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Fire Detection Using Infrared Images for UAV-based Forest Fire Surveillance

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Abstract— **Unmanned aerial vehicle (UAV) based computer vision system, as a more and more promising option for forest fires surveillance and detection, is now widely employed. In this paper, an image processing method for the application to UAV is presented for the automatic detection of forest fires in infrared (IR) images. The presented algorithm makes use of brightness and motion clues along with image processing techniques based on histogram-based segmentation and optical flow approach for fire pixels detection. First, the histogram-based segmentation is used to extract the hot objects as fire candidate regions. Then, the optical flow method is adopted to calculate motion vectors of the candidate regions. The motion vectors are also further analyzed to distinguish fires from other fire analogues. Through performing morphological operations and blob counter method, a fire can be finally tracked in each IR image. Experimental results verified that the designed method can effectively extract and track fire pixels in IR video sequences.**

I. INTRODUCTION

Forest fires can potentially result in a great number of environmental disasters, causing vast economical and ecological losses as well as endangering human lives [1]. In order to preserve natural resources and protect human safety and properties, forest fire monitoring and detection have become a significant solution, which attract an increasing interest around the world [1]. Especially, the growth number of large-scale worldwide forest fires has made automatic fire detection as an important technique for the early fire alarm [2].

Conventional forest fire detection techniques make use of watchtowers and human observers to search and observe fires in hazardous environments. It consumes tremendous labour forces, threatens observers' safety and costs a great deal of time. Owing to the development of modern technologies, more advanced forest fire detection approaches integrating remote sensing techniques with various platforms (such as satellites, ground-based equipments, and aircrafts) are designed to overcome drawbacks of traditional methods. Particularly, due to their rapid maneuverability and improved personnel safety, there is an increasing demand to make unmanned aerial vehicles (UAVs) serve as powerful tools for operational fire-fighting. Recent decades, growing efforts have been devoted to the application of UAVs for forest fire monitoring and detection [3], [4], [5], [6], [7], [8], [9], [10], [11], [12].

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A typical UAV-based forest fire surveillance system is illustrated in Fig. 1, which is composed of a team of UAVs, different kinds of onboard sensors, and a central ground station. The goals are to take advantages of UAVs to detect and track fires, predict their propagation, and supply real-time fire information to human firefighters and even to execute fire extinguishment with UAVs. The system can fulfil the missions of fire monitoring (search a potential fire), detection (find potential fire and produce fire alarm to firefighting staff), diagnosis (compute parameters of the fire position, extent and evolution), and prognosis (predict the fire propagation) [1], [13]. Forest fire monitoring is to find the possible occurrence of fire before it has appeared, while fire detection is to confirm whether there is a real fire in progress. Fire diagnosis is for the purpose of finding detailed data of fire. Fire prognosis aims to track and predict the fire propagation based on real time information of weather, vegetation composition of forest and fire parameters.

In order to complete the above-mentioned tasks with minimum interference of human operators, the specific activities are the development of 1) UAV frames (fixed wing and rotary-wing types) carrying the necessary payload (remote sensing sensors for day-time, night-time, and all weather conditions) for fire detection and surveillance; 2) Remote sensing technologies for fires monitoring and detection; 3) Sensors fusion and image processing techniques for rapid fire detection, decision-making, and localization; 4) Guidance, navigation, control (GNC) algorithms for single UAV and multiple UAVs for monitoring, detection, tracking and prediction of fire development, and fire extinguishing operations; 5) Cooperative localization, deployment, and control strategies of UAVs for optimal coverage of fire areas for precise and rapid fire tracking, prediction, and assistance/guidance of firefighting; 6) Autonomous and reliable path planning and re-planning strategies before and after fire being detected based on the fire development situations; 7) Ground station which includes satellite and wireless communications, ground computation, image processing, visualization for fire detection, tracking and prediction with automatic fire alarm and for safe and efficient operation of UAVs systems during the entire mission.

It can be seen that the computer vision based fire detection technique is one of the most important elements in the UAV-based forest fire detection system. This is due to its numerous merits such as monitoring wide range object,

TABLE I: Brief review of UAVs forest fire monitoring and detection systems [1]

Test Types	References	UAV Class	Onboard Cameras (Resolution)	Engine Power	Payload Capacity
Near operational	[19]	1 fixed-wing	1 thermal (720×640)	Fuel	$340kg$
Operational	[20]	1 fixed-wing	4 mid-IR (720×640)	Fuel	$> 1088kg$
Near operational	[14]	2 rotary-wing; 1 airship	1 visual (320×240); 1 IR (160×120)	Fuel; Electric	$3.5kg$
Operational	[21]	1 fixed-wing; 1 rotary-wing	1 visual; 1 IR	Fuel	—
Near operational	[22]	1 fixed-wing	1 visual 1 IR	Fuel	$< 34kg$
Near Operational	[3]	2 fixed-wing	1 visual; 1 IR; 1 visual (1920×1080)	Fuel	$25kg$; $250kg$
Near operational	[23]	2 fixed-wing	1 thermal (160×120); 1 NIR (752×582); 1 VNIR (128×128)	Electric	$< 2.6kg$
Near Operational	[24]	1 fixed-wing	1 visual (720×480)	Gas	$0.68kg$
Near operational	[25]	1 rotary-wing	2 visual (4000×2656; 2048×1536); 1 thermal (320×240)	Fuel	$907kg$
Near Operational	[26]	1 fixed-wing	1 visual	Electric	—
Near operational	[27]	1 fixed-wing	1 visual (656×492)	Electric	$5.5kg$

Note: (-) Not mentioned; NIR: Near IR; VNIR: Visible-NIR.

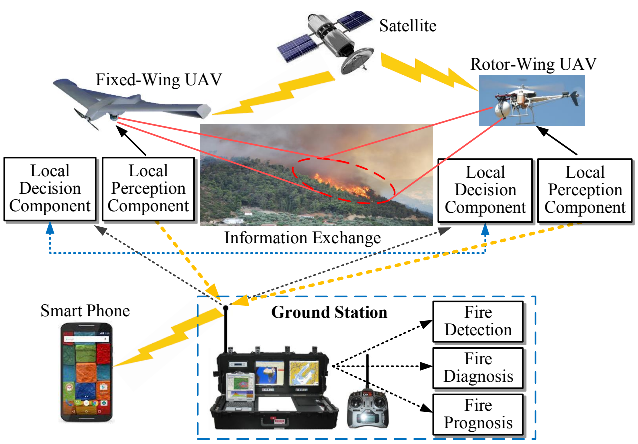

Fig. 1: Schematic illustration of the UAVs-based forest fire surveillance system [1].

offering intuitive and real-time images and recording information conveniently. More specifically, charge-coupled device (CCD) cameras and infrared (IR) cameras are usually mounted on UAVs. Table I provides a brief review of current UAV-based forest fire detection systems.

Massive efforts have been dedicated to the development of more effective image processing scheme for fire detection. The color and motion features in visual images captured by CCD cameras are mostly utilized for fire detection. However, the usage of CCD cameras is normally considered as not robust and reliable enough in some outdoor applications. Given highly sophisticated, non-structured environments of forest, the chance of smoke blocking the fire, or the situation for analogues of fire including reddish leaves swaying in the wind and reflections of lights, false fire alarm rate often tends to be considerably high. Due to the fact that IR images can be obtained in either weak or no light situations, and smoke can be seen as transparent in IR images, IR cameras are widely applied to capture monochrome images in both daytime and nighttime, even though IR camera is more expensive than CCD camera. By employing this effective solution, it is expected to significantly reduce false fire alarm rate and enhance adaptive capabilities of the forest fire detection system in various environments.

In the past decade, the IR image processing approaches have been utilized in numerous fire detection studies. In [14], a training-based threshold selection method is adopted to segment fire pixels from IR images, experimental results indicate that the false fire alarm rates are effectively reduced. Bosch et al. [15] develop a decision fusion method for the discovery of forest fires in IR images. Various helpful information of the fire are estimated by this method. Pastor et al. [16] take advantages of linear transformations to precisely compute the rate of spread (ROS) of forest fires in IR images. Besides, the flame front position is located by applying a threshold-value-searching criterion. Ononye et al. [17] evaluate the forest fire perimeter, active fire line, and fire propagation tendency via a multispectral IR image processing approach. Their presented method is designed based on a dynamic data-driven application system (DDDAS) concept and a sequence of image processing tools are utilized. Huseynov et al. [18] use a multiple artificial neural networks (ANNs) model to classify fire in IR images. The test results demonstrate that the devised method can decrease training time and increase the rate of successful detection.

Although many fire detection approaches have been developed for processing IR images, while only few applicable to UAV platforms are designed, and rare experimental validations have been conducted with forest fire scenarios. This paper presents a fast fire detection algorithms for the purpose of using UAV to automatically detect forest fire in IR images. The proposed fire detection approach can be described as follows: 1) hot objects are first detected as fire candidate regions, using histogram-based segmentation method so as to remove the non-fire background; 2) the classical optical flow method is then applied to detect moving objects for eliminating stationary non-fire objects in the fire candidate regions; 3) after that, the motion vectors calculated by optical flow are further analyzed to reduce false fire alarm rates caused by hot moving objects; 4) once the fire pixels are confirmed, fire zones are tracked by blob counter scheme.

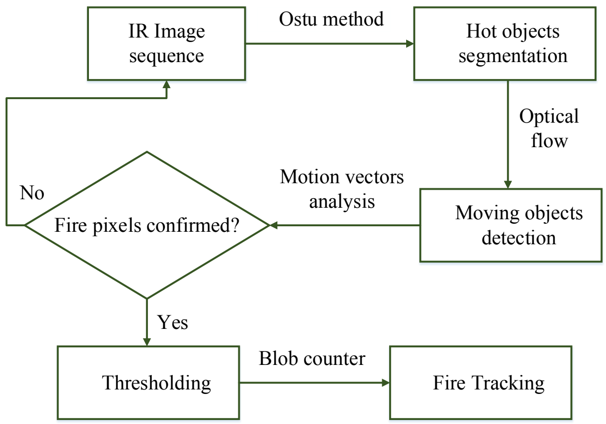

Fig. 2: Illustration of the proposed fire detection algorithm.

The remainder of this paper is organized as follows: Section II introduces the proposed fire detection algorithms. Section III addresses the experimental results. Concluding remarks and possible future work are summarized in the last section.

II. Fire Detection in IR Images

The presented fire detection method utilizes both brightness and motion features of fire appearance in IR images. The combination of these characteristics aims to significantly enhance the reliability of forest fire detection approach. Histogram-based segmentation technique is first adopted to extract hot targets, and optical flow method is then utilized to estimate motion of fire. Fig. 2 briefly illustrates the flowchart of the proposed approach.

A. Hot Object Detection

Most IR cameras measure the heat distribution in the scene and produce single channel images. In IR images, hot objects are represented as bright areas, while cold objects are displayed as dark regions. Therefore, fire pixels appear as high intensity regions, and local maxima of brightness is a dominant clue for fire pixel classification in IR images.

In this study, the histogram-based segmentation method is utilized to extract the hottest objects which represent possible fires in the IR images by distinguishing the high brightness objects from the less brightened objects. Only those hot objects are further analyzed by optical flow using the motion features.

The segmentation step takes advantage of Otsu method [28] which is adopted to automatically threshold histogram-based dynamic images. This thresholding method can be generally described in the following. It assumes that the images to be processed have two kinds of pixels: foreground pixels and background pixels. The optimum threshold t discriminating those two classes is iteratively computed so that their combined spread (intra-class variance) is minimum, or equivalently, for the purpose of making their inter-class variance is maximum.

In order to find the threshold that minimizes the intra-class variance (the variance within each class), it defines in Otsu method that intra-class variance as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t), \tag{1}$$

where weights ω_0 and ω_1 are the probabilities of the two classes (foreground pixels and background pixels) distinguished by a threshold value t, σ_0^2 and σ_1^2 are variances of these two classes.

The class probabilities $\omega_0(t)$ and $\omega_1(t)$ are calculated through the L histograms:

$$\begin{aligned} \omega_0(t) &= \sum_{i=0}^{t-1} p(i), \\ \omega_1(t) &= \sum_{i=t}^{L-1} p(i). \end{aligned} \tag{2}$$

Otsu minimizes the intra-class variance to maximize inter-class variance:

$$\begin{aligned} \sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) &= \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \\ &= \omega_0(t)\omega_1(t)\left[\mu_0(t) - \mu_1(t)\right]^2, \end{aligned} \tag{3}$$

where μ represents the class mean, while the class means $\mu_0(t)$, $\mu_1(t)$ and $\mu_T(t)$ are:

$$\begin{aligned} \mu_0(t) &= \sum_{i=0}^{t-1} i\frac{p(i)}{\omega_0} \\ \mu_1(t) &= \sum_{i=t}^{L-1} i\frac{p(i)}{\omega_1} \\ \mu_T &= \sum_{i=0}^{L-1} ip(i). \end{aligned} \tag{4}$$

The following equations can be obtained:

$$\begin{aligned} \omega_0\mu_0 + \omega_1\mu_1 &= \mu_T \\ \omega_0 + \omega_1 &= 1. \end{aligned} \tag{5}$$

By iteratively computing the class probabilities and class means, the threshold t is obtained.

Let A signifies the original image, the isolated binary image α from A can then be represented as follow:

$$\alpha(x,y) = \begin{cases} 1, & \text{if } (A(x,y) > T), \\ 0, & \text{otherwise}, \end{cases} \tag{6}$$

where T is the threshold value obtained by Otsu method, and (x, y) is the pixel position in the image plane A. The pixel values of image A are set to 1 if the pixel value outweighs T; otherwise, the pixel values are set to 0.

In order to separate hot object image β from A, the following description is also utilized:

$$\beta(x,y) = \begin{cases} A(x,y), & \text{if } (\alpha(x,y) = 1), \\ 0, & \text{if } (\alpha(x,y) = 0). \end{cases} \tag{7}$$

Through the above steps, image β is composed of hot object pixels (potential fire pixels) without background, and this image is selected to be further analyzed by motion estimation.

B. *Motion Detection Using Optical Flow*

As airflow makes fire moving, the motion feature of fire is widely used in vision-based fire detection to improve the performance of fire detection. Usually, a bright moving region is marked as a potential fire region in the scene captured by the IR camera. However, based on only clues of motion and brightness, many false fire alarms may be caused. This phenomenon is due to the fact that hot objects other than fire, such as vehicles, animals, and people, may also appear as bright regions. Therefore, in the proposed approach, in addition to motion detection, the motion features are further analyzed in optical flow field to distinguish fires from other moving hot objects.

1) Lucas-Kanade Optical Flow: Optical flow, which plays a vital role in motion detection and analysis for computer vision, is likewise used in this study for fire detection. It is generally described as two dimensional distribution of brightness patterns motion velocities in the images. Each pixel corresponds to one velocity vector which forms an optical flow field capable of being used for more advanced analysis. The core idea of optical flow is to use the following brightness consistency assumption:

$$\frac{d}{dt}I = \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = I_x u + I_y v + I_t = 0, \tag{8}$$

where $I(x, y, t)$ represents a function of image brightness with parameters of spatial coordinates (x, y) and time t. The flow vector $(u, v) = (x_t, y_t)$ is the velocity of moving pixel (x, y).

According to the concept introduced by Lucas and Kanade [29], an additional constraint is merged with the classical optical flow (8) for the calculation of optical flow. This constraint presumes that the flow vector (u, v) is locally constant within a neighborhood Ω. In this region, the following term can be minimized:

$$\sum_{(x,y)\in\Omega} W^2(x)(I_x u + I_y v + I_t)^2, \tag{9}$$

where $W(x)$ is a window function that favors the center section of Ω. The solution to (9) then gives:

$$\begin{bmatrix} \sum W^2 I_x^2 & \sum W^2 I_x I_y \\ \sum W^2 I_y I_x & \sum W^2 I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} \sum W^2 I_x I_t \\ \sum W^2 I_y I_t \end{bmatrix}. \tag{10}$$

2) Optical Flow Analysis for Fire Movement Detection: Compared with ordinary moving objects, fire movement is random, and the shape of fire changes irregularly. This feature can be used to reduce the false alarms which may be caused by ordinary moving hot objects by conducting optical flow analysis.

Through Lucas-Kanade method, the computation results of optical flow can be presented as $\{f_i | f_i = [f_{xi}, f_{yi}]^T, i = 0, 1, ..., k\}$, and k is the whole number of fire candidate pixels which are chosen by hot objects detection. The variation of optical flow velocity direction is utilized to further determine fire pixels:

$$\begin{aligned} \bar{b}_k &= \frac{1}{k-1}\sum_{i=1}^{k}(d_i - \bar{a}_k)^2, \\ \bar{a}_k &= \frac{1}{k}\sum_{i=1}^{k} d_i, \end{aligned} \tag{11}$$

where $\bar{a}_k$ denotes the average directional angles of velocity, $\bar{b}_k$ is the orientation variation, while d_i is defined as follows:

$$d_i = \begin{cases} \arctan(\frac{f_{yi}}{f_{xi}}), & \text{for } f_{xi} > 0, f_{yi} > 0 \\ \pi - \arctan(\frac{f_{yi}}{f_{xi}}), & \text{for } f_{xi} < 0, f_{yi} > 0 \\ \pi + \arctan(\frac{f_{yi}}{f_{xi}}), & \text{for } f_{xi} < 0, f_{yi} < 0 \\ 2\pi - \arctan(\frac{f_{yi}}{f_{xi}}), & \text{for } f_{xi} > 0, f_{yi} < 0. \end{cases} \tag{12}$$

Since fire oscillates irregularly, it is assumed that the movements of fire pixels outweigh the orientation variations. Fire pixels (F_p) are judged by the rule below:

$$\begin{aligned} F_p &= \begin{cases} 1, & \text{if } (b_i > \bar{b}_k), \\ 0, & \text{otherwise,} \end{cases} \\ b_i &= (d_i - \bar{a}_k)^2. \end{aligned} \tag{13}$$

If b_i exceeds the threshold $\bar{b}_k$, the pixel is then classified as fire pixel and its value is given by 1, otherwise it is set as 0.

After the fire regions segmentation, the morphological operations are also employed to remove the unconnected and irrelevant pixel regions, which may seriously influence the fire detection performance. Finally, the blob counter method capable of tracking the number and direction of blobs is used to track fire regions.

III. Effectiveness Evaluation and Analysis

The proposed fire detection method is developed in Matlab/Simulink software. A desktop equipped with Intel Core $i7$ processor and $8GB$ memory is adopted here for image processing. In this work, a database from the website (http://cfdb.univ-corse.fr/index.php?menu=1) is used for verifying the effectiveness of the proposed fire detection approach. The images, whose resolutions are 1024×768, are captured by NIR camera.

Fig. 3 presents the experimental results of the proposed approach that is tested on video sequences of the database. The first column of Fig. 3 lists the raw images (Figs. 3(a), 3(e), 3(i) and 3(m)); the second column of Fig. 3 is the segmentation results of hot object (Figs. 3(b), 3(f), 3(j) and 3(n)); the third column of Fig. 3 shows motion detection results processed by the optical flow analysis (Figs. 3(c), 3(g), 3(k) and 3(o)); the forth column of Fig. 3 displays fire zone tracking results obtained via the blob counter method (Figs. 3(d), 3(h), 3(l) and 3(p)).

In Figs. 3(b), 3(f), 3(j) and 3(n), it is shown that the high intensity regions which represent hot objects have been effectively extracted from the image background by using the

Otsu method, but non-fire hot regions with motion are also wrongly extracted (as shown in Fig. 3(j)). This phenomenon is caused by the heat radiation and light reflection of fire or lights. Therefore, in order to improve the accuracy of fire detection, the motion feature analysis utilizing optical flow for finding accurate fire regions are also employed to further check the extracted candidate areas.

Figs. 3(c), 3(g), 3(k) and 3(o) show the thresholding results after the further image processing using optical flow estimation. From these figures, one can obviously observe that the non-fire hot regions are all removed.

Figs. 3(d), 3(h), 3(l) and 3(p) display that the segmented fire areas are well tracked by employing the blob counter approach.

The experimental results demonstrate that the proposed method is capable of detecting, segmenting, and tracking the fires with satisfactory performance, while the false alarms potentially caused by the fire analogues in IR images are significantly reduced as well.

IV. Conclusions and Future Works

This paper proposes a fire detection method for the application of UAV-based forest fire surveillance using IR camera. This approach takes advantages of both brightness and motion features of fire in IR images to improve the accuracy and reliability of forest fire detection. By using histogram-based segmentation and optical flow analysis, fires from background as well as non-fire hot moving objects can be well differentiated. Experimental validations are conducted in IR fire video sequences, good experimental results are obtained with significantly improved performance. Future works can extend to the combination of IR images with visible range images together to reduce the false alarm rates of fire detection.

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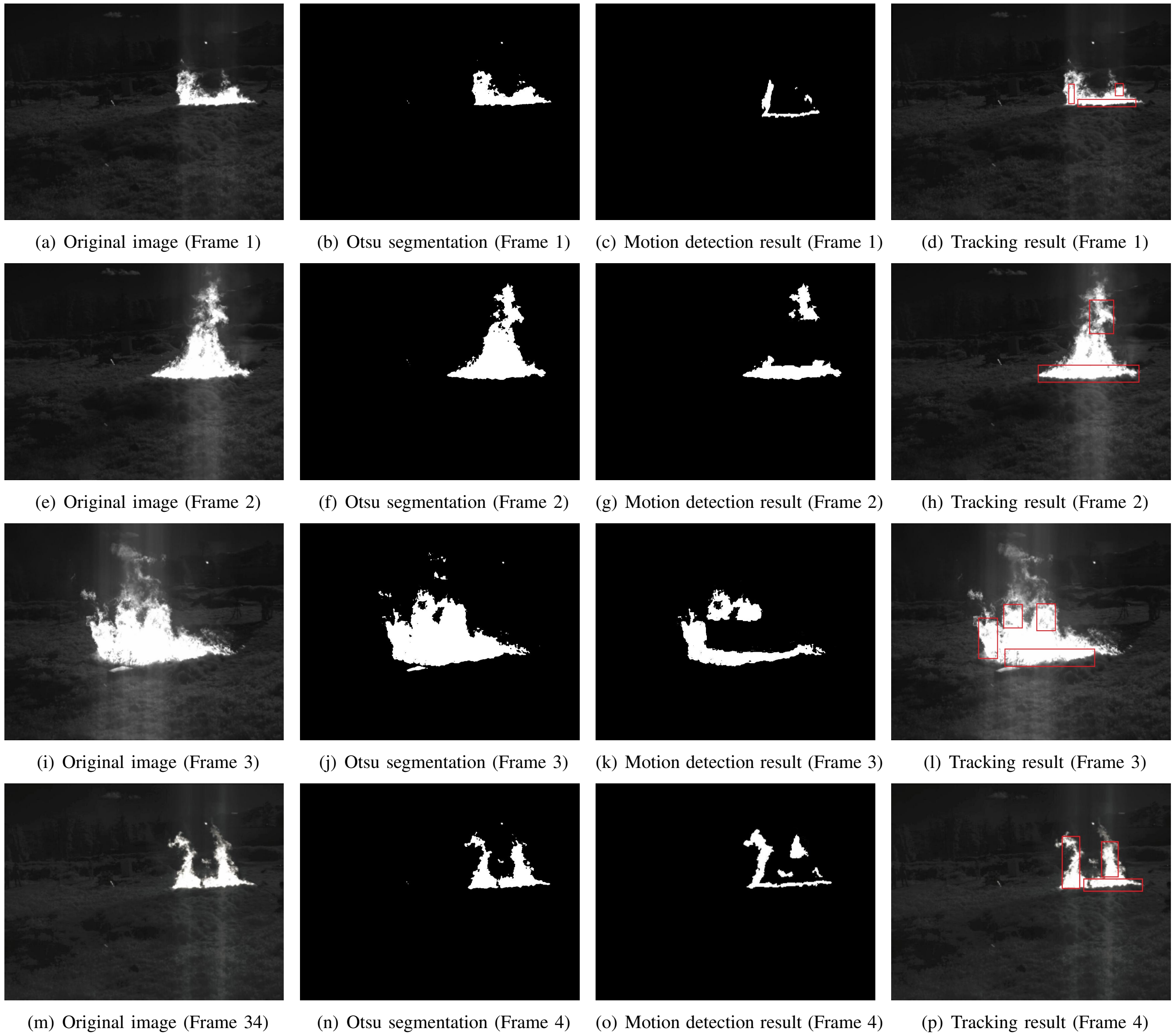

Fig. 3: Experimental results of sample frames.

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