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A Low-cost Fire Detection System using a Thermal Camera

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Abstract

In this paper, we present a low-cost fire detection system using a thermal camera and a smartphone. The developed system collects thermal and RGB videos from the developed camera. To detect fire, candidate fire regions are extracted from videos obtained using a thermal camera. The block mean of variation of adjacent frames is measured to analyze the dynamic characteristics of the candidate fire regions. After analyzing the dynamic characteristics of regions of interest, a fire is determined by the candidate fire regions. In order to evaluate the performance of our system, we compared with a smoke detector, a heat detector, and a flame detector. In the experiments, our fire detection system showed the excellent performance in detecting fire with an overall accuracy rate of 97.8 %.

Keywords: Thermal Camera, flame detection, fire detection, low-cost, BMV

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1. Introduction

With an increase in the population density of cities, the continued popularity of high-rise buildings has greatly increased the potential damage from fire. While property damage caused by fire from 2007 to 2011 was estimated to cost approximately 1.4 billion dollars, this rose to 1.7 billion dollars from 2012 to 2016 [1]. Thus, accurate fire detection is required to reduce false alarms, improve the detection time and thus limit potential damage. However, existing fire detection systems in South Korea have a number of issues. Even though traditional smoke detectors and heat detectors are less sensitive to dust and light reflection, automatic fire alarms connected to a fire station on average only detected 4 out of 500 alerts in 2013 [2].

In this paper, we developed an early fire detection system that uses a thermal camera to dynamically analyze a fire region, including its ambient temperature. We used the MCIMX6Q5EYM10AD microcontroller (Freescale, USA) [3] in the system. We also used Lepton (FLIR, USA) [4] as a thermal camera and Omnivision (Omnivision, USA) [5] as a RGB camera to obtain thermal videos and red, green, and blue (RGB) videos. Finally, an Android smartphone (Samsung, Korea) application was developed to monitor the thermal and RGB videos in real-time.

This paper is organized as follows. Section 2 introduces related researches. Section 3 describes the proposed methods. Section 4 presents the developed system. Section 5 shows the experimental results, and Section 6 provides a discussion and conclusions.

2. Related Work

Numerous auto-fire detection studies have been reported [6-8]. In [6], an automatic home fire detection system was proposed to detect fires using a camera. The system detects fires using only RGB colors by controlling the switching of a conditional circuit. First, the system obtains raw videos that are converted to RGB videos; then, their contrast is adjusted. The fire region is detected using a detection threshold calculated according to experiments featuring 100s of images, and by comparing the features and size of adjacent frames. In [6], the fire detection accuracy rate was 90%, where the accuracy was compromised by light reflection. In [7], smoke was detected by extracting static and dynamic features from images. Smoke is denoted by gray patches and motion using a morphology filter, edge extraction, and labelling. In [7], smoke was detected in 4 seconds to detect fire. In [8], a fuzzy-logic control system was developed to detect fire in a vehicle using an Arduino board.

Min Cai et al. proposed forest fire smoke detection algorithms based on intelligent video analysis [9]. They extracted a moving object based on an accumulative model considering energies of wavelet subimages, compactness and the direction of the moving region. Objects were classified as fires according to an analysis of the features of the smoke. In [10], De Zhang et al. proposed a novel method to detect fire in real-time using video sequencing data. They detected fires using a Markov model by analyzing changes in pixel color and form of the edge over time. The algorithm was tested using threevideos obtained during the day and three obtained at night. Indoor experiments, which had a mean detection accuracy rate of 96.4%, showed better results than outdoor experiments. The accuracy rate for videos featuring complicated backgrounds typically exceeded 90%.

Foggia et al. used color in the YUV space in combination with the movement of the blobs detected via SIFT descriptors [11]. They also used the shape variation of the minimum bounding boxes that enclose the detected blobs. Finally, they used a multi-expert system (MES) to achieve prediction over these three features. Their experiments showed good results in terms of accuracy, but with a considerable rate of false positives. Generally, video processing-based fire detection algorithms have been processed using two principal characteristics of fire, flame and smoke [12] [13]. The joint detection of smoke and flame with the utilization of video processing technologies is still a problem, mainly due to following reasons: different characteristics of smoke and flame, diversity of background, lighting and none of the primitive image features such as intensity, motion, edge and texture characterizes smoke and flame as well. However, The cost of installing a system using many sensors has increased significantly, leading to a decrease in the use of fire detection systems. In this work, we developd a low-cost fire detection system using a thermal camera and an RGB camera.

3. Fire Detection Method

Fig. 1 shows a flow chart of the proposed fire detection method. To detect fire, candidate fire regions are extracted from videos obtained using a thermal camera. Then, the block mean of variation (BMV) of adjacent frames is measured to analyze the dynamic characteristics of the candidate fire regions. When analyzing the dynamic characteristics of regions of interest (ROIs), if the BMV of the current frame (n) is greater than the BMV of the previous frame (n-1), the candidate fire regions are determined as being at ambient temperature. Finally, a fire was determined to be detected when the temperature ratio between adjacent frames of the candidate ambient fire area increased by more than 20%.

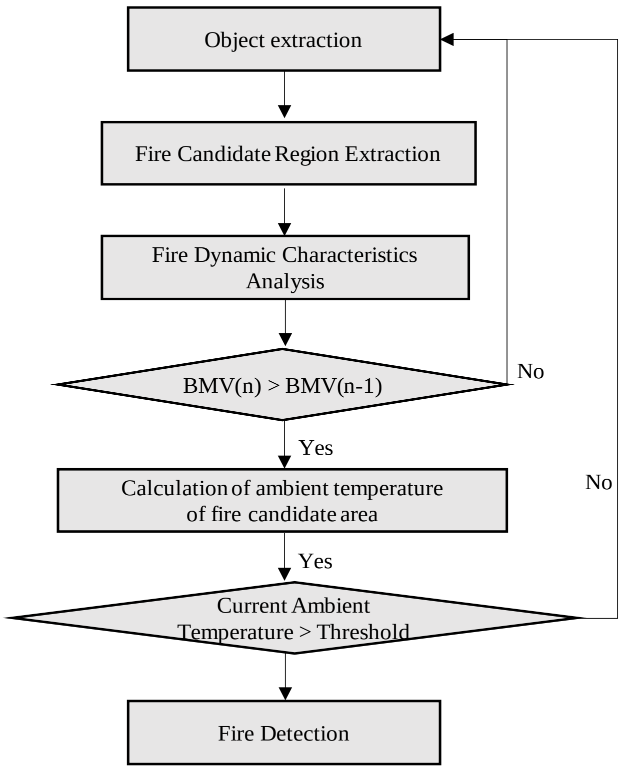


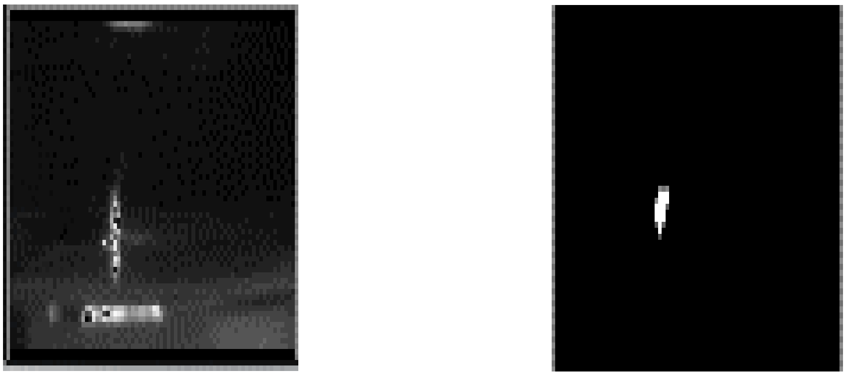
Fig. 1. Flow chart of the proposed fire detection method.

3.1 Extraction of Candidate Fire Regions

Since thermal videos can be affected by uncontrollable environmental factors, fire detection accuracy using only the fixed threshold values was low when the candidate fire regions were extracted. Thus, standard deviation (SD), average, and maximum values were calculated to improve the fire detection accuracy [14]. The threshold *T* was calculated as follows:

$$T = \mu + 3 \cdot \alpha \cdot a + (1 - \alpha) \cdot d, \tag{1}$$

where μ, a, d, represent the mean, SD, and maximum brightness, respectively, and α is a weighting factor. The brightness of the thermal videos was decreased using Equation 1. **Fig. 2** shows an example of extraction of a candidate fire region.



(a) (b)

Fig. 2. Extraction of a candidate fire region. (a) Raw image, (b) extracted image.

3.2 Flame Image Analysis

Flames can be affected by external factors, such as wind and combustibles. **Fig. 3** shows changes in the thermal image of flame radiance during large-scale open burning. BMV is calculated by the size change in thermal images [15]. The mean difference δ between five continuous frames was calculated according to the BMV. Ambient temperatures were calculated when δ exceeds a threshold. The BMV was calculated using the following equation:

$$mBMV(m, n) = \frac{1}{5}\sum_{k=1}^{5} BMV_k(m, n), \tag{2}$$

where *m* and *n* represent the block coordinates of the candidate fire regions and *k* is the number of frames. **Fig. 4** shows the BMVs calculated from continuous frames of a thermal video. While changing from Area 1 to Area 2, the flame radiance was rapidly reduced due to external factors, such as wind.

Fig. 3. Changes in flame size at (a) 0.3 seconds and (b) 0.9 seconds.

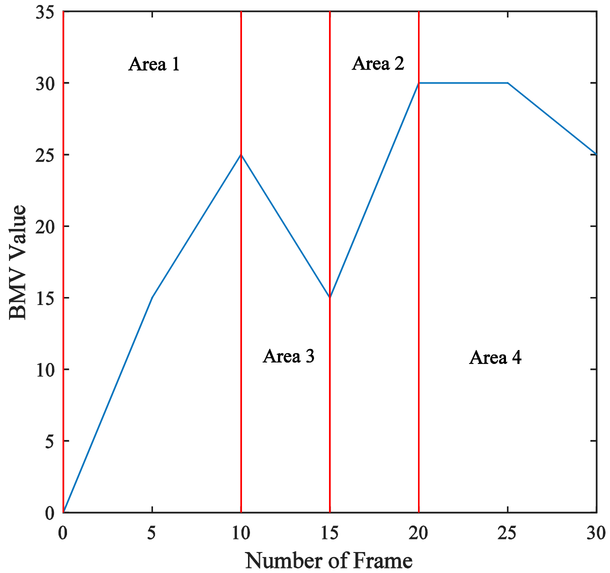


Fig. 4. Calculated block mean of variation (BMV) values from a thermal video.

3.3 Temperature Calculation

To calculate the temperature of the thermal images, we conducted several experiments. The thermal images were obtained with a temperature control panel; the temperatures of the thermal images ranged from 0 to 80 ℃, in 5 ℃ increments, as shown in **Fig. 5**. The mean temperature of the top 1% pixel values was calculated using linear regression. The temperature was calculated using the following equation:

$$Temperature\ (°C) = k \cdot 0.0217 + 156.77, \tag{3}$$

where k is the RGB value.

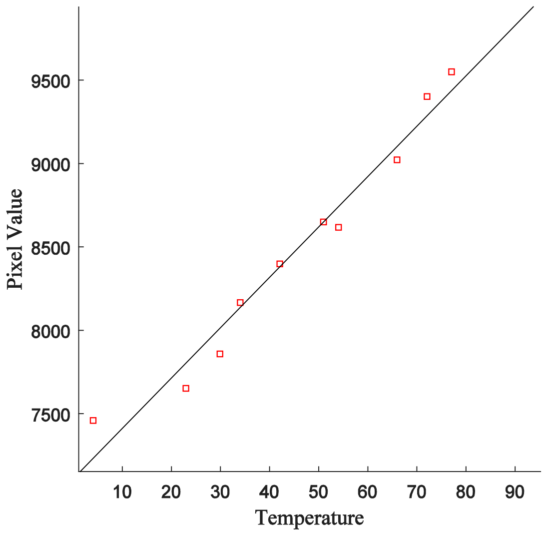


Fig. 5. Temperature calculated with a ground true value using a temperature control panel.

3.4 Flame Temperature Analysis

We used a Lepton thermal camera [4] for the flame temperature analysis. Because the Lepton camera only measures temperatures ranging from -20 to 60 ℃, it cannot be used to detect fire when the flame temperature exceeds 2,000 ℃. Thus, our system detects fire by calculating the ambient temperature of the flame. To measure the flame temperature, the average temperature of several high-temperature pixels, extracted from areas around fire regions, was determined using Equation 3. A fire was considered to be present when the calculated temperature was above the detection threshold. **Fig. 6** shows an example of changes in the ambient temperature over time.

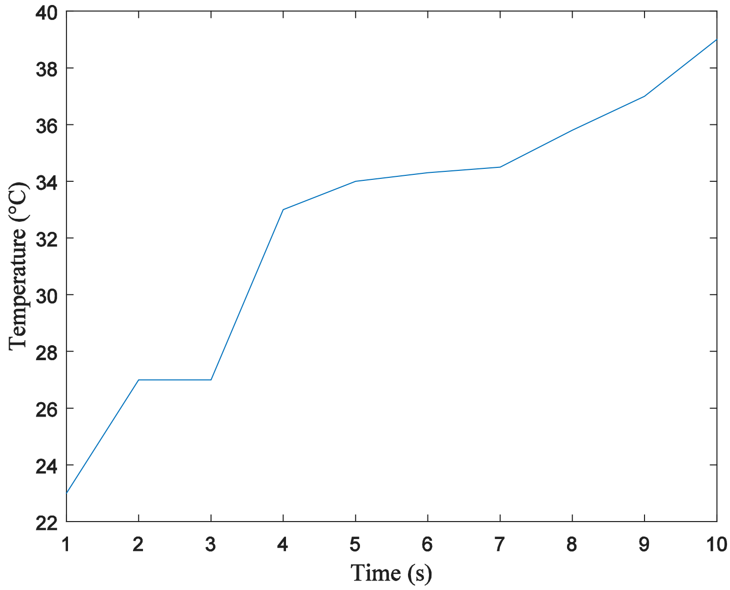


Fig. 6. Change in ambient temperature over time.

Ambient temperature analysis represented the most significant step in the proposed method. To observe changes in ambient temperature, the temperature of the region surrounding the fire was measured (i.e., the area within 1–5 m of the fire) in 0.3-m increments when the temperature in the room was approximatelty 18 ℃. **Fig. 7** shows changes in temperature in the area between the fire and the thermal camera. As the distance between the fire and camera increased, the temperature rapidly decreased.

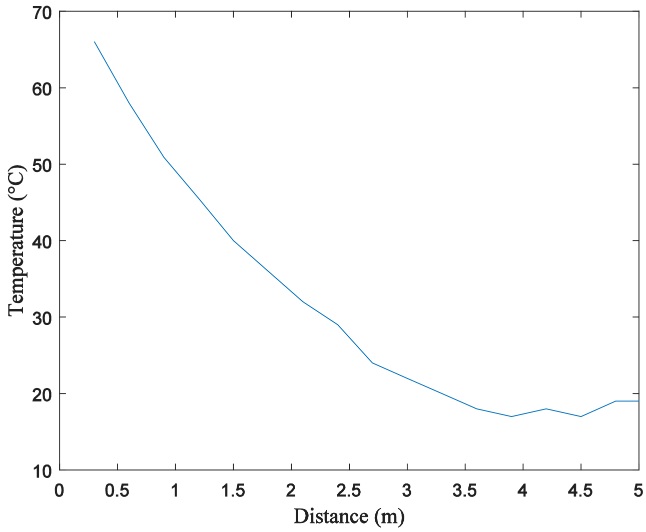


Fig. 7. Changes in ambient temperature by distance between the fire and thermal camera.

The number of flame pixels was measured over a distance ranging from 1 to 5 m, in 0.3-m increments. **Fig. 8** shows thermal images of the flames. When the distance between the fire and thermal camera was 0.3 m, 1 m, 3 m, and 5 m, the number of pixels was 50, 24, 7, and 1, respectively. **Table 1** shows the number of pixels obtained at each distance.

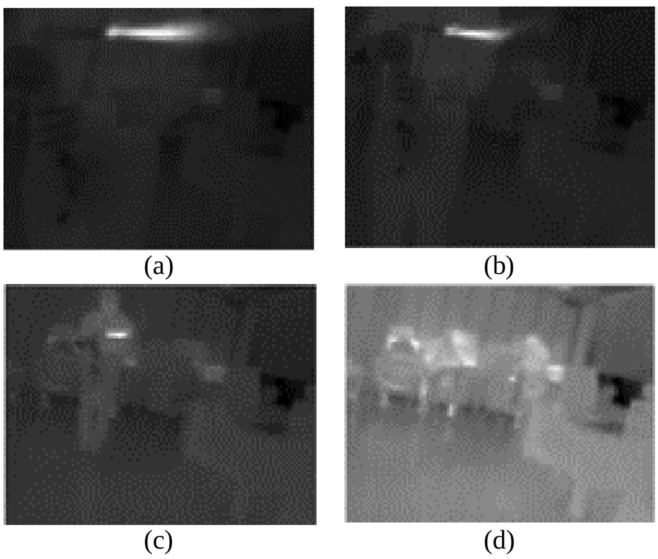


Fig. 8. Thermal images of the flames at a distance, between the fire and thermal camera, of (a) 0.3 m, (b) 1 m, (c) 3 m, and (d) 5 m.

Table 1. Number of flame pixels according to the distance between the fire and thermal camera.

Distance (meter)	The number of pixels
0.3	50
0.6	35
0.9	30
1.2	24
1.5	20
1.8	19
2.1	14
2.4	11
2.7	9
3	7
3.3	5
3.6	4
3.9	3
4.2	3
4.5	1
4.8	1
5	1

4. Fire Detection System

4.1 System Structure

The system is composed of a fire detection camera and a smartphone application that monitors target areas and sends alerts to a smartphone when a fire is detected. The application displays both RGB videos and thermal videos, and sends a fire detection message to a monitoring agent.

4.2 Hardware

We used the MCIMX6Q5EYM10AD (Freescale, USA) as the main chipset. **Fig. 9** shows the architecture of our system.

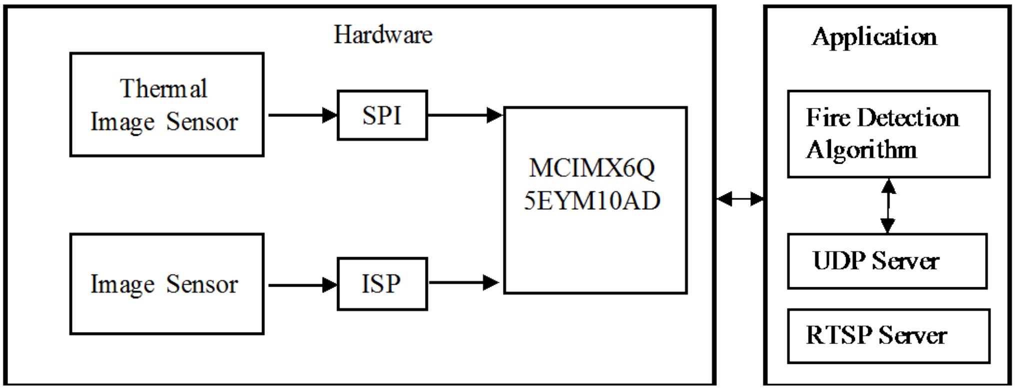


Fig. 9. Architecture of the developed system

The developed camera consists of a Lepton thermal image sensor and an Omnivision image sensor. Data obtained from the Omnivision are sent to the MCIMX6Q5EYM10AD for image sensor processing (ISP). Then, the video data are compressed by an H.264 encoder and sent to a WiFi module. Finally, the video data are sent to the monitoring application using a real-time streaming protocol (RTSP) [16] server. Data obtained from the thermal sensor are sent to the main chipset by a serial peripheral interface (SPI). Then, the video data are sent to the monitoring application via the user datagram protocol (UDP) server. Furthermore, the video data are analyzed to check whether a fire was detected. Fig. 10 shows the developed fire detection camera.

(a) (b)

Fig. 10. The developed camera (a) top view, (b) side view

4.3 Fire Detection Application

Fig. 11 shows a block diagram of the developed system. The thermal camera sends videos to the UDP server for analysis. Then, the UDP server sends a thermal image and alarm packets to the application, and the application displays the information by parsing the received packets. Meanwhile, an RTSP server sends RGB videos to the Android application.

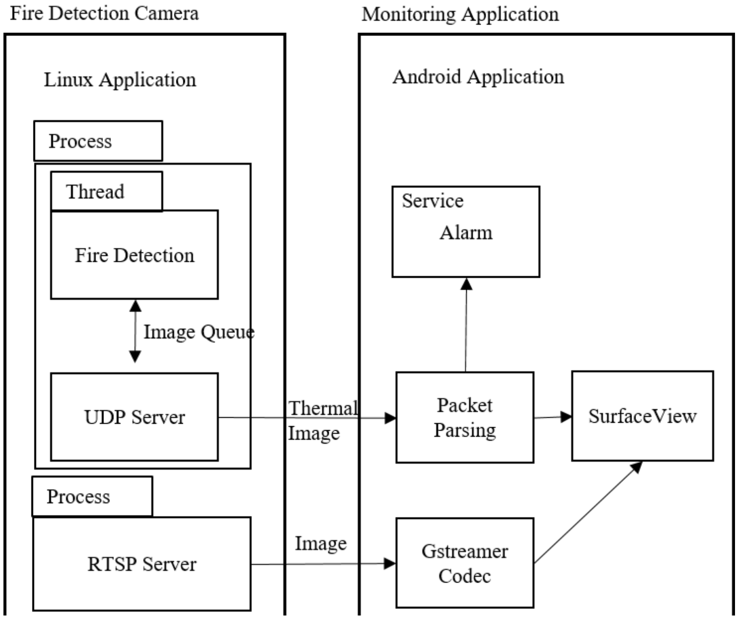


Fig. 11. Block diagram of the developed system

4.4 Camera Server Application

The camera server application is composed of ThermalThread, FireDetection and SafeQueue classes and has been developed using C++. The ThremalThread class opens an SPI bus port, receives videos from the thermal camera, and then sends the thermal videos to a remote device.

A video of the flames is sent through the ThermalImageReadFuction by SPI to a remote device via UDP. The FireDetection consists of ImageQueue for saving thermal images and running the fire detection thread, FireArea for storing fire candidate regions, and a TCP socket for sending a fire message to the remote device. The GetArea function identifies candidate fire regions from thermal videos obtained via ImageQueue. The FireKinetic function analyzes the dynamic features of the fire. Finally, a thermal video and fire detection message are sent to the remote device using the TCP socket when a fire is detected.

4.5 Monitoring Application

The monitoring application was developed using Android Studio (Samsung) for the Android 5.0 smartphone. **Fig. 12** show a class diagram and a screenshot of the application.

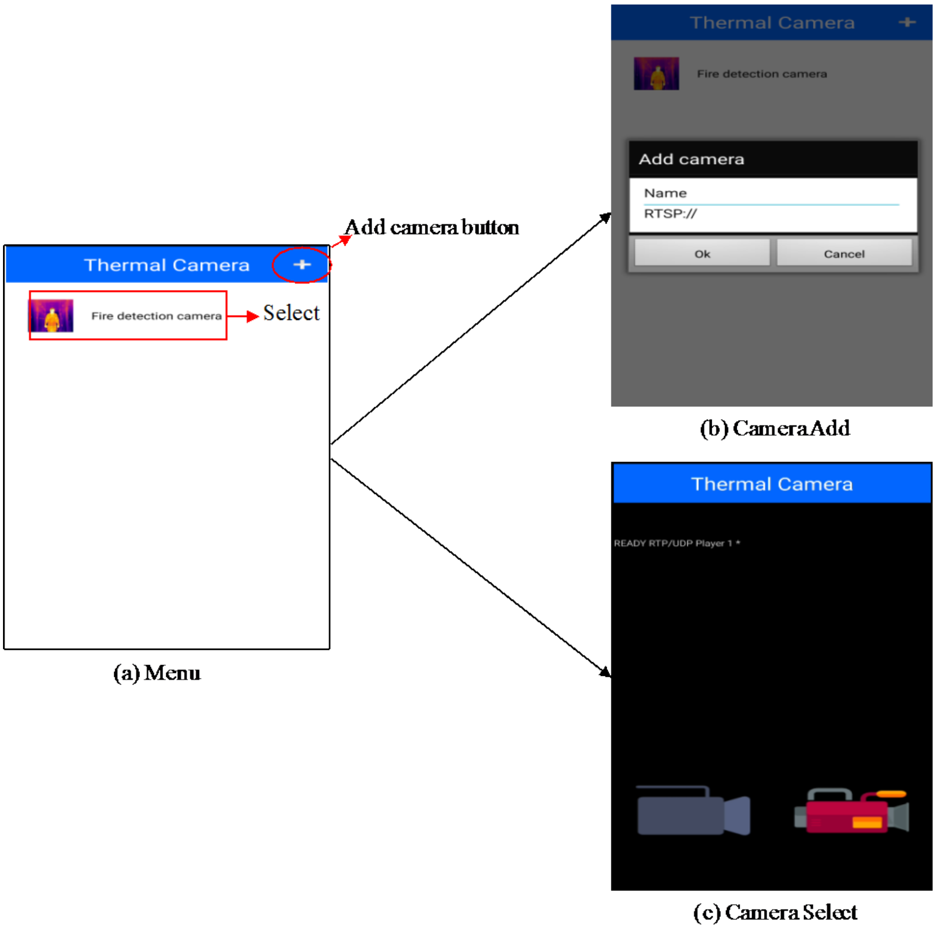
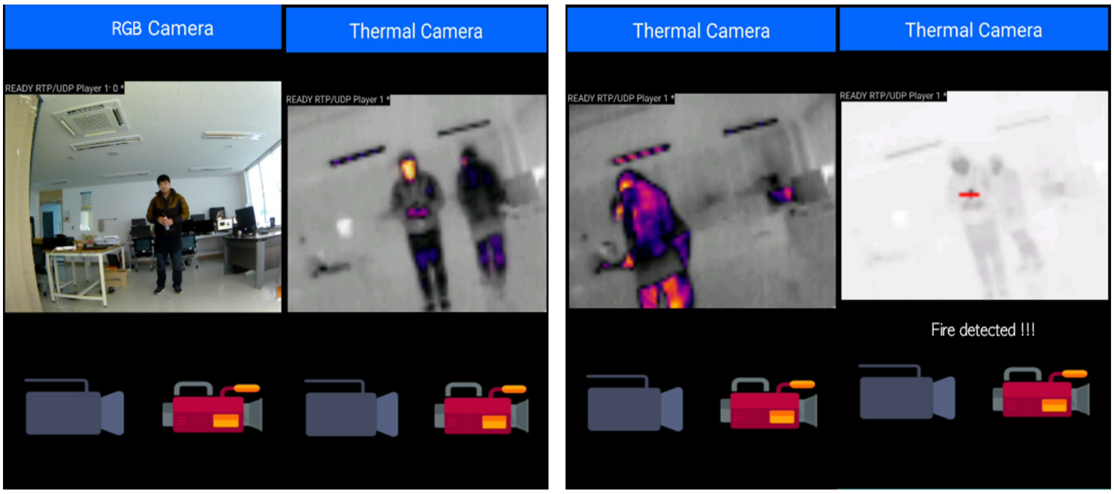


Fig. 12. Screenshot of the developed application.

Since Omnivision sends high-definition (HD) videos to the application, delays of over 8 s occur when decoding videos using Java. Thus, the Gstreamer [17] C++ library was applied to our system using a native development kit (NDK). Videos obtained by the RTSP are decoded and displayed using an H.264 decoder. **Fig. 13-(a)** shows a screenshot of the application, which is displaying RGB and thermal videos. **Fig. 13-(b)** shows a screenshot of the application displaying a fire detection message.



(a) (b)

Fig. 13. Smarthphone application. (a) Red, green, and blue (RGB) and thermal videos displayed on the smartphone application, and (b) detection of a fire.

5. Experimental Results

Experiments were conducted in both indoor and outdoor environments to evaluate the developed fire detection system. A fire was determined to be present when a 10-cm flame was detected within 10 s and at 3 m. The fire detection accuracy rate was 97.8%, as shown in **Table 2**. Regarding the cases of failure, heat, smoke, and fireworks were not detected from a thermal video due to dust and sunshine.

Table 2. Experimental results of the developed thermal camera at a distance of 3 meters between the fire and camera.

Indoor/Outdoor	**Accuracy Rate (%)**			
	Temperature	**Smoke**	**Flame**	**Total**
Indoor	97	97	97	**97**
Outdoor	100	100	100	**100**
Total	97.8	97.8	97.8	**97.8**

Table 3 shows a comparison between the performance of the developed camera and a commercial thermal camera, Therm-App [18]. The developed camera and the Therm-App camera both had a 100% accuracy rate at 1 meter. The accuracy rate of the developed camera was 100% at 2- and 3-m distances from the fire, while that of the Therm-App camera was 33% at both distances.

Table 3. Experimental results of the developed system using a Thermal-App camera

Indoor/ Outdoor	The Developed Camera			Thermal-App		
	# of experiments	Distance (m)	Accuracy Rate (%)	# of experiments	Distance (m)	Accuracy Rate (%)
Indoor	25	1	100	25	1	100
Indoor	25	2	100	25	2	0
Indoor	25	3	100	25	3	0
Outdoor	25	1	100	25	1	100
Outdoor	25	2	100	25	2	0
Outdoor	25	3	100	25	3	0
Total	**150**		**100**	**150**		**33**

Table 4 shows a comparison between the developed system and other commercial products. The accuracy rates of the temperature detector and the smoke detector were 0%, while those of the developed camera and flame detector were 100%.

Table 4. Results of the developed system compared with commercial products.

Indoor/Outdoor	# of experiments	Accuracy Rate (%)			
		The Developed Camera	Commercial products		
			Readers (Temperature detector)	SSV-10i (Smoker Detector)	FS-1000e (Flame Detector)
Indoor	25	100	0	0	100
Outdoor	25	100	0	0	100
Total	**50**	**100**	**0**	**0**	**100**

6. Conclusion

In this paper, we developed a fire detection system using a low-cost thermal camera. The developed camera sends thermal and RGB videos, as well as fire detection messages, to a monitoring application. The videos are subjected to time-series analysis to extract candidate fire regions. Finally, the ambient temperatures of candidate fire regions are analyzed to confirm fire occurrence. To evaluate our system, experiments were conducted in both indoor and outdoor environments. The fire detection accuracy rate of the system was approximately 97.8%. We also compared the performance of our system with that of other commercial products. Our system and flame detector successfully detected fires, whereas commercial temperature and smoke sensors did not. In future work, we will improve the accuracy of the detection rate using other thermal cameras.

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