from other items. As a result, the suggested technique's third phase is color detection, that combines the YCbCr and HSV color spaces to identify potential fire zones.

2.4.1. HSV color space

The image is numerically represented as an $m \times n \times 3$ arrays with numbers between [0, 1]. A third dimension of HSV defines the hue, saturation, and value for each pixel. The hue is a value ranging from 0 to 1 that denotes the location of a particular color on a color wheel. By increasing from 0 to 1, the hue progresses through a spectrum of colors, starting with red and moving on to orange, yellow, green, cyan, blue, and magenta before returning to red. On the other hand, saturation relates to the intensity of color or degree of deviation from neutrality. A zero value represents a neutral shade, while a value of one represents the highest level of saturation. The color's value is determined by its red, green, and blue components, with the maximum value being taken. The HSV color can be produced using the non-linear RGB transformation (2)–(4) [19].

$$H = \begin{cases} \theta & if b \leq g \\ 360° & if b > g \end{cases} \qquad where\ \theta = cos^{-1} \frac{\frac{1}{2}(r-g)+(r-b)}{[(r-g)^2+(r-b)(g-b)]^{1/2}} \quad (2)$$

$$v = max(r, g, b) \quad (3)$$

$$s = \frac{v-\min(r,g,b)}{v} \quad (4)$$

Given the range of colors that fire exhibits, including yellow, red, and white at higher temperatures, we have chosen to use the HSV color system in this particular scenario. After conducting several tests, we determined an optimal threshold for segmenting flame colors. The following equation provides a clear representation of this threshold:

$$0 < H < 0.2 \qquad 0.47 < S < 0.98 \qquad 0.7 < V < 0.98 \quad (5)$$

Where V, S, and H denote the value, saturation, and hue elements of a frame. The frame is divided into two parts by these thresholds: the foreground denotes fire colors, while the background denotes non-fire colors. To determine the color of the flame in the HSV color space, the results of each channel are added together. Small pixels are often represented as noise, which is removed using morphological procedures [14]. In the final stage of the section, the binarized frame is generated with the aim of combining the flame color information in the HSV color space with that of the YCbCr color space using the logical operator AND.

2.4.2. YCbCr color space

The YCbCr color scheme is widely used in digital video components to represent color as luminance and two color difference signals. The luminance component is denoted by Y, while the chrominance-blue and chrominance-red components are represented by Cb and Cr. The YCbCr color space has the feature of better discriminating between chrominance and brightness, making it a preferred choice for testing the effectiveness of various color spaces in distinguishing fire pixels [20].

The RGB color space can distinguish between a variety of colors, but it is sensitive to changes in lighting. This means that the fire detection color rules will not work properly if the lighting in the frame changes. In order to tackle this problem, it is necessary to transform the RGB color space into a color space that offers improved discrimination in terms of intensity and chrominance. To achieve this, the YCbCr color space can be obtained by applying the subsequent formula for the conversion of RGB [21].

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2568 & 0.5041 & 0.0979 \\ -0.1482 & -0.2910 & 0.4392 \\ 0.4392 & -0.3678 & -0.0714 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \quad (6)$$

The YCbCr color space decomposes a frame into three components: luminance (represented by Y) and chrominance-blue and chrominance-red components (represented by Cb and Cr, respectively). The mean values of these components can be calculated for a specific frame.

$$Y_{mean} = \frac{1}{k}\sum_{i=1}^{k} Y(x_i, y_i),\ Cb_{mean} = \frac{1}{k}\sum_{i=1}^{k} Cb(x_i, y_i), \text{ and } Cr_{mean} = \frac{1}{k}\sum_{i=1}^{k} Cr(x_i, y_i) \quad (7)$$

The spatial position of a pixel is denoted by (xi, yi), while the mean luminance and chrominance values are represented by Y-mean, Cb-mean, and Cr-mean. K signifies the number of pixels in a frame. Notably, in frames depicting fire, the brightness of the flame surpasses that of chrominance-blue, and chrominance-red is higher than chrominance-blue. This fact is evident from the frames, as exemplified in Figure 2(a), Figure 2(b), Figure 2(c), and Figure 2(d). Thus, rule one can be formulated as:

$$Rule\ 1: F(x,y)\begin{cases} 1, f\ Y(x,y) > Cb(x,y) \cup Cr(x,y) > Cb(x,y) \\ 0, otherwaise \end{cases} \quad (8)$$

In addition to (8), as the flame zone is frequently the brightest area in the observed picture, it is also useful to know the mean values of the three components, Y-mean, Cb-mean, and Cr-mean. The value of the Y component in the fire zone is greater than the mean Y component for the entire frame, but the value of the Cb component is often lower than the mean Cb value for the entire frame. Moreover, the flame region's Cr component exceeds the mean Cr component [6], which may be summarized as the following rule:

$$Rule\ 2: F(x,y)\begin{cases} 1, if\ Y(x,y) > Y_{mean} \cup Cb(x,y) < Cb_{mean} \cup Cr(x,y) > Cr_{mean} \\ 0, otherwaise \end{cases} \quad (9)$$

As a result, the YCbCr color space-selected zone of flame can be satisfied by combining the two rules. The HSV and YCbCr color space rules are then combined using the binary AND operator to create the two-color model. Which is then applied to a frame to find the fire regions of interest, which are defined as $R_{color}\ (i, j, n)$.

(a) (b) (c) (d)

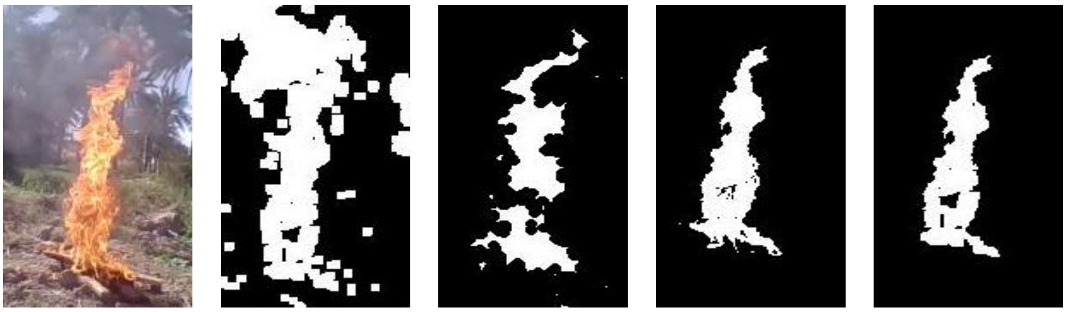
Figure 2. The Y, Cb, and Cr channels of the RGB input frame: (a) the initial RGB frame, (b) the Y channel, (c) the Cb channel, and (d) the Cr channel

2.5. Combining Otsu's algorithm, the frame differences and two-color

Using Otsu's threshold or frame differences, or two-color detection alone to specify fire would lead to a lot of false alarms due to the complex nature of the attributes of fire mentioned earlier. Therefore, we need to integrate the outputs of all three approaches, as shown in Figure 3(a), Figure 3(b), Figure 3(c), and Figure 3(d), to fully exploit their properties and accurately identify the fire area $R_{fire}\ (i, j, n)$ using (10).

$$R_{fire}(i,j,n) = \ binary\ image(i,j,n)\ \cap\ R_{color}(i,j,n)\ \cap\ I_{d(k,k+8)}(i,j,n) \tag{10}$$

This combined approach is illustrated in Figure 3(e), where the flame region is determined and bounded by a green box. The fire boundary is subtracted from the original RGB frame to get the area of the bounded zone, and if it is above a certain threshold, it is considered a fire. The region's criteria for fire detection are set at a minimum of 55.



(a) (b) (c) (d) (e)

Figure 3. Results of combination: (a) the original frame; (b) result the automatic threshold; (c) motion detection result; (d) two-color detection result; and (e) the outcome of combining (b), (c), and (d)

3. RESULTS and DISCUSSION

The proposed proposal is implemented with MATLAB, version R2021b, and on a PC with an Intel Core i7 2.70GHz CPU, 16GB of RAM, and the Windows 10 operating system. The test video database is compiled in real time and off-line [14] with an assortment of diverse circumstances, including a variety of backdrops and environmental conditions.

A real-time outdoor flame is shown in Figure 4, and three different fire video scenes (F62, F61, and F56). The color of the sun is known to be identical to that of the flame, yet the system only recognizes the flame. Table 1 summarizes the real-time experiment findings, where Nn stands for both the total number of video frames and the total number of fire frames. The suggested technique's Nd stands for the number of frames successfully identified, and Rd stands for the rate at which a video detects fire.

$$Rd = N_d/N_n \tag{11}$$

The average detection rate for real-time video can exceed 93%. The most important factor is the time required to identify a fire. Consequently, the suggested system can detect a fire in less than 0.26 seconds, allowing for the detection to occur in real-time.

Figure 5(a) to Figure 5(e) show a recorded video of the results of testing in six distinct scenarios. Fire detection was not limited to the database video in order to cover the largest number of forecasted forest fire episodes and assess the efficiency of the proposed method, as shown in Figure 5(a), Figure 5(c), and Figure 5(d). It is also worth noting that the algorithm may disregard the impact of the fire-color backdrop regions depicted in Figure 5(e). Based on color and other characteristics, we compare the proposed approach to previous fire detection systems. Chen *et al.* [22] used RGB and HIS color spaces, Celik *et al.* [23] used RGB color space, and Marbach *et al.* [24] used YUV color space, while Shidiks's method [14] combines RGB, YCbCr, and HSV as multicolor features with background subtraction based on color and other parameters. We compare the proposed technique to earlier fire detection systems. Our system achieved an average detection rate of 99% for the identical fire database, as demonstrated in Table 2, presenting the experimental findings.

In terms of detection rates, our proposed system beats earlier techniques. However, because the background of the video "barbeq.avi" is simple and constant, Shidik's methodology outperforms ours. Video "Controlled1.avi" exhibits a high detection rate using the Chen, Celik, and Marbach methods. The scenario is simpler to notice in movies like Controlled2, Forestfire1, and Forest 1–4 because there are no distractions from flame, such as moving objects, and the features of flame are clearly identified. As a consequence, when applied to each of these movies, practically all of these techniques provide the same detection rates.

Table 3 displays the amount of false positive frames generated by various methodologies. N_f, which means the number of frames that do not contain the fire but are given an alarm, is fire detection. Moves 1, 2, 3, and 4 are represented by a passing fire-colored vehicle, three people entering the room, road transport, and a dancing person wearing fire-colored clothing [25]. Table 3 demonstrates that our approach achieved a lower average false positive rate compared to other strategies, indicating its superior performance. Moreover, except for mov 4, the approach we presented generated better outcomes in every video. To reduce the number of false positives, future research should include additional characteristics. Our method demonstrates superior performance compared to other alternatives in terms of both rapid detection and effectiveness, as evidenced by the preceding explanation.

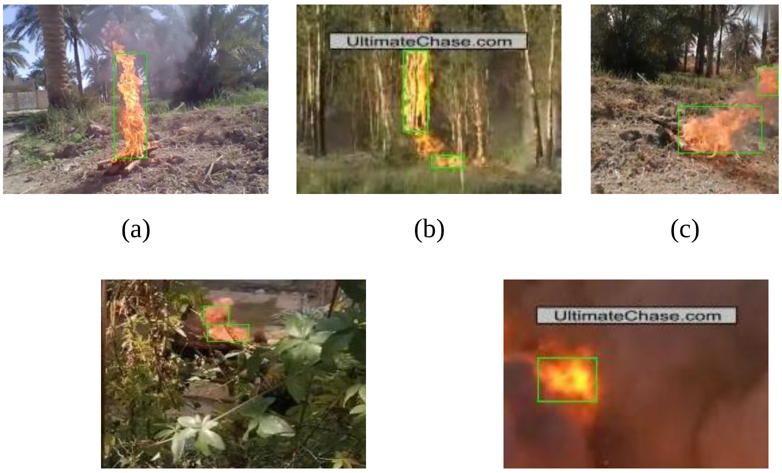
Figure 4. Real-time flame detection result

Table 1. Display the outcomes of the suggested approach (real-time)

Video	Nn	Nd	Rd
F62	49	39	0.796
F61	97	96	0.989
F56	15	15	1.000
Total	161	150	0.931

Table 2. Display the outcomes of the suggested approach (offline)

Database		The proposed		Chen [22]		Celik [23]		Marbach [24]		Shidiks [14]	
Video	Nn	Nd	Rd	Nd	Rd	Nd	Rd	Nd	Rd	Nd	Rd
Barbeq	439	430	0.979	412	0.959	415	0.945	400	0.911	439	1.000
Controlled1	260	250	0.961	259	0.996	259	0.996	259	0.996	105	0.404
Controlled2	246	246	1.000	246	1.000	246	1.000	246	1.000	246	1.000
Controlled3	208	208	1.000	207	0.995	207	0.995	207	0.995	208	1.000
Forest1	200	200	1.000	200	1.000	200	1.000	200	1.000	200	1.000
Forest2	245	245	1.000	245	1.000	245	1.000	245	1.000	245	1.000
Forest3	255	254	0.996	254	0.996	254	0.996	254	0.996	254	0.996
Forest4	219	218	0.995	218	0.995	218	0.995	218	0.995	218	0.995
Forestfire	218	218	1.000	218	1.000	218	1.000	218	1.000	218	1.000
Total	2290	2269	0.990	2259	0.986	2262	0.987	2247	0.981	2133	0.931



(a) (b) (c)

(d) (e)

Figure 5. The flame detection results for recoded video in many scenarios: (a) flame under the sun, (b) flame in the forest, (c) two flame detections, (d) small flame detections, and (e) flame with heavy smoke

Table 3. False positive frames in video

Video	N_f	Ours	Chen [22]	Celik [23]	Marbach [24]	Shidik [14]
Mov1	0	7	10	23	21	13
Mov2	0	4	8	10	12	6
Mov3	0	0	0	0	0	0
Mov4	0	27	26	34	39	30
Total	0	9.5	11	16.75	18	12.25

4. CONCLUSION

This paper offered an autonomous method for detecting fire over a video stream. The proposed approach for fire detection involves five stages. Firstly, the input video is pre-processed using integer Haar lifting wavelet transforms to decompose it and reduce data size while preserving information. This reduces flame detection time by at least 0.26 seconds. Secondly, an automated threshold selection technique utilizing Otsu's method is used to identify flame intensity pixels. Thirdly, frame differences are used to detect fire motion. Fourthly, the YCbCr/HSV color space models are employed to identify likely flame regions. Finally, the fire area is calculated using a simple and innovative approach. The fire zones are then determined by combining the results. This approach is currently being tested using multiple video feeds. According to the experimental results, the approach achieves 99% accuracy for offline videos and surpasses 93% accuracy for real-time video. Despite its simplicity, the system is quick, efficient, and minimally complex.

REFERENCES

[1] S. -J. Chen, D. C. Hovde, K. A. Peterson, and A. W. Marshall, "Fire detection using smoke and gas sensors," *Fire Safety Journal*, vol. 42, no. 8, pp. 507–515, 2007, doi: 10.1016/j.firesaf.2007.01.006.
[2] J. Fonollosa, A. Solórzano, and S. Marco, "Chemical sensor systems and associated algorithms for fire detection: A review," *Sensors*, vol. 18, no. 2, 2018, doi: 10.3390/s18020553.
[3] K. Muhammad, J. Ahmad, I. Mehmood, S. Rho, and S. W. Baik, "Convolutional neural networks based fire detection in surveillance videos," *IEEE Access*, vol. 6, pp. 18174–18183, 2018, doi: 10.1109/ACCESS.2018.2812835.
[4] B. U. Töreyin, Y. Dedeoğlu, U. Güdükbay, and A. E. Çetin, "Computer vision based method for real-time fire and flame detection," *Pattern Recognition Letters*, vol. 27, no. 1, pp. 49–58, 2006, doi: 10.1016/j.patrec.2005.06.015.
[5] 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 Processing*, vol. 11, pp. 1419–1425, 2017, doi: 10.1007/s11760-017-1102-y.
[6] R. A. Khan, J. Uddin, S. Corraya, and J. -M. Kim, "Machine vision-based indoor fire detection using static and dynamic features," *International Journal of Control and Automation*, vol. 11, no. 6, pp. 87–98, 2018. [Online]. Available: http://article.nadiapub.com/IJCA/vol11_no6/9.pdf
[7] A. Khalil, S. U. Rahman, F. Alam, I. Ahmad, and I. Khalil, "Fire detection using multi color space and background modeling," *Fire Technology*, vol. 57, pp. 1221–1239, 2021, doi: 10.1007/s10694-020-01030-9.
[8] Z. Zhong, M. Wang, Y. Shi, and W. Gao, "A convolutional neural network-based flame detection method in video sequence," *Signal, Image Video Processing*, vol. 12, pp. 1619–1627, 2018, doi: 10.1007/s11760-018-1319-4.
[9] K. Muhammad, J. Ahmad, Z. Lv, P. Bellavista, P. Yang, and S. W. Baik, "Efficient deep CNN-based fire detection and localization in video surveillance applications," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 7, pp. 1419–1434, 2019, doi: 10.1109/TSMC.2018.2830099.
[10] 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 (WorldCIST'19)*, 2019, pp. 240–251,

doi: 10.1007/978-3-030-16184-2_24.
[11] H. R. Farhan, H. H. Abbas, and H. I. Shahadi, “Combining multi-resolution wavelets with principal component analysis for combining multi-resolution wavelets with principal component analysis for face recognition,” in *Proc. of the International Conference on Information and Communication Technology*, 2019, pp. 154–159, doi: 10.1145/3321289.3321325.
[12] H. I. Shahadi, R. Jidin, W. H. Way, and Y. A. Abbas, “Efficient FPGA architecture for dual mode integer Haar lifting wavelet transform core,” *Journal of Applied Sciences*, vol. 14, no. 5, pp. 436–444, 2014, doi: 10.3923/jas.2014.436.444.
[13] N. Otsu, “A Threshold selection method from gray-level histograms,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979, doi: 10.1109/TSMC.1979.4310076.
[14] 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 *2013 International Conference on Robotics, Biomimetics, Intelligent Computational Systems*, 2013, pp. 115-120, doi: 10.1109/ROBIONETICS.2013.6743589.
[15] T. Song, L. Pan, T. Wu, P. Zheng, M. L. D. Wong, and A. R. -Paton, “Spiking neural P systems with learning functions,” *IEEE Transactions on NanoBioscience*, vol. 18, no. 2, pp. 176–190, 2019, doi: 10.1109/TNB.2019.2896981.
[16] T. Song, X. Zeng, P. Zheng, M. Jiang, and A. R. -Paton, “A parallel workflow pattern modeling using spiking neural P systems with colored spikes,” *IEEE Transactions on NanoBioscience*, vol. 17, no. 4, pp. 474–484, 2018, doi: 10.1109/TNB.2018.2873221.
[17] A. Aggarwal, S. Biswas, S. Singh, S. Sural, and A. K. Majumdar, “Object tracking using background subtraction and motion estimation in MPEG videos,” in *Computer Vision–ACCV 2006*, 2006, pp. 121–130, doi: 10.1007/11612704_13.
[18] W. Yang, M. Mörtberg, and W. Blasiak, “Influences of flame configurations on flame properties and NO emissions in combustion with high-temperature air,” *Scandinavian Journal of Metallurgy*, vol. 34, no. 1, pp. 7–15, 2005, doi: 10.1111/j.1600-0692.2005.00710.x.
[19] Ganesan P. and V. Rajini, “Assessment of satellite image segmentation in RGB and HSV Color space using image quality measure,” in *2014 International Conference on Advances in Electrical Engineering, (ICAEE)*, 2014, pp. 1-5, doi: 10.1109/ICAEE.2014.6838441.
[20] V. Venugopal, “Image processing based forest fire detection,” *International Journal of Emerging Technology and Advanced Engineering*, vol. 2, no. 2, pp. 87–95, 2012. [Online]. Available: https://www.researchgate.net/publication/362187130_Image_Processing_Based_Forest_Fire_Detection
[21] T. Çelik and H. Demirel, “Fire detection in video sequences using a generic color model,” *Fire Safety Journal*, vol. 44, no. 2, pp. 147–158, 2009, doi: 10.1016/j.firesaf.2008.05.005.
[22] J. Chen, Y. He, and J. Wang, “Multi-feature fusion based fast video flame detection,” *Building and Environment*, vol. 45, no. 5, pp. 1113–1122, 2010, doi: 10.1016/j.buildenv.2009.10.017.
[23] T. Celik, H. Demirel, H. Ozkaramanli, and M. Uyguroglu, “Fire detection using statistical color model in video sequences,” *Journal of Visual Communication and Image Representation*, vol. 18, no. 2, pp. 176–185, 2007, doi: 10.1016/j.jvcir.2006.12.003.
[24] G. Marbach, M. Loepfe, and T. Brupbacher, “An image processing technique for fire detection in video images,” *Fire Safety Journal*, vol. 41, no. 4, pp. 285–289, 2006, doi: 10.1016/j.firesaf.2006.02.001.
[25] B. U. Toreyin, “Fire detection algorithms using multimodal signal and image analysis,” Ph.D. dissertation, Department of Electrical and Electronics Engineering, Institute of Engineering and Science of Bilkent University, 2009. [Online]. Available: http://repository.bilkent.edu.tr/bitstream/handle/11693/14870/0003818.pdf?sequence=1&isAllowed=y

BIOGRAPHIES OF AUTHORS

Zahraa Shihab Al Hakeem received her B.ESc degree in Electrical engineering from the university of Babylon-Iraq in 2015. Now, she is a master’s student in Electrical and Electronic engineering from University of Kerbala. Her research interests include image processing and computer vision. She can be contacted at email: zahraa.shihab@s.uokerbala.edu.iq.

Haider Ismael Shahadi received his B.ESc degree in information engineering from the university of Baghdad-Iraq in 2001, his master’s degree in Electronic and Communication Engineering from the University of Baghdad-Iraq in 2004, and his Ph.D. in Electronic and Communication Engineering from the Tenaga National University-Malaysia in 2014. Currently, he is professor at the University of Kerbala-Iraq. His research interests include digital signal and multimedia processing, data security, FPGA design and implementation and embedded systems, IOT systems, and smart systems. He can be contacted at email: Haider_almayaly@uokerbala.edu.iq.

Hawraa Hassan Abass Doctor of Engineering. Professor at University of Kerbala a Ph.D. from Cardiff University/UK. She received her B.Sc. degree in computer engineeringfrom Baghdad University, Iraq and M.Sc. degree in computer engineering also from Baghdad University, Iraq. Her research interests include 3D face modeling, classification of facial traits, image processing, computer network design, genetic associations, computer vision. She can be contacted at email: hawraa.h@uokerbala.edu.iq.