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Smart city and fire detection using thermal imaging

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***Abstract*—In this paper, we summarize the results obtained from fire experiments. The aim of the work was to develop new methods of fire detection using IR thermal imaging cameras and dedicated image processing. We conducted 4 experiments in different configurations and with the use of different objects. The conducted experiments have shown the great usefulness of infrared cameras for detecting the seeds of a fire. Even cheap low-resolution bolometric detector modules can detect hot spots.**

***Index Terms*—fire detection, thermography, smart city, image processing**

I. Introduction

The aim of the research project planned to be realized by OKE Poland is to develop a modern Smart City solution for automatic image and sound analysis of public spaces using machine learning technology. Additionally, system will allow measuring meteorological parameters, controlling LED lighting and creating statistics based on the recorded data. The system will be integrated with the application to neighborhood communication, so the citizens will be informed about incidents automatically detected near them. System consists both of hardware and software layer. While designing the Smart Community system, OKE Poland anticipated functionalities that are the answer to the most important diagnosed needs: low level of security, low efficiency of municipal services, barriers in communication between residents and municipal services and city authorities, and between the residents themselves, high energy consumption or environmental pollution. Implementation of the system will directly affect the innovation of the community/city, reduction of infrastructure costs, better management of the community/city. Fire detection is one of the important goals of the project. The developed intelligent monitoring system is to be installed, among others in storage areas/warehouses as well as open and underground parking lots. Therefore, it is important to develop systems that are able to distinguish the developing fire from other heat sources, such as a hot engine of a parking car.

Early fire detection is a very important task that could save human life and properties. Traditionally, fire events in open spaces have been detected by humans using visual observation. The introduction of digital cameras and image processing platforms allowed application of technical methods to support observation and detection of fire events. Some methods include the use of cameras mounted at the aeroplanes or at the autonomous unmanned aerial vehicles (UAVs).

Standard fire detection methods using smoke or heat detectors require short distance from the detector and are not suitable for outdoors or large open spaces. Additionally, they often suffer from the false triggering. For these reasons, systems based on the analysis of visible spectrum camera images - widely used in security applications - are more and more popular in the field of fire safety. In general, two approaches can be distinguished in the fire detection algorithms developed in recent years. First one is based on traditional computer vision techniques. These methods focus on manual selected features and machine learning classification. The features usually used are: color [1], [3], [2] and motion detection [4], [5], sometimes the combination of both [6], [7]. Qiu in [8] proposed an auto-adaptive edge detection method. The covariance method for a SVM based classification process was introduced in [9].

Although the presented methods were low-cost and could work in real time, their accuracy in recognizing various fires under various conditions was low. Therefore, another approach of fire detection systems was applying Convolutional

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Neural Networks which provide the automatic and effective feature extraction from images.
The modifications of AlexNet, VGG, Inception and ResNet model was introduced in [10] and [11] to develop smoke and flame detection algorithms. Sharma et al. [12] applied Resnet50 and VGG16 as baseline architectures, but the large sizes of both models prevented their widespread use. Muhammad et al. also have tried to design an appropriate Convolutional Neural Network (CNN) architecture for fire detection and localization. They utilized and fine-tuned architectures of deep learning like AlexNet [13], GoogleNet [14], SqueezeNet [15] and MobileNetV2 [16] and build a tuned models in order to reach a trade off between detection accuracy and efficiency. The first approach of large in size AlexNet as well as smaller but still large GoogleNet models were replaced by the SqueezeNet which was much faster, but its smaller number of parameters had a negative impact on performance. The last approach - MobileNetV2 obtained the best performance of all previous.

However, these studies are focused on fire events observable during a day, when the flames or smoke could be easily detected. The problem is still unsolved for events that happen in poor light conditions, especially during night, when flames are not present (only e.g. embers, smoldering wood, etc.). Recently there is an increase interest in the application of thermal cameras for fire detection. In [17] authors present a simple case study focused on the detection of fire using FLIR SC660 (laboratory test) and FLIR Vue Pro thermal camera (field tests). Using a few experiments they demonstrated the examples of fire representation in images, the change of temperature values in time and potential applications.

Chacon et al. [18] present fire detection method in a thermal video. They use shape regularity and intensity of saturation as a fire features, which are extracted from candidate regions. The linear classifier is used for detection. This method has more than 75% of correct detection and it works with static and moving cameras. In [19] authors are using infrared thermal images for indoor fire detection. Localization and detection suspicious areas in thermal images was made using the assumption of searching for points with a temperature greater than 65 Celsius degrees. To extract features and for dimension reduction Principal Component Analysis method was used. For classification a potential flame of a fire and a light, Support Vector Machine was trained. Yuan et al. [23] proposed algorithm for fire detection in sequences of infrared images acquired by UAV based computer vision system. Histogram-based segmentation (Otsu method) is used to extract fire candidate regions (hot objects). Then, motion vectors of the candidate regions are calculated using optical flow and analyzed to confirm that they are fire regions. Tracking is done through the use of morphological operations and blob counting.
In times of widely popular artificial intelligence, many authors decide to use it also in fire detection. Bhattarai and Martinez-Ramon [20] use state of the art deep learning techniques for improving safety of firefighters rescue missions. Infrared images are used here as such cameras are carried by firefighters. The constructed system is based on CNN algorithms for classification and detection objects of interest. The fire is only one of the detectable object, another objects (e.g. doors, windows, firefighters) or human poses can also be detected. In [22] algorithm based on CNN and Support Vector Machine (SVM) was proposed. Fire features extraction in thermal images was made using CNN named IRCNN, while SVM was trained for fire detection using extracted features. The proposed method achieved high precision and recall.

Some other methods use a combination of visible and thermal images to detect fires. In [21] the UAV used by the authors had two types of cameras (thermal and visible) which registered roughly the same image. Human and fire detection algorithms are mainly based on blob detection, due to the flight height (about two kilometers). The use of thermal imaging is to improve the accuracy of the algorithms. One of the assumptions of fire detection is to use the large temperature difference between the fire and its background. A blob detector (MSER) is used to detect a fire - on the thermal image, combined with a color-based descriptor (chromaticity based moments) applied to the optical image. Classification of the moment-based color pattern between two classes: fire or not, is done using SVM.

II. Materials and Methods

A. Experiments set-up

Testing the possibilities of recognizing fires with the use of thermographic cameras requires appropriate measurement experiments. For this purpose, the following four experiments were designed. All measurements were made in an open space in a separate, controlled zone with fire protection (fire extinguisher and fire extinguishing equipment). Due to the low emission of fire, there was no significant fire hazard. Four different thermal cameras were used for the measurements:

- Flir A655SC (640x480), FOV 45, 13.1mm - radiometric camera used as reference, radiometric seq files for analysis,
- Flir Boson (640x512), FOV 24, f=18mm, mp4 video recording software and radiometric raw own file format,
- CAT S61 smartphone with a Flir Lepton camera (160x120) with built-in mp4 video recording software,
- Thermal Expert i3 System TE-M1 (240x180) connected to a smartphone with dedicated software with built-in mp4 video file format.
- Flir Lepton module (160x120).

Experiment 1: Thermographic cameras were placed at a height of 4.52 m above the ground, and then the thermographic sequences (high 14 bit resolution raw data) were recorded for the situation from: a) The minimum emission of fire (open flame) obtained by lighting a candle, b) Minimal emission of heat (no flame) obtained by a glowing cube of sawdust from the fireplace (typically present heat that may not be noticed or recognized by vision cameras, especially after dark).

Two cameras were used for the measurements: Flir Boson (640x512) and Flir Lepton (160x120). The investigation scene is shown in Fig. 1. The aim of the experiment was to check whether, by means of infrared imaging, it is possible to detect a fire with relatively low resolution cameras equipped with a bolometric detector.

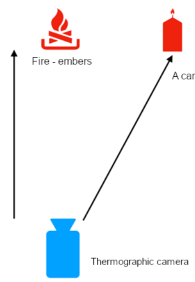


Fig. 1: Experiment 1 set-up. The embers and a candle as reference source

The aim of the *Experiment 2* was to investigate the effect of the distance between the thermographic camera and the source of the fire on the detection efficiency. A cubic cube with dimensions of 10cmx10cmx10cm was prepared as the source of the heat, which was initially incandescent. A lit candle was used as a reference. Ambient temperature in the range of 0-2 degrees Celsius. The measurements were repeated for the increasing distance of the embers (heat source) from the thermographic cameras in the range of 10m, 15m, 20m, 25m, 30m, 35m, 40m and 50m. The image of the ember is presented in Fig. 2a and a scene in Fig.2b.

(a) (b)

Fig. 2: Experiment 2 set-up: a) the ember cubic and b) a scene with ember and candle as a reference source

Experiment 3 - long-term observation of a glowing wood block (A655SC camera, temperature range $-40°C$ to $160°C$). The aim of the Experiment 3 was to investigate the long effect of fire developing. The observation was carried out from a distance of 20m and 15m, recording time 10 minutes with a resolution of 1 frame/s.

Experiment 4 consisted in observing the parking area in order to detect and analyze the temperature distribution of the arriving vehicles. The experiment was performed in winter conditions in the morning hours. The outside temperature was $-8°C$. The exemplary thermogram with the heat sources marked with blue rectangles is shown in Fig. 3.

Fig. 3: Experiment 4 set-up. The thermogram with indicated heat sources like: cars engine, car tires and people

B. *Database*

We have created a collection of recordings for different types of fires: candle flame, open fire and embers. In order to investigate the effect of the distance from the camera on the detection results, we have obtained images of the fire at various distances. A long-term recordings of the extinguishing fire were also made to investigate the nature of temperature changes. In total, about 13,000 frames of fire recordings were collected.
We have also recorded 1500 frames of objects with potentially high temperatures, like moving cars (Experiment 4).

III. Data processing

A. *Spatial resolution of thermal cameras*

We used two types of detectors in our experiments: high spatial resolution (640x480 px) and low resolution (160x120 px). The array of detectors used has an impact on the number of usable pixels that will be in the region of interest - ROI. Of course, there will be more pixels in ROI for high resolution cameras, which is of great importance especially in the case of large object-camera distances. Another issue is the focal length of the lens used and what is related to it, the field of view (FOV) of the camera. We must remember that there are no zoom lenses for thermographic systems. The optics is fixed focus so it will not be possible to zoom in when a heat source is detected (hot spot). Table I shows the number of pixels in the region of interest depending on the detector type and the camera-object distance.

B. *Data conversion*

Images from Flir Boson, Flir Lepton and FLIR A655SC cameras are saved as a sequence of raw data expressed in

TABLE I: Number of pixels in ROI region according to detector type and distance object-camera

Distance [m]	Detector type	
	High resolution (640x480)	*Low resolution (160x120)*
10	182[a]	13[a]
15	72	4
20	42	2
25	25	1
30	25	1
35	12	ROI is too small to detect
40	9	ROI is too small to detect
50	6	ROI is too small to detect

[a]ROI size fitted to hotspot. Number of pixels.

arbitrary units. In order to display the image from one of the recorded frames, the data recorded for each pixel in the image should be converted accordingly. In our case, the original frame data must first be converted from the stored integer to Q14.2 format. Then, using linear interpolation, the current range of values that occur in a given frame is mapped to the 0-255 range (grayscale image). The warmer an object is in the image, the higher the pixel value of that object will be. Mapping the entire range in a given frame, due to the wide range of possible values (14 bit), will result in a low contrast (we will see only the warmest objects). Assuming that the place of fire will have a high temperature - that is, these places will have as high pixel values as possible compared to the surroundings, interpolation can be used to increase the contrast, limiting the upper range of values. As a result, small objects which temperature is lower but could pose a threat, will also be visible while not detected at low contrast.

C. Preprocessing

In order to detect and determine the location of potential fires, we suggest dividing the image into regions for which the analysis is performed separately. If a fire hazard is found, its place is immediately narrowed to a smaller area than the observed one.

Image preprocessing in order to detect high-temperature areas is a simple task for thermal data and comes down to image thresholding on the basis of temperature. Fig. 4 presents the image of Experiment 1 and the results of preprocessing. After thresholding, only embers and candle were detected in ROI 1 and 2 respectively. The candidate regions created in this way can be further processed in order to reject cases of incorrect fire detection in the form of other hot materials like working engines (as long as their temperature is above the threshold).

D. Fire Detection Algorithm from sequence analysis

We have a sequence of images at our disposal (see Fig. 5). So it is worth counting the difference between subsequent images. If a fire develops, the temperature rises and the differential image is a hot area while the rest should be at the noise level. The Δ T images can be calculated for one of the methods which are described by (1) or (2).

$$\Delta T^{n}_{i,j} = T^{n}_{i,j} - T^{n-m}_{i,j} \tag{1}$$

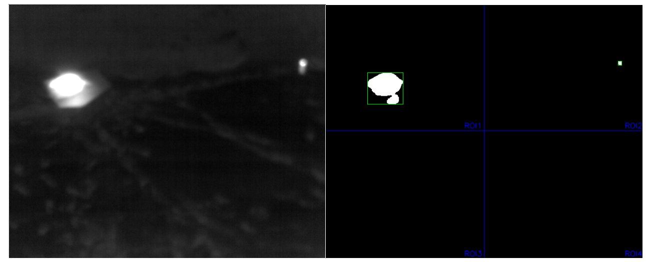


Fig. 4: The thresholding results for Experiment 1

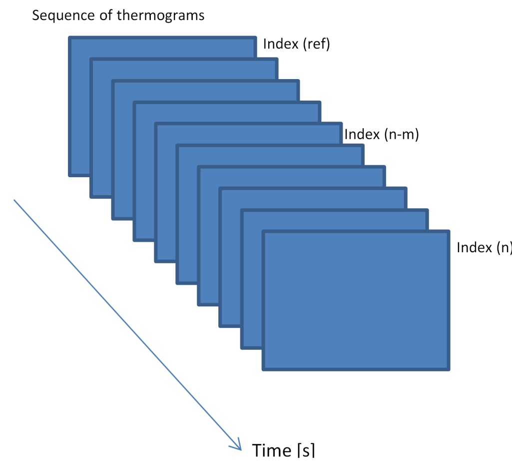


Fig. 5: Time sequence analysis - indexing

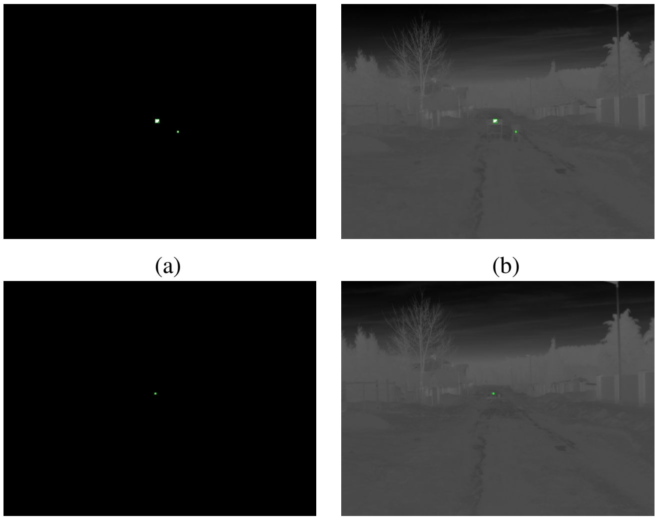
$$\Delta T^{n}_{i,j} = T^{n}_{i,j} - T^{reff}_{i,j}, \tag{2}$$

where: i,j - pixel index in the thermogram, n - actual frame index, m - image interval, reff - reference frame.

E. Influence of distance from thermographic camera on the fire detection efficiency

The recordings made during Experiment 2 were analyzed for the effect of the distance between the thermal imaging camera and the source of fire on its detection efficiency. First method is to use image thresholding applied to image pixels values expressed in arbitrary unit. Detection in binary images was performed by finding the contours of objects that are likely to be the source of the fire. Figure 6 shows the images recorded for the camera positioned at a distance of 15 meters (6a, 6b) and 50 meters (6c, 6d) from the source of fire. In Figures 6a and 6c images after thresholding with the fire sources detected by the first method are shown. Original images with marked regions of fire are presented in Fig. 6b and 6d.

The second method is to apply detection, similarly like in the first method, but on ΔT images. Fig. 7 shows two image examples: for 10 (first column) and 50 meters distance (second column). ΔT images have been calculated using equation 2 (Fig. 7a and 7b). The first frame of the recording was selected as the reference frame and detection was performed for frame number 60 (1s interval between frames). Using a differential



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

Fig. 6: Fire source detection between (a, b) 15 meters and (c, d) 50 meters from thermal camera

image, thresholding was applied to get rid of noise in places where there is no potential source of fires, and then objects were detected in the binary image (Fig. 7c, 7d). Finally, Fig. 7e and 7f present the original images after marking detected fire sources using second method.

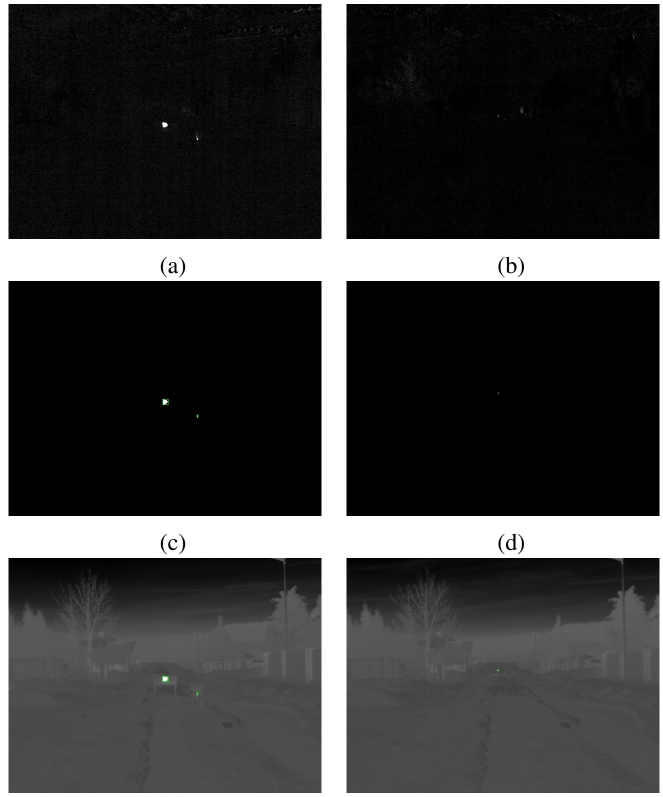
F. Analysis of the temperature changes during fire extinction

Recordings made in Experiment 3 were analyzed for the detection of temperature changes in the fire area over time. In the first frame, the region of interest was determined based on the thresholding result. In the following frames, the average temperatures in a given ROI were calculated. We have verified the nature of these temperature changes by fitting them to the curves. The measure of fit was calculated in the form of the determination coefficient R^2.
Another measurements of the temperature variability during the recording were calculated in the form of standard deviation and the difference between the maximum and minimum average temperature values in ROI ($Diff$, see Equation 3). For the $Diff$ parameter, a normalized value ($Diff_n$) was also introduced (4) in the form of the ratio of the extreme values difference to the number of frames in the recording, in order to eliminate the influence of the recording length on the results (the longer the recording, the greater the temperature difference).

$$Diff = avgT_{max} - avgT_{min} \tag{3}$$

$$Diff_n = \frac{Diff}{n_f} \tag{4}$$

where:
$avgT_{max}$ - maximum value of the mean ROI temperature in the recording,
$avgT_{min}$ - minimum value of the mean ROI temperature in the recording,
n_f - number of frames in the recording.



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

Fig. 7: Fire source detection using Δ T images for 10 meters - (a, c, e) and 50 meters - (b, d, f) distance.

To compare the results with other hotspots, that might be miss-classified as a potential fire based on the high temperature, we have also made all the measurements for the Experiment 4 images of the hot bonnet of a car parked in the parking lot.

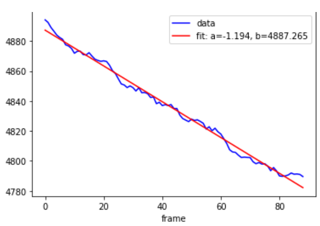
IV. Results

A. Influence of distance from thermographic camera on the fire detection efficiency

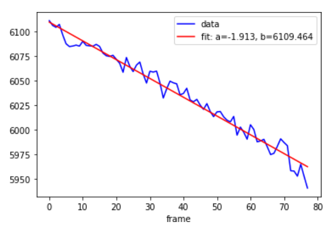
For eight different distances (between 10 and 50 meters) it has been verified that fire can be successfully detected at each of the distances using two different methods (as shown in Figures 6 and 7). For closer distances (i.e. between 10 and 40 meters) the first as well as the second method successfully detect candle flame (as shown in the Figure 6). The use of a high resolution camera (i.e. 640x480) made it possible to detect a fire hazard even from a distance of 50 meters from the camera, with small dimensions of the prepared heat source (cubic cube dimensions was 10cmx10cmx10cm). Table I presents the number of pixels in the ROI, marked manually, in the images recorded for different distances for a high-resolution camera (640x480) and for a low-resolution camera (160x120). A glowing cube was assumed as ROI. When analyzing the obtained results, it can be noticed that for a high resolution camera, the source of fire can be detected even at a large distance from the camera (which was confirmed by the performed experiments). Using a low resolution camera (Lepton - 160x120), hot objects can be successfully detected, but only for closer distances between the source and the camera (for distances above 30 meters - the source of the fire was unnoticeable, and for distances between 20 and 30 meters was almost undetectable). Therefore, when using low resolution cameras, the observation area where a fire is expected should be approximately 20 meters from the camera.

B. Analysis of the temperature changes during fire extinction

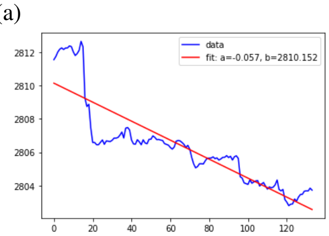
Fig. 8 shows the exemplary temperature measurement results and fitting to the linear function. The average coefficient of determination R^2 for fitting eight different fire recordings to the linear functions was equal 0.86±0.18. Figure 8c shows the temperature changes for the heated bonnet of a car parked in a parking lot (average R^2=0.32±0.28).



(a)



(b)



(c)

Fig. 8: The changes of the average temperature of ROI a), b) for two different examples during fire extinction and c) for the warm hood of a car parked in a parking lot

As it can be seen from Fig. 8, both the temperature of the fire during extinguishing and the temperature of the car while cooling down decrease in a linear manner. However, the process of extinguishing the fire is more rapid. Table II presents the standard deviation of the average temperature measurements in subsequent frames, as well as the difference between the maximum and the minimum values ($Diff$ - Eq. 3) and normalized by the number of recorded frames ($Diff_n$ - Eq. 4).

All parameters show over 40 times higher values for fire detection than for car hood. Such a significant difference makes it possible to use these measures to distinguish the origin of analysed hot region.

TABLE II: Mean parameters of the temperature changes during two examples of hotspot detection

	standard deviation	$Diff$	$Diff_n$
fire	121.85	441.74	1.97
car	2.81	10.22	0.03

V. Conclusions

The conducted experiments have shown the great usefulness of infrared cameras for detecting the seeds of a fire. Even cheap Lepton detector modules can detect hot spots. Thermal image analysis systems also enable the detection of a fire of a smaller size (like candle light) and at a greater distance from the camera. However, it has been observed that the long distance combined with the gusts of wind which temporarily significantly lower the radiation reaching the detector, disturbs the detection

In our experiments, we already had glowing sawdust or a piece of wood. We have observed that when we have a separate (single) glowing piece of wood, it actually goes out. So in our case, the temperature in the area of a developing fire decreased with the passing time of observation. In our considerations, we assumed that a developing fire would be a phenomenon opposite to that observed in the experiments. The temperature will increase over time and the area will become more and more bright, the nature of the process will be the same as for the experiments carried out. The analysis shows that the temperature in a developing fire increases linearly with time and this process model can be used in the developing fire detection algorithm. It is also possible to define parameters that clearly distinguish the source of a detected hotspots. In this work, we considered distinguishing fire from hot car parts, however correct detection of other false positives is possible and depends on the nature of these objects.

It would be necessary to repeat the experiments for other weather conditions - for the summer months, where flat and dark surfaces can heat up to temperatures exceeding 60 degrees Celsius, and to develop thermogram analysis algorithms so as to exclude false positive alarms.

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