A Real-time System for Fire Detection and Localization in Outdoors

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Abstract

This paper presents a fire detection and localization system designed to address the increasing incidence of fires in farms and outdoor areas. The proposed system utilizes a video camera capable of withstanding environmental changes, such as illuminance and color correlation to fire smoke and flames, offering a suitable alternative to traditional smoke sensor-based detection methods, which does not operate in open areas. By integrating color and motion detection approaches, the proposed fire detection system achieves accurate results. The input video decomposes using lifting wavelet transform to reduce the data size and as a result reduce the data processing time while preserving fire features for detection. The decomposed video frames are processed for color and motion detection to identify fire characteristics, with morphological post-processing eliminating unwanted pixels. The system calculates the detected fire area and applies threshold conditions for bounding. Fire localization is achieved through inverse camera parameter calibration and fire position mapping in pixels. The approach utilizes a projective transformation matrix to establish the relationship between frame pixels and real-world positions. Experimental results demonstrate a high accuracy rate for both offline and online (real-time) tests. The system achieves an average accuracy of 96% for real-time smoke and flame detection and 98% for offline flame and smoke detection. Fire localization is achieved with an error of less than 0.4 meters.

Keywords: Fire detection, color detection, motion detection, object localization, lifting wavelet transform (LWT).

1. Introduction

Fire poses a significant threat to lives, property, and the environment. In 2022, the number of fire incidents in various regions of Iraq exceeded 32,477 according to government statistics (Iraqi Ministry of Interior, 2023). Rapid detection and accurate localization of fires are crucial for effective emergency response and minimizing the potential damage caused by these destructive incidents. Over the years, advancements in technology have played a pivotal role in enhancing fire safety measures, with fire detection and localization systems emerging as essential components in various settings, ranging from residential and commercial buildings to industrial facilities.

The primary objective of fire detection and localization is to provide early alarm, allowing occupants to evacuate safely and enabling emergency responders to quickly mitigate the fire. Traditional methods of fire detection, such as heat sensors and smoke alarms, have been effective to some extent. However, they often lack the ability to precisely identify the location of the fire, which can lead to delays in response times and increased risks.

In recent years, technological advancements, including the integration of artificial intelligence (AI), computer vision, and sensor networks, have revolutionized fire detection and localization systems. These advanced systems utilize a combination of sensors, algorithms, and data analysis techniques to detect the presence of fire, accurately locate its origin, and provide real-time alerts to the relevant authorities.

One of the key technologies employed in modern fire detection and localization systems is computer vision. By leveraging sophisticated algorithms and image processing techniques, these systems can analyze video footage or images captured by cameras to detect flames, smoke, or other signs of fire. Computer vision algorithms can differentiate between normal activities and fire-related events, allowing for early detection and triggering timely responses.

This research paper presents a novel automated approach to detecting and locating flames and smoke using a camera. The proposed method is applicable in various environments, including both enclosed and open spaces, such as indoor and outdoor areas. It utilizes advanced techniques to automatically identify smoke and flames. The method incorporates multi-thresholds for the International Commission on Illumination (CIE) L*a*b* color space to detect smoke, while flame detection is performed using HSV\YCbCr color space with frame difference. Additionally, fire localization is accomplished by employing a projective transformation matrix that maps frame pixels to real-world positions. To enhance efficiency and extract better features, the pre-processing stage employs the integer Haar lifting wavelet transform. This technique helps reduce the size of processed data and extract more meaningful features.

2. Related Works

Fire detection and localization are critical components of fire safety systems, aiming to promptly identify and locate fires for effective response and mitigation. Over the years, researchers have made significant progress in developing innovative methods and technologies for accurate and efficient fire detection and localization. This introduction provides an overview of some notable research works and advancements in this field.

In the study conducted by Gong et al. (Gong et al., 2019) , a fire detection system was proposed using frame differences and color analysis methods to identify fires based on distinct fire characteristics. They improved the accuracy of fire identification by calculating the mass center of the fire in each frame, enabling the extraction of shape, spatial, and area variations in the images. Consequently, the false positive rates were reduced. However, despite its effectiveness, Gong et al.'s methodology is not widely adopted in practice.

Ting Wei Hsu (Hsu et al., 2020)introduced a system that achieved a high detection rate and a low false alarm rate by employing local and global feature analysis, a decision unit, and an automatic threshold mechanism. This approach facilitated effective fire detection in diverse environments. However, it should be noted that the system's reaction time was prolonged due to information buffering from previous detections.

To further enhance the accuracy of fire detection, Khalil et al. (Khalil et al., 2021)proposed a method that utilized multi-space color models and motion detection with Gaussian Mixed Models (GMMs) to detect moving objects. Although their methodology demonstrated high accuracy, the false positive rate remained relatively high at 88.81%.

Addressing this challenge, Wahyono et al. (Wahyono et al., 2022) developed probabilistic models using Gaussian multiples to identify fire color characteristics and dynamic fire movements through moment-invariant analysis. Their experiment exhibited a relatively high true positive rate of 89.92%. However, implementing their model poses a significant challenge due to the installation difficulties associated with physical cameras.

Li et al. (Li et al., 2023) proposed real-time fire detection and localization techniques specifically designed for indoor environments. Their approach employed a fully convolutional, one-stage CNN for fire detection. The localization of the fire is determined by two cameras, which work together to pinpoint the exact location of the flame. The fire localization process involves two steps. In the first step, camera calibration is performed using two frames. In the second step, the relative coordinates of the firing position with respect to the anchor point are computed. While this method achieves high accuracy with a compact model size, it necessitates a substantial amount of training data to cover various indoor and outdoor scenarios.

As previously mentioned, in the field of fire detection and localization video research and development, multi-domain technology has been utilized to increase accuracy of the fire detection. However, there are several challenges still exist such as continuous change of the environment colors, unsuitability of some methods for real time processing, the big difference of accuracy respect to the change of weather conditions. Therefore, the proposed approach overcomes these drawbacks and it is suitable for real-time outdoor fire detection for different environments. Moreover, it is able to localize the position of the fire in real-word based on the video only.

3. Proposed System

This section offers a comprehensive explanation of the proposed system that is shown in Figure 1. The proposed system consists of five main stages include: preprocessing, color detection, motion detection, fire area computation, and finally, fire localization. The details of each main stage illustrate in the next subsections.

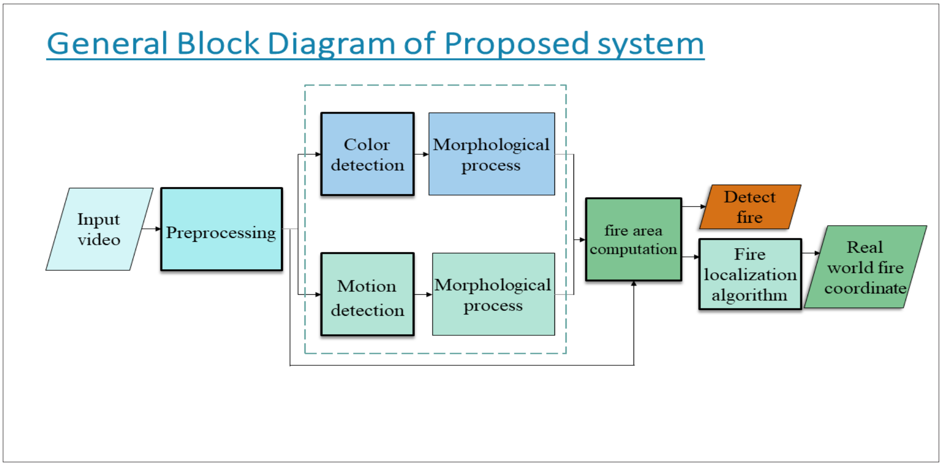

Figure 1. The main stages of the proposed system.

3.1. Pre-Processing Stage

Image preprocessing refers to the procedure of preparing an image for subsequent analysis or processing. It encompasses a set of operations performed on the image to enhance its suitability for a specific task or purpose. The source video is acquired either from an online camera or imported from a dataset, as elaborated in references (Çetin, 2014; KMU Fire & Smoke Database, 2012). As shown in Figure 2, preprocessing in this research uses one of the wavelet transform types.

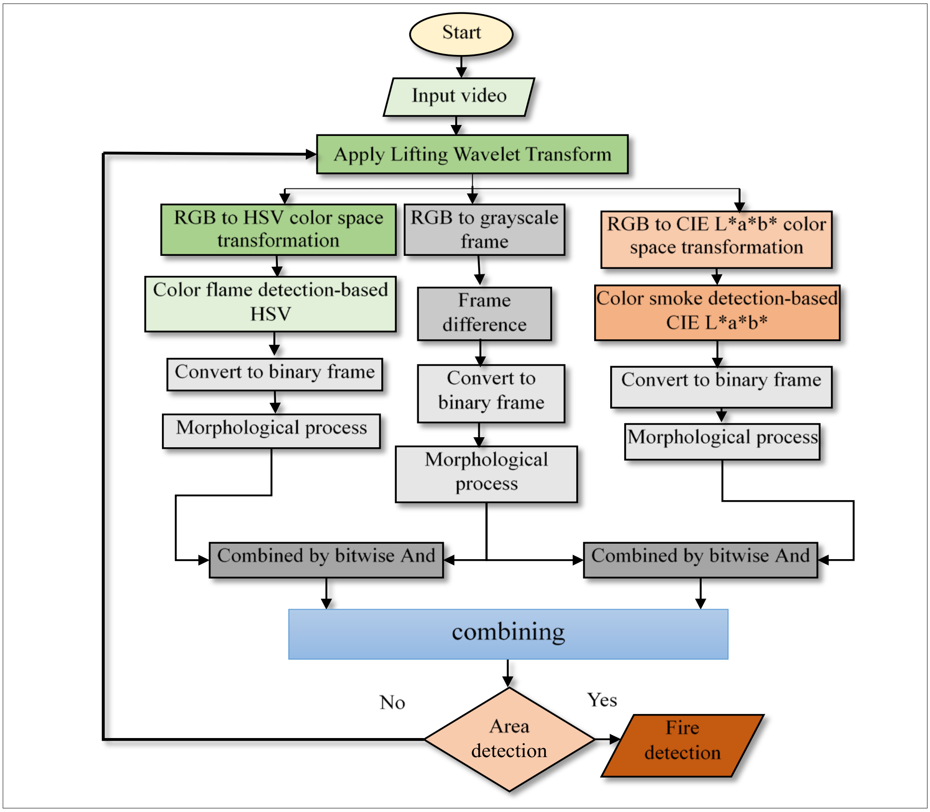

Figure: 2, Flowchart of the proposed fire detection

3.1.1. Wavelet Transforms

Wavelets refer to sets of nonlinear basis functions utilized to approximate a given function. In wavelet analysis, each basis function is meticulously chosen and approximated to better represent the input function. Wavelets depend on a dynamic assortment of basic functions to effectively capture the characteristics of the input signal or image. Among the various types of wavelets, the discrete wavelet transform (DWT) stands out as a widely used mathematical technique for decomposing a signal or image into localized wavelets in both time and frequency domains (Váňa et al., 2011).

The integer lifting wavelet transform presents a method to implement the DWT using only integer arithmetic. This is achieved by decomposing the wavelet into a collection of elements using a lifting scheme. The Haar wavelet serves as a simple example of such a lifting scheme, where the wavelets are dilated and shifted to perform the transformation (Ramalingam & Isa, 2014).

In the integer-to-integer lifting scheme based on the Haar DWT, the approximation coefficients in (Int-to-Int-HLWT) are constructed by taking the average of each adjacent sample in the input image. On the other hand, the detailed coefficients are computed by determining the difference between the surrounding samples of the input image. The correlation between neighboring samples in the input image is strong, resulting in the approximation coefficients closely resembling the actual input samples. Consequently, the detail coefficients exhibit low power relative to the original coefficients. Since Sj represents an input sample with an integer value, the prediction {Sj(e)} = Sj(e) holds true in the Haar DWT-based lifting scheme. Furthermore, the integer nature of Sj allows for straightforward calculation of the prediction of odd to obtain the detailed coefficients as depicted in Equation (1).

$$\text{Int-to-int-HLWT prediction:} dj\text{-}1=Sj(o)\text{-}Sj(e) \qquad (1)$$

As indicated in reference (Shahadi et al., 2013), Sj(o) and Sj(e) correspond to the odd and even image inputs, respectively. The frame is divided into four sections (LL, HL, LH, and HH), where the low-level band frequency (LL) holds significant information for the detection system. Through the utilization of the integer Haar lifting wavelet transform, the size of the input data can be reduced by 75%.

3.2. Color Detection

Flame detection involves utilizing color-based methods, the hue\saturation\value (HSV) color space, to identify the characteristic colors associated with flames. On the other hand, smoke detection employs the International Commission on Illumination (CIE L*a*b*) color space for efficient smoke identification. By leveraging these color detection techniques, it becomes possible to distinguish flames and smoke in various applications.

3.2.1 Flame Color Detection

Flames typically exhibit reddish hues. While the RGB color space is known for its lower computational complexity compared to other color spaces, flame image recognition often employs the HSV color space due to its ability to offer a more human-centric approach to describing colors. The HSV color space is a representation of colors based on three components: hue, saturation, and value. Hue determines the color's position on the color wheel, saturation represents the intensity or purity of the color, and value corresponds to the brightness or lightness of the color (Smith, 1978). Through our experiments, we have determined that each pixel in the HSV color space representing fire flames must meet the following conditions:

$$\begin{gathered} 0 \leq H \leq 0.2 \\ 0.47 \leq S \leq 0.98 \\ 0.7 \leq V \leq 0.98 \end{gathered} \quad (2)$$

The image is partitioned into two segments using these thresholds: the foreground representing fire colors Rcolor and the background representing non-fire colors. The flame color in the HSV is determined by summing up the results from each channel. Additionally, morphological procedures are applied to eliminate noise caused by small pixels (Gonzalez et al., 2009). In the final phase of this process, the binarized image is created to combine the flame color information in the HSV color space with motion detection, utilizing the logical operator AND.

3.2.2. Smoke Color Detection

Smoke exhibits prominent color characteristics, although they are not entirely distinctive. Smoke can vary in color from whitish gray to blackish gray, and color remains a noticeable aspect of smoke despite significant differences in color between smoke classes and within each class. Although frames are typically captured in RGB format, using RGB color for smoke color detection may pose challenges due to its limited capacity to capture the subtle nuances and variations in smoke color accurately, thereby hindering accurate differentiation of smoke from other elements in the image. A more effective and innovative approach to addressing this issue is to convert the frame into the International Commission on Illumination's (CIE) L*a*b* color space (León et al., 2006).

The CIE L*a*b* color space is a device-independent color model that separates color information into three channels: L (lightness), a (green-red axis), and b (blue-yellow axis). This color space is designed to mimic human perception of color, allowing for more accurate representation and analysis of color differences, especially in smoke color detection.

Table 1 provides the multi-threshold values for the CIE L*a*b* color space, which define the range of colors from whitish gray to blackish gray corresponding to smoke. These thresholds are used to partition the frame into the foreground, representing the smoke color in the CIE L*a*b* color space, and the background, representing non-smoke elements.

Table 1. The multi-threshold of the CIE Lab color space for smoke color detection

Thresholds / The rules	The values of threshold 1	The values of threshold 2	The values of threshold 3
Rule 1: L	(0.058~98.32)	(8.876~36.748)	(87.955~100)
Rule 2: a	(-8.067~4.853)	(-2.377~2.773)	(-2.211~5.546)
Rule 3 : b	(-24.653 ~-9.788)	(-10.399~4.065)	(-9.359~3.12)

The smoke color region, denoted as Rcolor , is represented in the formula:

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

Additionally, morphological procedures are applied to eliminate noise caused by small pixels (Gonzalez et al., 2009). In the final phase of this process, the binarized image is created to combine the smoke color information in the CIE L*a*b* color space with motion detection, utilizing the logical operator AND.

3.3. Motion Detection

The conventional frame differences technique (Singla, 2014) commonly used for motion detection, may not be suitable for accurately detecting the motion of a smoke or flame due to its unique movement characteristics. To address this, an alternative method called "frame difference with a time delay" is employed. This approach involves subtracting frames that are spaced apart by a specific number of frames, such as 8 frames, allowing for a more precise evaluation of pixel value changes associated with the smoke's or flame's motion. Initially, the frames are converted to grayscale to simplify the analysis by focusing solely on intensity information. Grayscale frames are sufficient for motion detection and help reduce computational complexity. The absolute differential frames are then calculated using the equation shown in Equation (4), where the resulting frames highlight significant changes in the smoke's or flame's appearance. These differential frames enable accurate motion detection and analysis.

$$I_{diff(k,k+7)} = |I_{(k+7)} - I_k| \qquad (4)$$

In the video, Ik represents the value of the kth frame, while I(k+7) represents the value of the (k+7)th frame (Singla, 2014)To prepare the motion detection frame for combination with the phase of color detection, it needs to be binarized and undergo morphological operations (Gonzalez et al., 2009) to remove small pixels.

3.4. Flame and Smoke Area Computation

Upon thorough analysis of frame difference and color features in fire detection, it has been determined that relying solely on either method would lead to a high rate of false alarms. To accurately identify the fire region, a combination of both methods must be performed effectively. The improved frame difference technique, called selected frame Ns, allows fire detection within just four frames per second, significantly faster than the traditional 30 frames. This method enhances processing speed, maintains accuracy, and enables timely fire alarm notifications. By applying the bitwise AND operation, the combination of color and motion fire regions, denoted as Rfire, is obtained, Figure 3 show sample of how flame and smoke detection processes combined to obtain more accurate results.

$$R_{fire}(M,N,i) = R_{color}(M,N,i) \cap I_{diff}(M,N,i) \qquad (5)$$

Once the fire region is identified, it is enclosed within a green bounding box for flames or a red box for smoke. The area of the bounded region is then calculated by subtracting the original frame from the bounding frame. If the resulting area exceeds the specified threshold values (55 for flames and 85 for smoke), it is considered to be indicative of a fire.

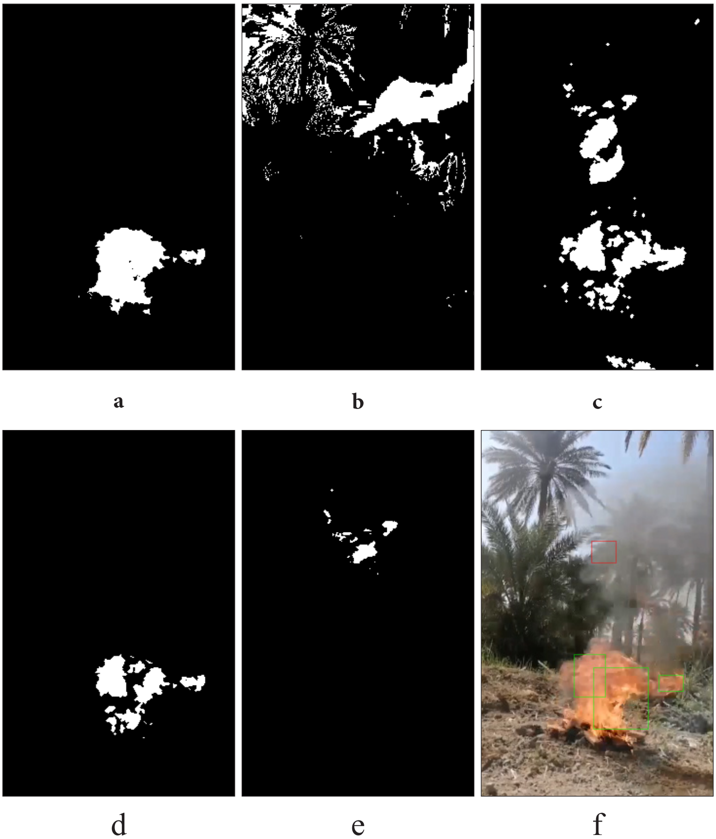

Figure:3, Sample of resulted frame that shows the combination of smoke and flame detection processes (a) flame color detection (b) smoke color detection (c) motion detection (d) combinations (a) and (c). (e) combinations (b) and (c). (f) Final result.

3.5. Fire Localization

Fire localization is the process of determining the precise location of a fire within a building or outdoor area. This information is crucial for firefighters and emergency responders, as it enables them to quickly and effectively allocate resources to combat and extinguish the fire.

In real-time flame and smoke detection systems, the position of the fire is provided in terms of pixel coordinates within the current frame. To accurately determine the real-world location of the fire, a two-step method for real-world fire localization is introduced.

The first step involves camera calibration, which entails determining the camera's intrinsic and extrinsic parameters. Intrinsic parameters describe camera-specific properties such as focal length, principal points, and distortion coefficients, while extrinsic parameters define the camera's position and orientation in 3D space. Rotation and transformation matrices are utilized for performing the necessary coordinate system conversions.

The second step involves establishing the relationship between the fire's position in the video (represented by pixel coordinates M and N) and its real-world coordinates (represented by Xrw, Yrw, and Zrw). This relationship is achieved through a projective transformation, as described in Equation (6) by (Zhang, 2021). The method outlined in Figure 4 demonstrates the overall process of real-time fire localization using these two stages.

$$\begin{bmatrix} M \\ N \\ 1 \end{bmatrix} = \begin{bmatrix} fx & 0 & cx \\ 0 & fy & cy \\ 0 & 0 & 1 \end{bmatrix} \left(R \begin{bmatrix} Xrw \\ Yrw \\ Zrw \end{bmatrix} + T \right) \qquad (6)$$

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Where fx, fy, cx, and cy are the focal length and principal point coordinates, respectively. R and T are the extrinsic matrices of the camera, which consist of the rotation matrix R and the translation vector T.

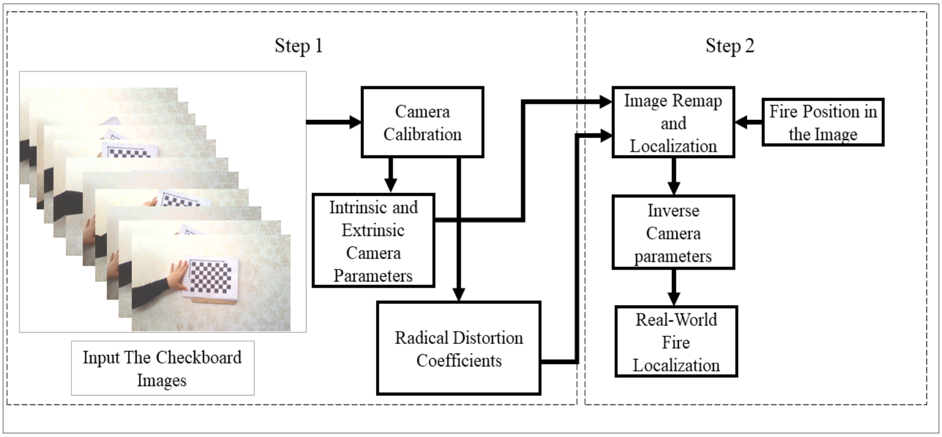

Figure:4, The two steps of the proposed fire localization method

The steps involved in the fire localization system can be summarized as follows:

1. Use a calibration pattern, such as a checkerboard, at different distances from the camera to accurately determine the camera's intrinsic and extrinsic parameters.
2. Capture multiple images of the calibration pattern from various angles and positions, ensuring the pattern is fully visible in each image.
3. Utilize camera calibration software, MATLAB's Single Camera Calibrator App (Using the Single Camera Calibrator App - MATLAB

& Simulink, 2023), to calibrate the camera using the captured images. This process yields the camera's intrinsic and extrinsic parameters, as well as radial distortion.

4. Identify the fire's position in each frame by determining the centroid of the bounding box obtained from flame and smoke detection systems.
5. Map the fire's position in pixels and perform localization.
6. Compute the real-world coordinates of the fire's location using the inverse of the intrinsic and rotation matrices, as described by Equation (7), derived by (Zhang, 2021).

$$\begin{bmatrix} Xrw \\ Yrw \\ Zrw \end{bmatrix} = \begin{bmatrix} fx & 0 & cx \\ 0 & fy & cy \\ 0 & 0 & 1 \end{bmatrix}^{-1} R^{-1}\left(\begin{bmatrix} M \\ N \\ 1 \end{bmatrix} - T\right) \quad (7)$$

The accuracy of the camera parameters plays a crucial role in accurately locating the real-world point of fire.

4. Experimental Results

The experimental results have been achieved for several fire videos that are divided into two groups: KMU and VisiFire datasets (Çetin, 2014; KMU Fire & Smoke Database, 2012) that include 43 videos, and our own recorded datasets that include 75 videos. The proposed system has been implemented using MATLAB version R2021b on a

Windows 10 PC with an Intel Core i7 2.70 GHz CPU and 16GB of RAM. The details of the tests of fire detection and localization as in the next subsections.

4.1. Fire Detection Results

The important parameters that are computed to test the performance of the proposed fire detection based on color (for both flame and smoke) and motion include: TP (True Positive) indicates the correct identification of actual fires, TN (True Negative) represents the accurate identification of non-fire situations,

FN (False Negative) refers to cases where the system incorrectly identifies a non-fire situation as a fire, leading to false alarms. FP (False Positive) indicates instances where the system fails to detect an actual fire, resulting in missed detections. These parameters are used to compute the accuracy, recall, and precision, respectively(Ryu & Kwak, 2022).

$$\text{Accuracy}=(TP+TN)/(TP+FP+TN+TP) \quad (8)$$

$$\text{Recall}=TP/(TP+FN) \quad (9)$$

$$\text{Precision}= TP/(TP+FP) \quad (10)$$

Figure: 5 وdisplays samples of the real-time fire detection based on smoke and flame in outdoors areas that we have achieved. The samples in the figure include featuring seven different scenarios (vid1,

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vid2, vid3, vid 4, vid5, vid6, and, vid7) with varying colors of smoke and flames, and in different environments. The details of each video and the performance results of the propose fire detection system corresponding to each video are presented in Table 2.

Figure:5, Test results of the real-time flame and smoke detection

Table:2, Evaluation of the real-time flame and smoke detection

Video name	Number of frames	NS	True Positive	True Negative	False Positive	False Negative	Accuracy %
Vid1	49	6	**5**	0	0	1	83.3
Vid2	48	6	6	0	0	0	100
Vid3	97	12	11	0	1	0	91.6
Vid4	84	11	11	0	0	0	100
Vid5	70	9	9	0	0	0	100
Vid6	50	6	6	0	0	0	100
Vid7	30	4	4	0	0	0	100
Total	428	54	52	0	1	1	96.2

*Note: Ns the number of the selected (see Section 3.4)

The flame and smoke detection system achieves an average accuracy of 96.2% across all seven videos, as calculated using Equation (8). Figure 5 (Vid1) and (Vid2) showcase the system's capability to differentiate between the color of the flame and the color of sunlight. Additionally, Figure 5 (Vid3 and Vid7) demonstrate the system's effectiveness in detecting various flame colors. Furthermore, the system can detect different colors of smoke, as shown in the test videos (Vid5) and (Vid6). Moreover, the system successfully distinguishes smoke from smoke-colored backgrounds, preventing false detections, as demonstrated in Figure 5 (Vid4).

The proposed system efficiently tackles the crucial task of timely fire detection by swiftly identifying flame and smoke in real-time. The integration of the LWT has played a pivotal role in enhancing the system's response time, reducing it to less than 0.1 seconds. This significant improvement has resulted in a substantial reduction of over 50% in the overall duration required for flame and smoke detection, as compared to the previous duration of 0.2 seconds.

The performance evaluation of the system is conducted using two datasets: VisiFire and KMU Fire & Smoke Database (Çetin, 2014; KMU Fire & Smoke Database, 2012). These datasets encompass a wide range of resolutions, scenes, fire environments, and backgrounds, allowing for an effective assessment of the system's performance. Table 3 provides details about the videos within the dataset. To evaluate the proposed method on this dataset, a comprehensive empirical evaluation is conducted using a total of 7400 frames sourced from 17 positive and negative video clips obtained from the internet. The videos have different frame rates and resolutions. A sample of these videos is illustrated in Figure 6. The proposed system was compared with related work (Chen et al., 2004; Han et al., 2017; Khalil et al., 2021; Shidik et al., 2013).

Table:3, The specification videos used for testing the flame and smoke detection

Video sequence	Total frames	Fire frames	Non-Fire frames	Video description
Video 1	708	708	0	Fire 1 400 × 256
Video 2	439	433	6	Barbeq
Video 3	1201	1070	131	Backyard
Video 4	260	260	0	Controlled Environment 1 320 × 240
Video 5	200	200	0	Forest 1 400 × 256
Video 6	246	246	0	Controlled Environment 2 320 × 240
Video 7	245	245	0	Forest 2 400 × 256
Video 8	208	208	0	Controlled Environment 3 320 × 240
Video 9	255	255	0	Forest 3 400 × 256
Video 10	218	218	0	Forest 6 400 × 256
Video 11	216	216	0	Forest 5 400 × 256
Video 12	219	219	0	Forest 4 400 × 256
Video 13	402	402	0	Farm 320 × 240
Video 14	1201	1129	72	Field 320 × 240
Video 15	789	625	164	Highway 640 × 360
Video 16	306	0	306	Person with fire colored shirt 320 × 240
Video 17	357	0	357	Fire moving color car 320 × 240
Total	7470	6434	1036	

Figure:6, Proposed flame and smoke detection using KMU and VisiFire datasets.

The flame and smoke detection results are shown in Table 4, and for the method presented in this study, the recall was 90.15%, precision was 94.95%, and accuracy was 98.22%. In terms of recall and precision from Equations (9 and 10), the proposed method demonstrates excellent performance compared to existing methods, except for the recall in the Khalil method (Khalil et al., 2021)The experimental results confirm that our proposed method achieves high accuracy and stability, with an approximate correct rate of 98%. Furthermore, our new approach surpasses previous methods in precision. However, it is important to acknowledge that our algorithms have limitations, and the presence of low-quality videos may lead to false negatives.

Table:4, Comparison of the proposed system with the related work

Refrences	True Positive	False Positive	True Negative	False Negative	Recall %	Accuracy %	Precision %
(Chen et al., 2004)	5791	382	643	746	88.59	85.08	93.81
(Shidik et al., 2013)	5167	347	1267	791	86.72	78.68	93.71
(Han et al., 2017)	6278	431	189	697	90.01	92.59	93.58
(Khalil et al., 2021)	6293	1087	137	41	99.35	97.42	85.27
Proposed work	790	42	15	86.75	90.15	98.22	94.95

4.2. Real-World Fire Localization

In the final experiment, the proposed system's localization accuracy was assessed by choosing four outdoor locations and using the laptop camera for camera calibration and flame\smoke detection to determine the real-world coordinates of the fire. Figure 7 illustrates the four distinct fire locations, with the camera serving as a reference. The results, presented in Table 5, reveal an average localization error of 0.4 m. It is observed from the table that the error slightly increased as the test location moved farther from the camera, but the localization error consistently remained below 5 m.

Place 1

Place 2

Place 3

Place 4

Figure:7, Different videos for flame and smoke localization in four place

Table:5, The True and predicted coordinates of four random locations

	True Coordinates	Predicted Coordinates	Error (Meters)
Place 1	(0.5, 0.7, 0.9)	(0.51, 0.75, 0.9)	0.05
Place 2	(3, 3.4, 2.2)	(3.3, 3.1, 2)	0.47
Place 3	(4, 3, 5)	(4, 3.2, 5.5)	0.54
Place 4	(4.3, 4, 1.5)	(3.8, 4.2, 1.3)	0.57

5.Conclusion

This paper has presented an efficient method for real time fire detection and localization. The proposed fire detection decomposes the input by LWT to reduce the processing time without effect to the essential fire features. The decomposed frames are then subjected to color and motion detection, followed by morphological post-processing to eliminate unwanted pixels. The system calculates the detected fire area and applies specific threshold conditions for bounding. The fire localization approach utilized in the study effectively maps frame pixels to real-world positions using a projective transformation matrix, providing high identicality to the actual fire locations. The results demonstrate the system's ability to detect smoke under various densities, even in the presence of sunlight and against gray and white backgrounds, as well as accurately detect flames under sunlight and backgrounds with similar colors to flames. The proposed methods exhibit high accuracy rates, with an average accuracy of 96% for smoke and flame detection in real-time scenarios and 98% for offline flame and smoke detection. Additionally, the integration of Int-to-Int-HLWT in preprocessing significantly reduces processing time without compromising accuracy, achieving a 50% reduction compared to non-preprocessed cases. In summary, the research paper presents robust flame and smoke detection methods, offering efficient processing, accurate fire localization, and high detection rates in various outdoor environments.

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