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Automatic Real-time Fire Distance, Size and Power Measurement Driven by Stereo Camera and Deep Learning

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Abstract:

Automatic real-time fire characterization is a crucial requirement of future smart firefighting. This work proposes a novel computer vision method to automatically measure the fire heat release rate, even when the camera is moving in real-time. Firstly, a portable binocular stereo camera is used to capture the real-time fire video stream that is fed into a pre-trained computer-vision model frame-by-frame to detect the fire region. By identifying the fire location inside the image, the real-time distance between the camera and the fire source is determined. This fire distance helps re-scale the images to match the input scale of the AI-image Fire Calorimetry. Then, the deep learning model can automatically output the transient fire power in real time. Results show that the stereo vision system is capable of accurately measuring the distance between the camera and the fire source, flame height, and power, with a relative error of less than 20%. This work provides an automatic and flexible way to measure the distance, power and hazard of fire in real-time, and such a method has broad applications in firefighting operations and decision-making.

Keywords: *fire calorimetry; object detection; computer vision; heat release rate; smart firefighting*

1. Introduction

Fire incidents, both indoors and outdoors, pose significant risks in terms of property damage, human injuries, and loss of life (Fig. 1). For example, recent UK data highlights the substantial financial investment in fire protection services, reaching £3.13 billion in 2020/21. Despite these efforts, Fire and Rescue Services responded to a staggering 147,295 fire incidents during the same period. Tragically, these fire incidents resulted in 280 fatalities and 6,201 injuries, underscoring a profound impact on individuals and communities.

The heat release rate (HRR) or power of fire serves as a key parameter in assessing the magnitude and impact of fires. Knowing the fire HRR plays a pivotal role in predicting fire propagation patterns [1], evaluating potential structural damage [2], estimating heat and smoke production [3], and determining required firefighting resources [4]. Furthermore, the fire HRR is instrumental in evaluating the effectiveness of fire safety measures, including sprinkler systems and fire barriers [5]. Consequently, comprehensive measurement and understanding of transient fire HRR are paramount for improving fire safety practices and firefighting strategies.

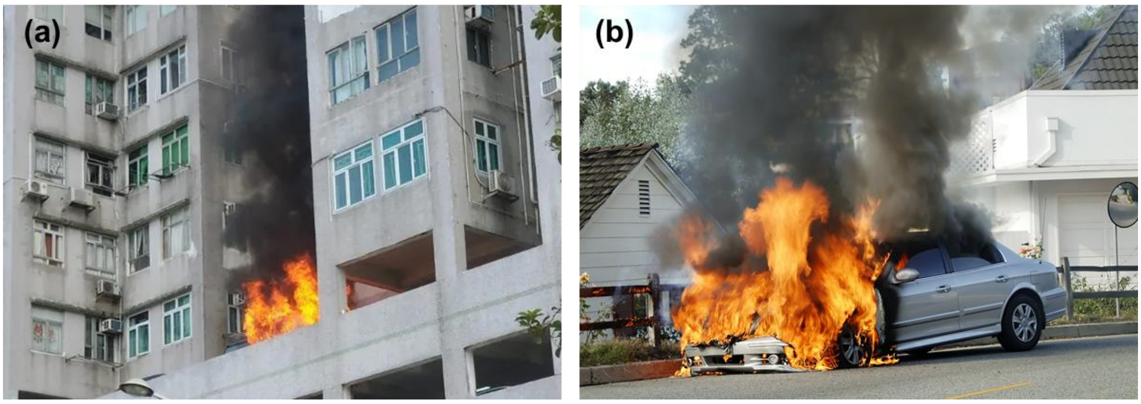

Fig. 1. (a) Building fires (indoor fires) [6], (b) vehicle fires (outdoor fires) [7].

In a fire lab, the measurement of HRR often relies on the utilization of a balance to measure fuel burning rate or an oxygen calorimeter to measure oxygen consumption in flame [8]. However, due to the unpredictable nature of most fires, it is impossible to pre-install measurement equipment before or during a fire event. Thus, conventional lab methods fail to provide real-time HRR measurements for real fire scenarios. As a result, firefighters primarily rely on their own intuition and experience [9,10], as well as visual observations of the fire intensity and smoke generation, to estimate the fire size and risk. Unfortunately, such intuitive assessments are rough and insufficient to support effective firefighting resourcing and decision-making.

The camera undoubtedly captures more detailed fire information, and the video footage of fire incidents is largely available from CCTV cameras or mobile phones. Recently, computer vision and artificial intelligence (AI) methods are merging in fire identification and measurement [11–18]. For example, using one or more cameras can easily measure the flame geometry, flame-sheet area [13] and volume [14] via the post-processing of fire image/video. Hosokawa *et al.* [15] utilized image analysis to determine the upper and lower end heights, total area, and color division of polyolefins and polystyrene flames of varying molecular weights. Toulouse *et al.* [16] developed a novel multi-modal stereovision framework that enables the extraction of the three-dimensional geometrical features of wildfires captured through 3D vision systems. Several researchers employed stereo camera or radar to locate objects in fire scene [17–19]. However, extensive image post-processing is required for these methods, so they are unsuitable for supporting firefighting operations.

To achieve fast imaging processing, deep learning techniques have been employed to analyze sensor data and images, render the real-time 2D/3D fire scene, and generate fire forecasts for critical events, such as flashover in compartment fire and smoke back-layering in tunnel fire [20–24]. The utilization of deep learning has demonstrated notable advancements in enhancing the efficacy of intelligent building fire safety design [25–27], as well as facilitating fast fire forecasting and supporting smart firefighting operations [20–24]. The deep-learning computer vision approaches enable real-time processing and analysis of fire images, thus fostering the development of practical applications, including fire detection [28,29], fire segmentation [30,31] and fire calorimetry [11,12].

Previously, we proposed an AI-image Fire Calorimetry to identify the transient fire HRR by feeding smoke or fire videos [11,12]. The camera was stationary and positioned at a known distance, allowing an easy scaling of fire images as the input of the AI model, but it cannot be applied without giving the fire distance or a reference length. In a real fire, the camera carried by firefighters or unmanned aerial vehicles (UAVs) is often moving. Consequently, there is no fixed reference distance for scaling fire images, so it cannot directly get fire dimensions from the camera.

This study presents a novel approach for automatic and real-time measurement of fire distance and HRR using a binocular stereo camera and AI-image Fire Calorimetry. The proposed method involves employing a well-calibrated binocular camera to capture the fire video. The captured images are then processed using a pre-trained model to localize the flame within the image and determine the fire-camera distance and flame height. Based on the measured transient fire distance, the flame image can be re-scaled to feed into the AI-Fire Calorimetry to evaluate the fire power and hazard in real fire scenes.

2. Methodology

The objectives of this study are (1) to realize stereo camera-based fire distance measurement, (2) to locate the position of the flame in the image, and (3) to scale the fire image for automatic fire calorimetry. A comprehensive framework for fire calorimetry in motion scenes is then presented. The framework of the proposed computer vision-based fire calorimetry is illustrated in Fig. 2.

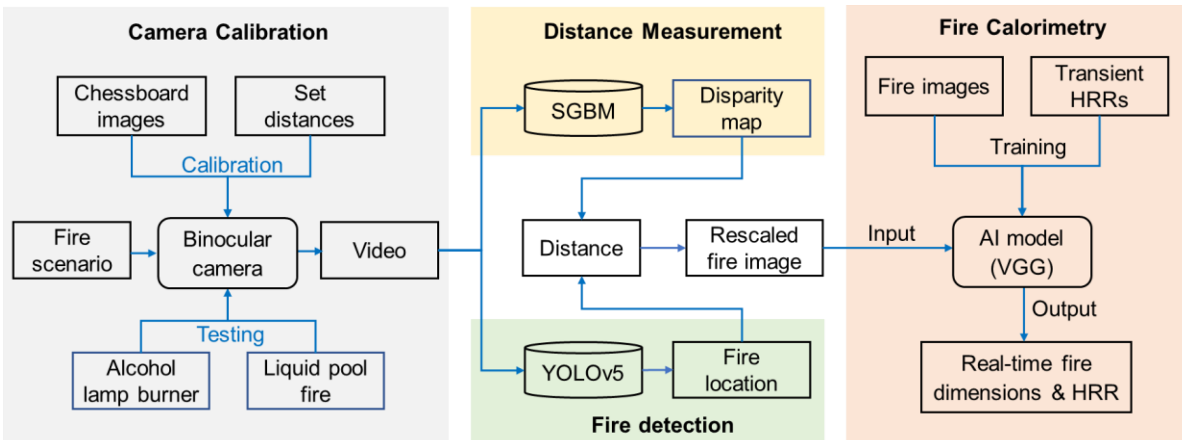

Fig. 2. Framework of automatic real-time fire calorimetry by computer vision and distance measurement.

In this study, a stereo camera is utilized to capture the fire scenario, which is calibrated using the stereo vision calibrator provided by MATLAB. The Semi-Global Block Matching (SGBM) algorithm is employed to perform stereo matching and provide depth information for the fire image. Additionally, the YOLOv5 is utilized to perform real-time fire detection in the captured video, which is capable of detecting and bounding boxes for the flame within an image. Through the disparity map generated by SGBM and the location of the flame in the image, the distance between the camera and the fire source is calculated. The dimensions of the flame are then evaluated, and the flame image is scaled based on the fire distance from the camera and the camera focal length. Finally, the scaled flame image is inputted into a VGG model that has been trained using the NIST database [32], enabling the identification of the transient fire HRR.

2.1. Experimental setup

The utilization of stereo vision [33] for fire distance measurement has been increasingly prevalent in recent years due to its ability to perform accurate distance estimation based on visual information. This method is an alternative to traditional fire distance measurements like sonar and LIDAR, while it won't be hindered by the presence of flame and smoke in fire scenarios. Implementing stereo vision for fire distance measurement allows a more reliable and efficient way of obtaining the required distance information to estimate the fire dimension and power.

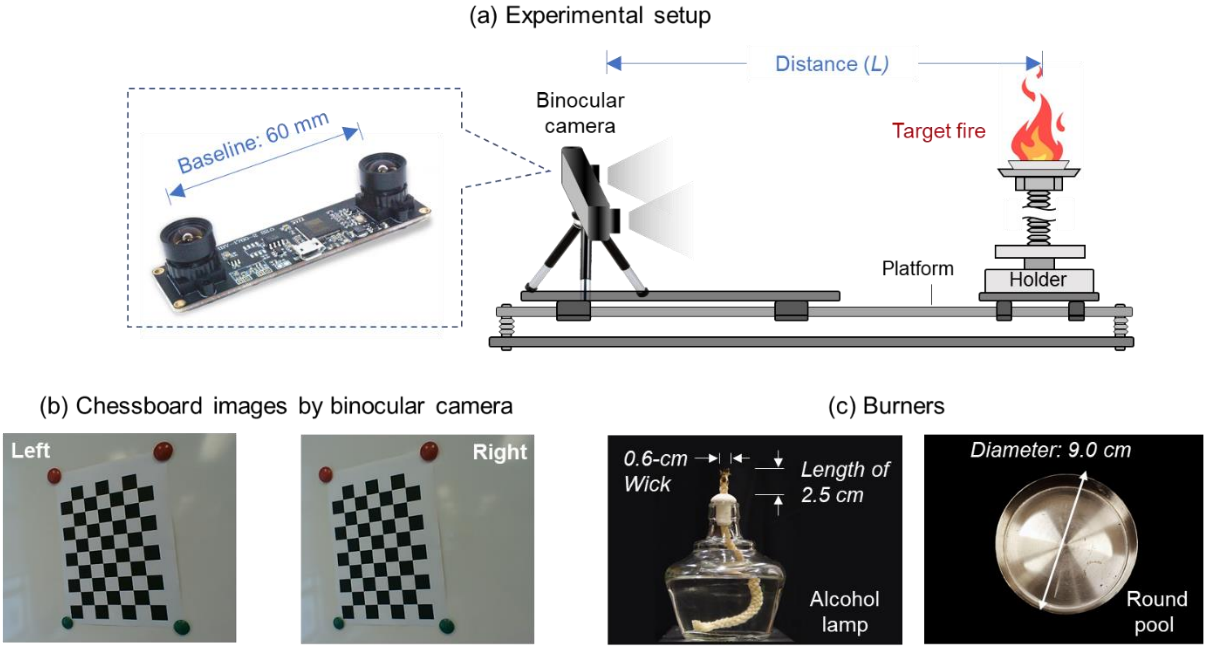

Fig. 3. (a) Experimental setup for flame distance and HRR measurement by a binocular stereo camera, (b) examples of chessboard image for camera calibration, and (c) different burners.

A group of experiments were conducted to assess the accuracy of fire distance measurement using stereo vision. Fig. 3a shows the experimental setup that is consisted of a stereo camera to acquire images, a burner as the source of fire, and a platform to regulate the distance between the camera and the burner. The stereo camera (HBV-1780-2 S2.0) is a type of camera that incorporates two lenses to capture two slightly offset images of the same scene (see an example in Fig. 3b). It consists of two CMOS cameras, whose baseline is 60 mm. The sensor type of the camera is OV9732 (1/4″) CMOS (640 x 480 pixels, up to 50 fps) with a focal length of 2.1 mm and a default setting of exposure time.

First of all, the intrinsic and extrinsic parameters of each camera were calibrated by chessboard images from two cameras. Then, the relationship between the two cameras and flame distance was established and processed by MATLAB code. By capturing images from both cameras with well-calibrated intrinsic parameters, the difference between the images was utilized to compute the depth information of the scene through the implementation of the SGBM algorithm. This makes stereo camera a useful tool for measuring distance and further assessing the fire dimension.

For fire distance measurement, two types of burners were used as fire sources in the experiment. The first type was an ethanol burner, where its cotton wick has a diameter of 0.6 cm and a length of 2.5 cm, so its flame width is about 1 cm, and the flame height is about 5 cm. The second type was propanol pools with diameters of 9 cm and 30 cm, as shown in Fig. 3c. Using an ethanol burner with a stable flame was ideal for demonstrating the accuracy of distance measurement. However, in real-life fire scenarios, the flame is typically less stable, so a round pan of propanol fire was also tested. It should be noted that the flame in the propanol pool is continuously puffing, so it is more challenging to track the flame and measure the distance accurately.

During the experiment, the stereo camera was fixed at one end of the platform, while the burner was positioned at a designated spot on the opposite end. The distance between the camera and burner (represented as L in Fig. 3a) was able to be adjusted from 0.5 to 0.8 meters by moving the burner through the bottom holder. After the ignition by a propane torch, the entire burning process, along with the corresponding distance between the camera and the burner, was recorded as video file.

2.2. Fire detection by YOLOv5

For the original flame image, there are many irrelevant objects in the background, which may negatively impact the accuracy of distance measurement. Then, it is necessary to accurately detect the position of the flame inside the image in real time. Thus, YOLOv5 [34] will make a box around the flame, reducing the impact of extraneous objects on the measurement process.

YOLOv5 is a state-of-the-art object detection model that uses a single convolutional neural network to detect objects in an image, and it has been demonstrated to be highly effective in real-world scenarios. The use of YOLOv5 has several advantages, such as fast object detection speed, high accuracy, and efficient use of computational resources. This makes it a suitable choice for detecting flames in an image, improving the overall accuracy of distance measurement.

Fig. 4 shows the detailed architecture of YOLOv5 used for fire detection, consisting of several components, including a backbone network of CSPDarknet [35], a neck of PANet [36], a head of YOLOv3 [37], and anchor boxes. The backbone network extracts low-level features from the input image, while the neck network passes these features to the head network to generate predictions. The head network consists of multiple convolutional layers and a dense layer, which generates the final predictions for object classes and object locations. The anchor boxes are used to adjust the predictions based on the size and aspect ratio of the objects. These components work together to detect objects in an image and generate accurate object bounding boxes.

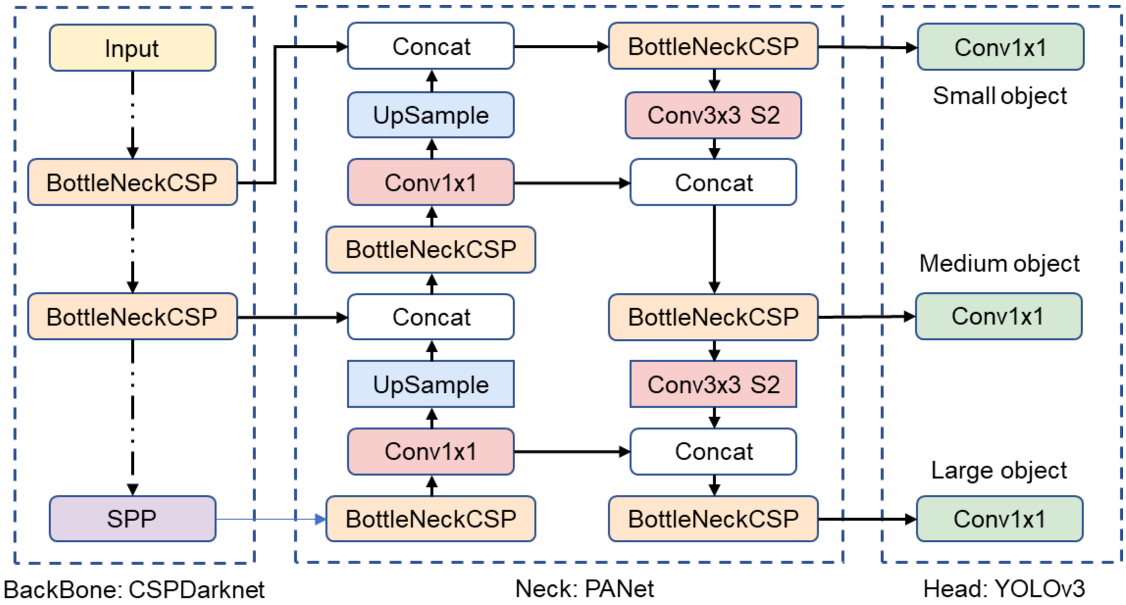

Fig. 4. The architecture of YOLOv5 for fire detection.

2.3. Fire calorimetry using VGG

Determining the fire HRR quantitatively by using only visual information is a challenge, as it goes beyond human intuition and traditional analytical methods. Thus, the deep learning algorithm is utilized to establish the relationship between fire images and HRR. This approach has been demonstrated to be effective in previous studies [11,12] through the use of the VGG16 method in extracting features from numerical smoke images and real fire images, leading to accurate HRR identification. In this work, we still used VGG [38] to estimate the fire HRR, where the training database includes over 200 fire tests in the NIST Fire Calorimetry Database (FCD) [39,40]. The items burned in these fire tests are commonly seen in our daily life, such as plastic bins, paper boxes, wood pallets, etc.

Fig. 5 presents a comprehensive illustration of the VGG architecture applied in fire calorimetry, which is composed of five convolutional blocks and three fully connected layers. The first two convolutional blocks comprise two consecutive convolution operations and one max-pooling operation, while the remaining three convolutional blocks consist of three successive convolution operations and one max-pooling operation, all with a convolution kernel size of 3×3. Due to its simple and well-understood architecture, it has been widely used in different computer vision tasks, including image classification, object detection, and semantic segmentation. Furthermore, by modifying the activation function of the final layer to linear, it can also be utilized in visual regression tasks, such as the real-time evaluation of fire HRR.

The entire network structure contains a total of 28 million parameters, which is adequate to capture the relationship between the image data and the fire HRR. The ReLU activation function is employed in the fully connected layer except the final one, and multiple loss functions, including mean square error (MSE), mean absolute error (MAE), and R^2 value, are utilized to evaluate the difference between the actual and predicted HRRs.

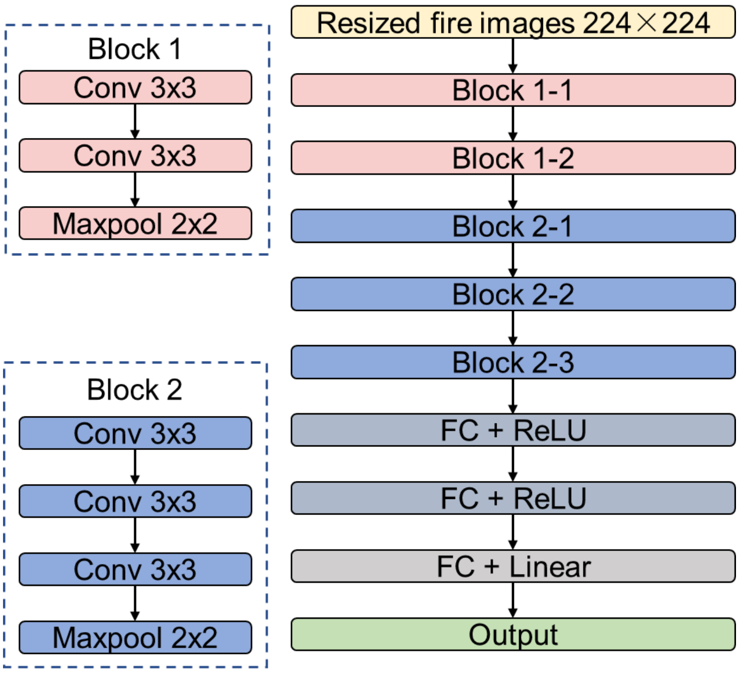

Fig. 5. The architecture of VGG for AI-Image Fire Calorimetry.

3. Results

3.1. Distance measurement demonstration

Since the flame of an ethanol burner is stable with no visible oscillations, it is an ideal candidate for demonstrating the accuracy of fire detection and distance measurement using a stereo camera system. The disparity map generated by the stereo camera contains all the depth information. However, it is necessary to first locate the fire source to determine its distance from the camera. Fire detection is a crucial step in this process to accurately identify fire region within the disparity map.

To validate the accuracy of fire distance measurement, four different fire locations were selected, shown in Fig. 6a. The center of the flame root is chosen as the reference point to calculate the flame distance from the camera. The results of the flame distance measurement performed on an ethanol burner using a camera and a ruler are illustrated in Fig. 6b. The performance of distance measurements is evaluated by MAE, MSE, and MRE, and their values are shown in Table 1.

Additionally, fire behaviors during each test and the distance measurements can be found in Supplemental Video S1. All the tests were conducted in a bright environment to ensure accurate stereo matching. The results indicate that the proposed flame distance measurement method can effectively measure the distance between the alcohol lamp flame and the camera. Specifically, the relative error is less than 5%, as shown in Fig. 6b. The accuracy of measurement cannot be further improved because the error of distance is already comparable to the flame width of about 2 cm.

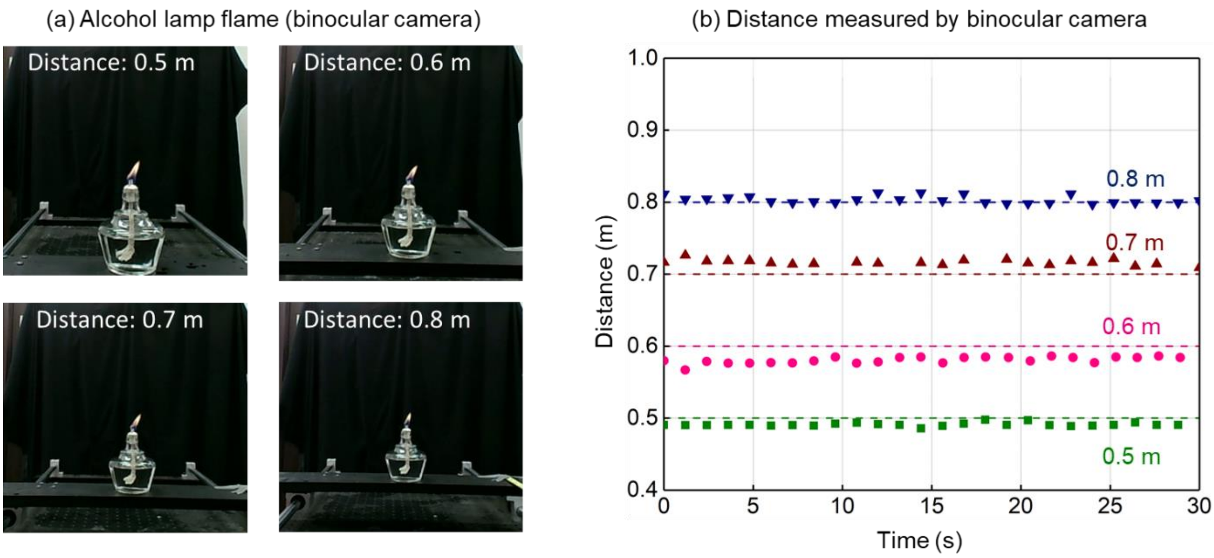

Fig. 6. Distance measurement of alcohol lamp flame, (a) flame image captured by stereo camera, and (b) flame distance measured by the stereo camera (line: set value, and marker: measurements).

Table 1. Performance of the flame distance measurements of an alcohol lamp.

Distance	MAE [m]	MSE	MRE [%]
0.5 m	0.009	8.86×10^{-5}	1.83
0.6 m	0.020	4.40×10^{-4}	3.38
0.7 m	0.017	3.66×10^{-4}	2.49
0.8 m	0.004	3.20×10^{-5}	0.51

Due to the relatively stable flame of the alcohol lamp, the measurements are stable and close to the ruler-set values throughout the 30-s burning time. Noteworthy, achieving flame distance measurement through the utilization of a stereo camera requires the integration of two key factors: efficient fire detection and accurate depth information calculation. The detection of the flame position enables the determination of the distance value, which is obtained from the depth information. However, as the flame of the alcohol lamp gets further away from the camera, e.g., 0.9 m, or more, the fewer blocks of pixels the flame occupies in the image, considering that the lamp flame is very small. Then, the proposed fire detection will not be able to effectively identify where the flame is located. In this case, although the stereo camera can still acquire depth information, the method will not provide valid distance information about the flame as the position of the flame cannot be confirmed in the image.

In short, the proposed fire distance measurement powered by a stereo camera in bright environments has demonstrated its ability to effectively capture the position and depth information of the ethanol burner flame and determine the flame distance from the camera to the fire. Improving the efficiency of fire detection can be achieved through the increase of stereo camera resolution or the enhancement of the captured image resolution. The method only uses a stereo camera, without using reference length or larger equipment like sonar or LIDAR, so it is portable in firefighting application.

3.2. Flame height measurement of transient pool fire

To further demonstrate the feasibility of identifying the real-time fire distance, pool fire tests at different locations (Fig. 7a) were carried out to validate the system in a dark environment. The pool fire flame is puffing, presenting a new challenge for more accurate distance measurement. In pool fire tests, a pool fire with a 9-cm diameter and 30 mL of propanol was used as the target. Two different locations were used to demonstrate the performance of fire distance measurement. The burning process was recorded by the stereo camera.

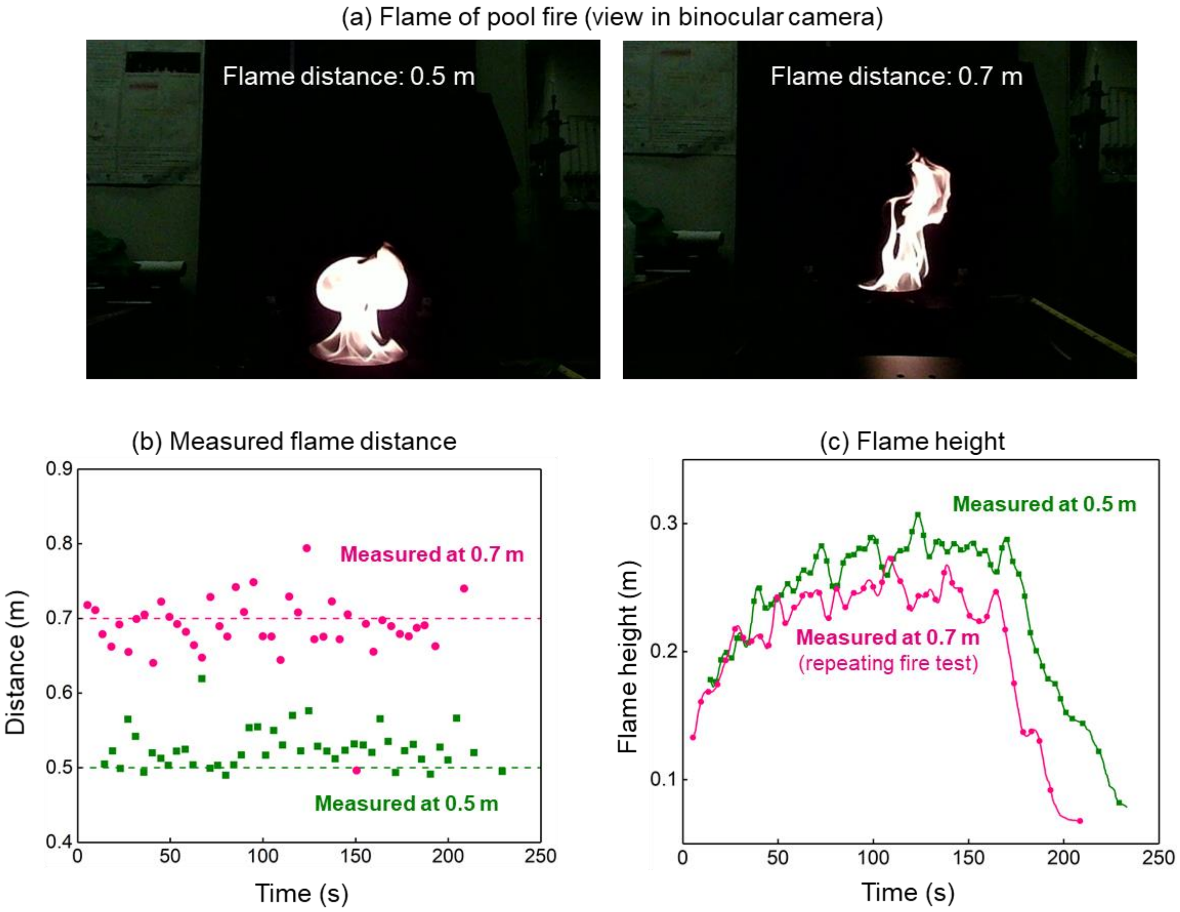

Fig. 7. Distance and flame height measurement of pool fire with 9-cm diameter, (a) images of pool fire at two distances, (b) fire distance measured by the stereo camera, and (c) flame height measured.

The comparisons between the fire distance measured by the stereo camera and the preset distance are shown in Fig. 7b and Table 2. The detailed transient flame distance measurement can be seen in Video S2. Despite the challenges posed by the puffing flame and dark environment, the stereo camera system displayed high accuracy in the fire distance measurement, showing an overall error of less than 20%. This measurement is already quite accurate because the flame has a width/depth of about 0.1 m, and it oscillates and puffs continuously.

Table 2. Performance of the flame distance and height measurements.

Distance	Flame Distance measurement			Flame height measurement		
	MAE [m]	MSE	MRE [%]	MAE [m]	MSE	R^2
0.5 m	0.030	0.024	6.1	0.016	0.001	0.76
0.7 m	0.033	0.011	4.7	0.016	0.001	0.92

The methodology for determining the flame height uses the measured flame distance measured, its focal length, and the bounding box information generated during the fire detection process. This approach provides a straightforward and efficient solution for flame height measurement. The automatic measurements of dynamics flame height are shown in Fig. 7c, and they are compared to the calculated value by using the pool diameter as a reference length (i.e., a conventional method). Thus, even if there is no reference length in the camera view, we can measure flame height and shape accurately. Hence, this method is more adaptable in quantifying real-world fire dimensions and hazards.

3.3. Fire calorimetry in moving scenarios

In our previous research, real-time fire calorimetry was achieved through the utilization of a stationary camera [12]. This allowed for the fire image to be easily re-scaled based on the known distance or the reference length. However, when it comes to mobile cameras used by firefighters or mounted on UAVs, the situation becomes more challenging, as these cameras are in motion, and their distance from the fire is continuously changing. This makes the utilization of fire images for calorimetry difficult in such moving scenarios. To address this issue, there is a need for the automatic resizing of fire images, which will make fire calorimetry more practical and accessible in such environments.

Fig. 8 shows the pre-processing of fire images, which re-scales (i.e., zooms in or out) the fire images from a moving camera into the same scale or angle of view as images provided by the NIST database. In our lab test, the distance between the camera and the fire source (pool with a 30-cm diameter) is constantly changing, so the image re-scaling has to consider the real-time distance between fire and camera. To ensure the applicability of AI-Fire Calorimetry with a camera in motion, the automatic re-scaling of fire images is essential.

The images captured by the stereo camera are first scaled based on the measured fire distance by the stereo camera system and restored to a standard resolution of 1,920×1,080 through padding. This process ensures that the scale represented by each pixel in the pre-processed image is consistent with the images used in the training process. Subsequently, the images are then resized to the standard size of 224×224. The re-scaling and resizing of images enhance the model's adaptability to different image sizes and its generalizability, making it more suitable for dynamic fire measurement under a real fire scenario with a moving camera.

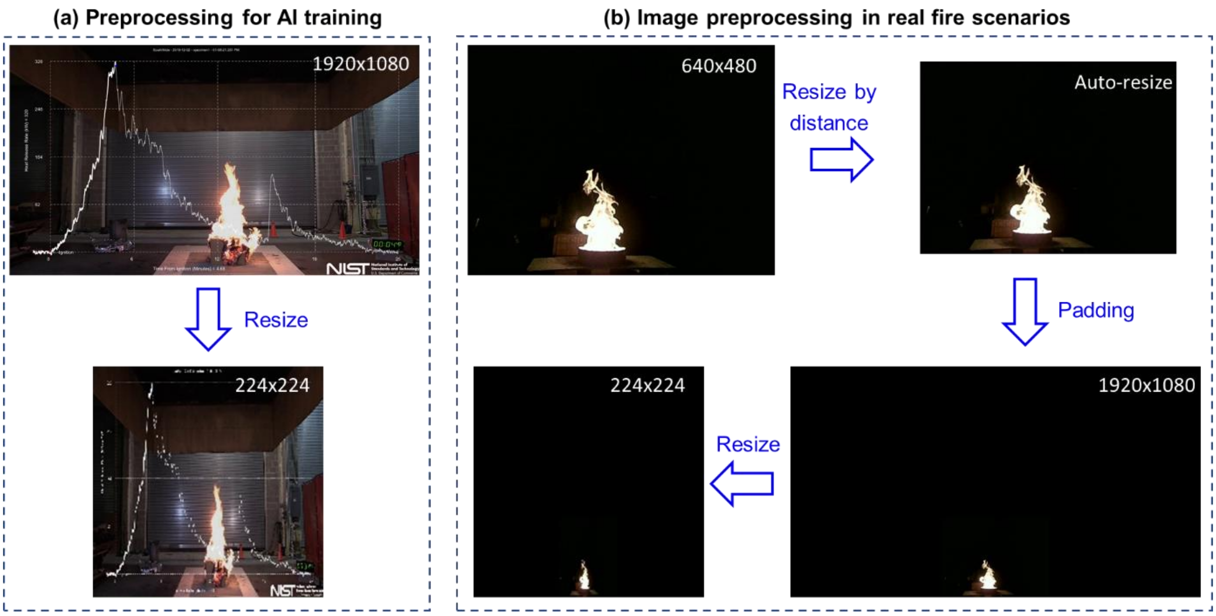

Fig. 8. Image pre-processing and re-scaling for camera in motion: (a) fire image of a fixed camera view from NIST database as a standard input to AI model, (b) pool fire images from camera in motion.

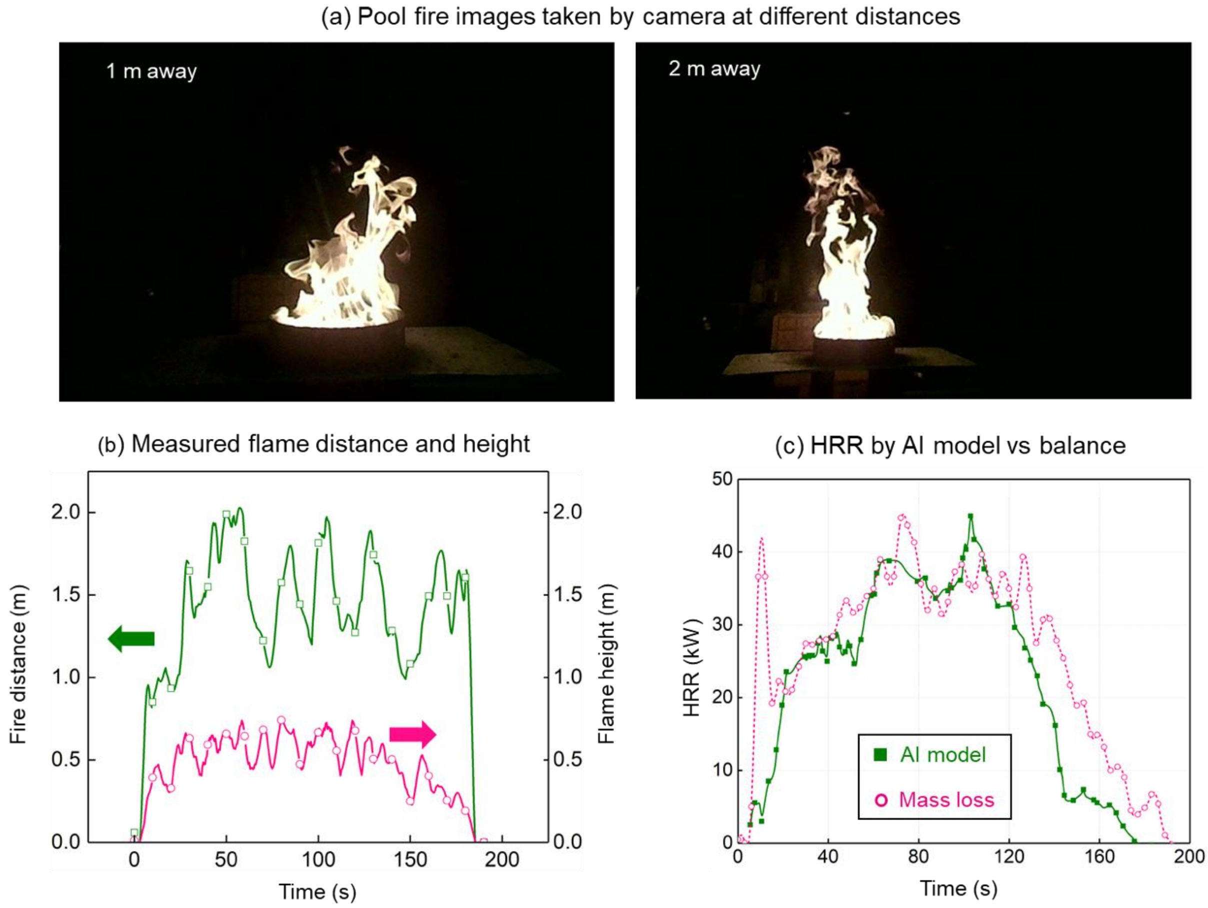

Fig. 9. Automatic fire distance and power measurements, (a) pool fire images taken by camera at different distances, (b) measured flame height, and (c) HRR predicted by AI vs balance.

To demonstrate the effectiveness of the stereo camera system in dynamic environments, a real-world fire scenario was simulated using a pool fire with a 30-cm diameter and 200 ml of propanol. The hand-held stereo camera was moved randomly to vary the distance from the fire source during the burning process. At the same time, the fuel-burning mass loss rate were recorded by the balance. The fire images were processed in real-time using the proposed automatic resizing method, that is, re-scaling and resizing the images to match the input requirement of the deep learning model.

The measure evolution of the fire distance, flame height, and HRR are plotted in Fig. 9, and the detailed evolution of fire distance, height and HRR can be seen in Video S3. Visually, with a moving camera, the measured flame height, based on fire distance and deep learning method, agrees well with the trend of fire development. Quantitively, the AI-measured HRR values also agree well with the balance-measured values, where the R^2 value is over 0.86.

4. Discussion

4.1. Limitations and Challenges

The stereo camera system is capable of accurately determining the distance from the fire source. Through automatic image re-scaling and resizing based on the distance measurement, the images captured by the system can be adapted to the same scale as the training set images, thereby enabling automatic real-time fire calorimetry in a dynamic fire scene. To enhance the efficacy of fire calorimetry, two approaches can be adopted. Firstly, enhancing the resolution of the stereo camera can improve flame identification by the object detection model, especially when the flame is small at the initial and decay stages. Secondly, expanding the fire database utilized for the AI calorimetry model training can significantly augment the model learning capabilities. By incorporating a larger number of diverse fire tests, the calorimetry model can acquire a broader range of knowledge, subsequently enhancing the accuracy of flame calorimetry achieved by the model.

This work demonstrates the applicability of the system for some small-scale fire experiments in the lab environment. Nevertheless, the performance of the model still needs to be validated by a large number of large-scale fire tests and real fire incidents, which will be conducted in our future work. As the real fire incident is more complicated than the lab fire test, there are several challenges that need to be effectively addressed.

Firstly, the camera in this study always views the fire horizontally, which simplifies the flame height calculation. However, in a real fire incident, the shot angle of a handheld or UAV-mounted camera is random. To identify the flame height and HRR accurately, either the camera needs to change the shot angle, which may not be possible in practice, or some algorithm is needed to adjust the fire image. Future work will address the effect of camera shot angle on the automatic fire calorimetry.

Secondly, the fire occupies a 3D volumetric space. Using one camera or taking from one angle of view only gives a 2D projection, which inevitably creates some uncertainty in the HRR estimation. When the fuel and fire have a large depth, using the 2D image from one camera or a fixed shot angle always underestimates the fire HRR. In order to further improve the accuracy of image-based fire calorimetry, using multiple cameras or moving the camera to shoot from different angles is needed, which will be our future work.

Thirdly, the fire and burning regions are often partially blocked by buildings or smoke, so the camera may not capture the whole fire, even if it can shoot from different angles. The demonstration in this work assumes that the flame can be fully captured by the camera. In reality, however, the presence of a dense smoke layer, flame merging, and limited camera view may limit the user's ability to capture the whole picture of fire, causing an underestimation of the fire HRR. Thus, how to eliminate or reduce the effect of flame and camera blockage will also be a major challenge in the application of this technology, which deserves more research. There are two potential solutions to mitigate the blockage of fire in video. One is to add more cameras to see flame from different angles of view [14] or move the camera to shoot from locations like those in UAV, so the flame can be reconstructed. The other is to employ random data augmentation techniques that can prompt the network to identify alternative descriptive features within the image, so it enables a more accurate estimation of the fire power.

Finally, the primary constraint impacting the practical implementation of the proposed method is the reliance on stereo cameras. Given the necessity of scaling the image based on distance for image calorimetry, the method necessitates the utilization of stereo cameras. Currently, many prevailing devices, including drones, smartphones, and conventional cameras, are equipped with only a single primary camera and lack the requisite support for stereo imaging. To overcome this limitation, our future research endeavors will focus on developing more flame distance measurement techniques, e.g., using Lidar to measure the distance, finding a reference length of objects inside the view, and using other known distance like the fly height of UAV.

4.2. Application in smart firefighting

Despite not being fully developed, image-based fire calorimetry holds significant potential in smart firefighting practices. This technology relies on a conventional stereo camera for estimating fire size, eliminating the need for pre-installed detection equipment in the fire zone. It can be employed for real-time fire monitoring and calorimetry using UAVs or handheld devices, offering ease of use and adaptability. Fig.10 illustrates the new framework for implementing the Real-time Patrol AI-Image Fire Calorimetry. Video S4 further demonstrates the UAV fire calorimetry, where the UAV has its altitude as the reference length, so it may not need stereo camera to measure the fire distance.

In this system, pre-installing stereo camera or deploying UAVs will facilitate fire-scene monitoring and enable real-time processing of captured images by using AI and computer vision. When a fire incident arises, monitoring devices, such as mobile-phone and UAV cameras, can be employed to track the fire source based on monitoring results. This enables the identification of the fire location, dimension and HRR and the recording of their time evolution. Real-time transmission of such key fire information to fire commanders will assist them in their firefighting and rescue endeavors, which may eventually improve decision-making, save more people and reduce casualties.

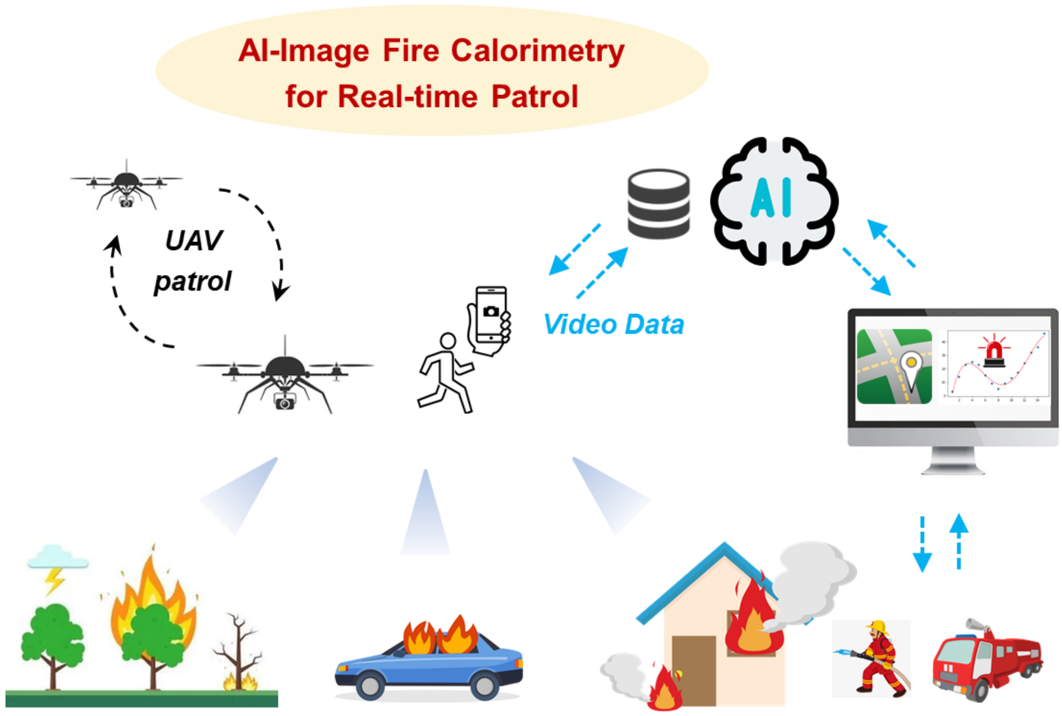

Fig. 10. Automatic fire distance and power measurements for smart firefighting.

5. Conclusions

This work proposes and demonstrates an automatic real-time fire distance measurement and fire calorimetry driven by a stereo camera system and deep learning computer vision method. The stereo camera system is utilized to obtain the fire images and then estimate the varied distance between the camera and the fire source in real time. The experiments conducted for the ethanol burner and pool fire demonstrate the accuracy in real-time fire distance measurement and HRR prediction (relative error < 20%).

The improved AI-Image Fire Calorimetry can be applied, even if the distance between the camera and fire is changing dynamically without providing any reference length. By adding the stereo camera system to the mobile phone and UAVs, etc., the proposed system can measure the fire distance, dimension, and power, which is critical information for firefighting strategies and operation safety. This work provides an automatic and flexible way to measure the distance, power and hazard of fire in real-time, and such a method has broad applications in firefighting operations and decision-making.

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Supplementary Materials

Video S1: Flame distance measurement for an ethanol burner when the camera position is fixed.

Video S2: Flame distance and height measurements of pool fires with camera at multiple locations.

Video S3: Fire calorimetry for a pool fire fed by real-time video from a moving camera.

Video S4: Automatic real-time fire calorimetry with video from a patrolling UAV.

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