The Potential of utilizing Near Infrared Spectrum for fire detection

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1 Abstract

Traditional fire detection in buildings usually uses heat detectors, smoke detectors, carbon monoxide or combined multi-sensor detectors. Those types of fire detection notoriously suffer from very slow response and high rate of false alarm. The advancement of machine learning in recent years has offered a new promising approach to develop fire detection systems. However, most vision-based fire detection algorithms are developed with features extracted from visible spectrum, which can be easily tricked by artificial fire, art work, advertising posters, etc. With IR cameras operating within selected NIR spectrum (850 to 1100nm), only real fire is observed because of high temperature IR emission. Moreover, based on experimental observations, the use of NIR imager greatly simplifies region-of-interest extraction, which is notedly a challenge for objection detection algorithms. This paper presents the potential use of NIR spectrum for fire detection regarding these two aspects.

2 Introduction

Fire safety is of the utmost concern when it comes to building safety. To prevent fire from escalation, the detection of fire at its incipient stage is crucial; timeliness and accuracy are the main necessities of fire detection systems. The conventional fire alarms in buildings employ point-based fire detectors including heat detectors, smoke detectors, and carbon monoxide detectors; besides the issue of slow response due to the diffusion delay, they provide no additional information regarding localization, dimension, etc. In addition, conventional fire detection systems generally have a limited use in small indoor situations [1]. The application of video fire detection can overcome the drawbacks of traditional techniques, as it is possible to detect an occurrence of fire immediately if there is a fire presence in the field of view. However, the performance of video fire detection varies greatly depending on the characteristics of algorithms and camera deployments. The advantages of using near IR for the task will be elaborated upon comparing to that with visible spectrum; meanwhile, its aid to image segmentation as pre-processing for CNN detection technique will be discussed.

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3 Fire detection algorithms

Colour detection is one of the earliest as well as most prevailing method. [2, 3, 4, 5] utilize colour information within RGB space in combination with HSV because common fire appears yellowish to reddish. More advanced colour models use rule-based methods; for example, [6] employs Gaussian smoothed colour histograms, while statistical descriptors are used in [7]. It must be noted that colour model alone cannot be reliable for fire detection because many objects and background may contain similar colour information. In addition, even under the same illumination of the scene, different cameras will register different colours because of its sensor type and build-in algorithms to compensate light. Therefore, the same colour model may not work properly when applied to another camera.

[8] combines colour features with pixel amplitude difference for fire detection in car park. These two methods serve as two separate pipelines for region proposal of fire candidate. Then based on the final region overlap analysis, it triggers the alarm if one or more region overlaps are found. The combined method makes fire detection more robust with a reported accuracy of 93%. However, its detecting spectrum is still within the visible band, which gives rise to potential false alarms in many situations. For example, the video advertisement displays in public areas containing fire will easily trigger the alarm.

There have been a few researches on fire detection with CNN, which are claimed to have higher detection accuracy comparing to expert or rule-based systems. [9] proposed a modified version of AlexNet by fine tuning it according to the specific task. They also make use of transfer learning to improve the detection accuracy to 94.39%. However, this system falls short on spatial resolution; the input image for the network is 224 by 224 resized full frame, which might lose a lot of information. The size of an early fire is very small and may be obscured by smoke. If small fire is far away from the camera, the resulted fire in the image may be smeared due to the drastic resizing. To overcome the loss of spatial resolution, ROI (region of interest) extraction is a promising technique. This not only provides better fire resolution comparing to resized whole image, but also reduces computational load of the detection system. [10] applies a combination of Adaboost and local binary pattern for ROI of fire and smoke. Then the extracted region is fed into a CNN for recognition. It is reported to have more than 95% accuracy with millisecond-scale of response time. Despite of the achieved high detection accuracy, most of CNN based detections use visible spectrum of the fire, which may have difficulties to generalize to be effective for many public situations.

3 Near Infrared physics

Near infrared has a typical range of 750 to 1700nm. This band at the vicinity of common visible spectrum is often overlooked. At its first record for photography in 1910 by Wood, who described the peculiarity of the photograph as intense darkness of the sky but vibrant brightness of trees and grass [11]. Later, this effect was studies to be the cholorophyll effect; when light shines on the epidermis of leaves, it will be scattered in deeper layers in which cellular walls are divided by the inclusion of air; then multiple scattering happens across the depth of leaves resulted in a prominent backscattering [12]. From a biological viewpoint, unlike visible light absorption by chlorophyll in leaves for photosynthesis, the high NIR reflectivity of leaves prevents the plant from overheating through solar radiation. Base on this feature, researchers can identify unhealthy vegetations by analysing the difference of reflectance between visible and NIR spectrums [13].

The high reflectance of NIR by vegetation may pose intensity disturbance for image segmentation, which will be demonstrated in later section. The NIR source in an outdoor situation mainly comes from the sun. Referring to figure.1, the solar radiation at sea level within NIR is slightly weaker than in visible range, which still provides plenty of NIR. It is also observed that outside atmosphere the NIR and longer wave spectrum closely resemble a blackbody at the temperature of 6000K [16]. According to the Planck blackbody radiation in figure 2, as the temperature decreases, the radiation peak shifts towards longer wavelengths. In other words, NIR cameras are able to see radiation emitting from objects at lower temperatures comparing to the common RGB cameras, which is demonstrated in figure 3 (right). This also helps to detect hot objects which can potentially cause a firebreak. Objects as hot as 375 Celsius or higher will appear glowing in the image taken by the Raspberry Pi camera.

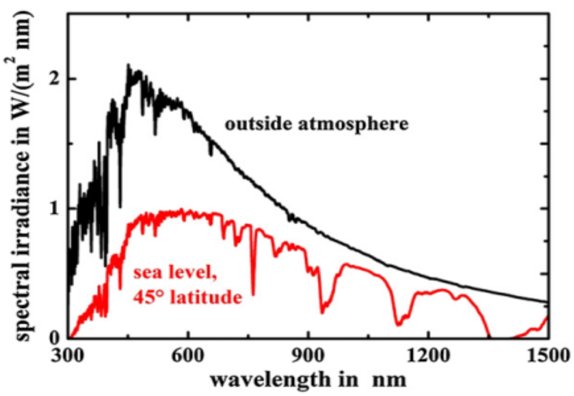

Figure. 1 Visible and NIR spectrum of sunlight [14]

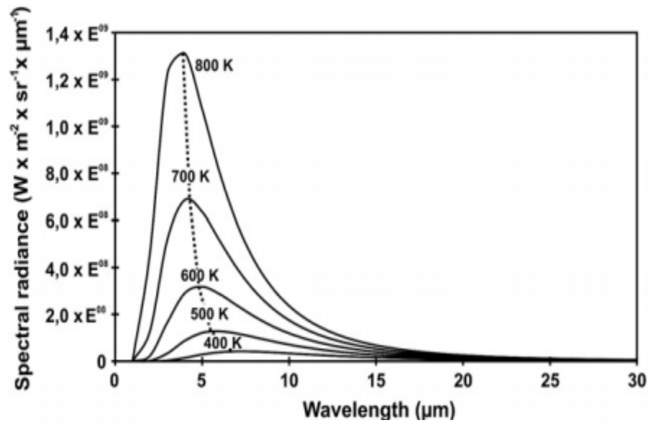

Figure. 2 Planck blackbody radiation at low temperature [15]

4 NIR image sensor

The NIR camera used for this study is the Raspberry Pi camera module v1.3 (5 Megapixels), which uses Si-based back illuminated CMOS sensor. Silicon based image sensors are innately more sensitive to NIR than to visible lights. However, due to its general photographical use, manufactures usually integrate an IR blocker to cut off the incident NIR rays to accommodate the cameras' build-in colour algorithms [17]. As shown in figure 3, the response of the Pi camera module in NIR band was measured; the sensor is responsive up to 1100nm wavelength with a peak at 930nm. This is also the reason why the NIR image from the camera gives a higher contrast of hot objects and fire comparing to the background. Moreover, it is also viable to combine the NIR module with the RGB module for dual band system development. Furthermore, the low cost of the camera module with a connected single board computer is capable for real-time applications.

The spectral response of the Pi camera sensor, in the range of 830nm to 1150nm, was measured using a monochromator. The true response of the Pi sensor is obtained by testing under the same light source as a reference GaInAs photodiode, whose spectral response is already known, by the monochromator. Then, the corrected Pi camera response was normalized by its maximum value.

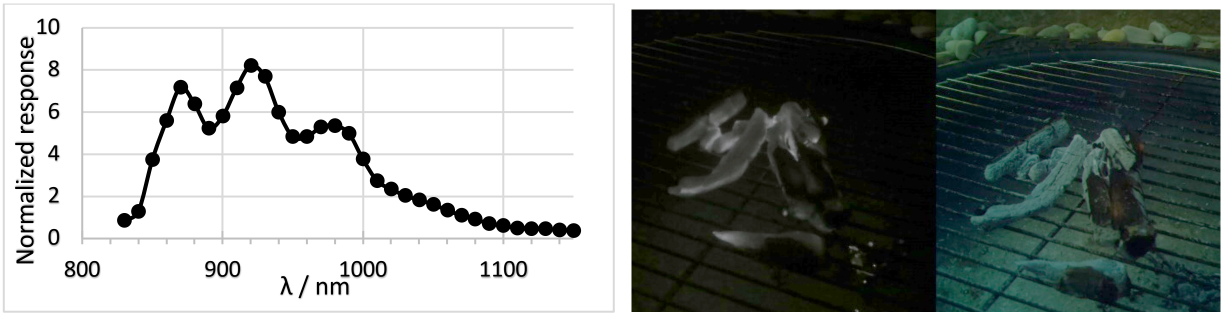

Figure. 3 (left) Normalized response within NIR band, (right) hot charcoal: NIR on the left, visible on the right

5 Proposed ROI extraction for CNN fire detection

At controlled camera setting, the contrast between fire and the background can be further enhanced. Because visible lights are completely cut off, the resulting image is essentially a one channel grayscale image, which requires less computation. Figure 4 illustrates the process of ROI extraction.

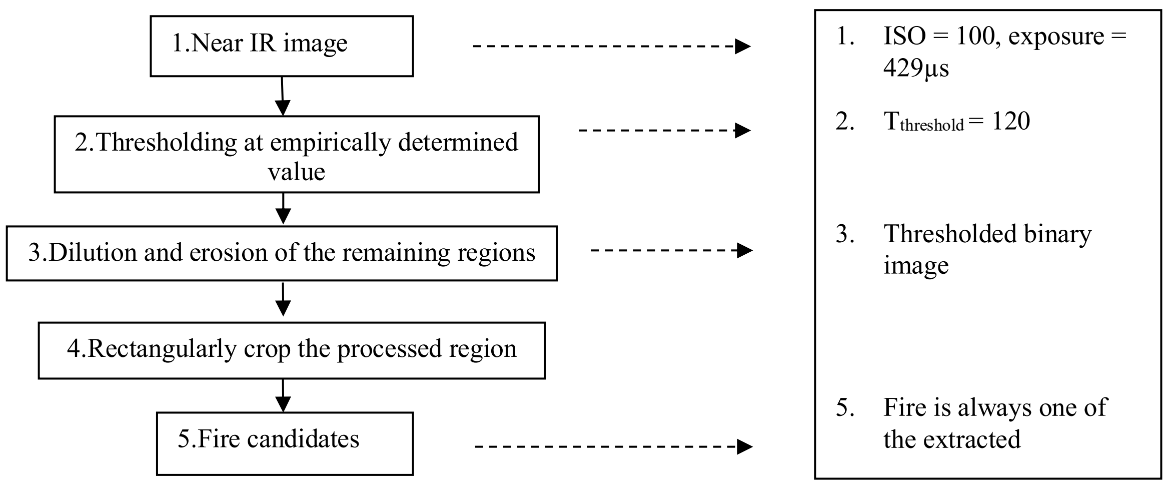

Figure. 4 ROI extraction computation flow chart

The test scene is specifically chosen on a sunny day during summer when the sunlight is most intensive, in order to investigate the near IR reflections from the surroundings. Near the centre of the image, a white cardboard was placed to observe its NIR reflection comparing to that of visible light. In addition, the test scene also contains large area of vegetation, which is the most significant source of NIR disturbance from outdoor environment. Moreover, the fire comes from British hardwood burning. The intention is that if the ROI extraction method shows its capability even when there is strong ambient interference, it will work in a more general situation.

Under intensive solar NIR radiation, the high percentage of scene has pixel values under 100, as seen in figure 5. This is due to the fact that solar radiation is weaker in NIR spectrum. However, as previously presented, the vegetation appears remarkably bright because of the backscattering, which accounts for the highlighted peak. The histogram also shows that fire intensities are distinctly separated from those of the background. It is worth noting that the NIR reflection from the white cardboard is rather weak (lower than 90); whereas its intensity in visible images should be very high because of its white colour. Figure 6 shows the resulted image at a range of values for thresholding. It can be observed that vegetations have a remarkable scattering of NIR comparing to the other objects in the scene, such as the pebble floor, white cardboard, rock slate, wood bench and brick wall. As the threshold increases, the cluster of blobs no longer appears. However, areas on the barbecue lid and leg remain because their glossy surface reflecting sunlight.

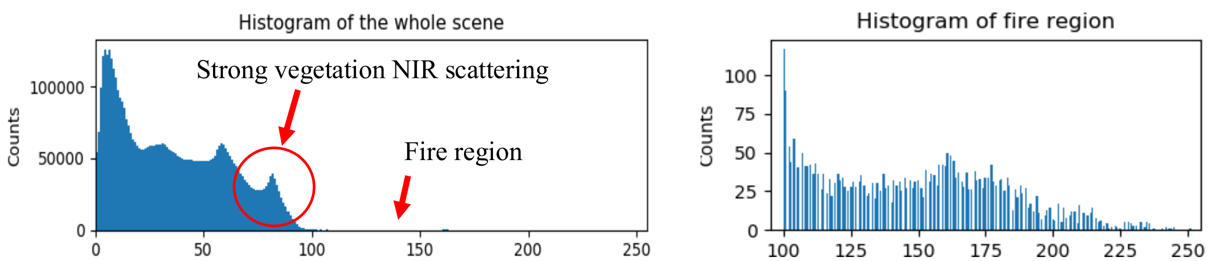

Figure. 5 Histogram of NIR image of the fire scene

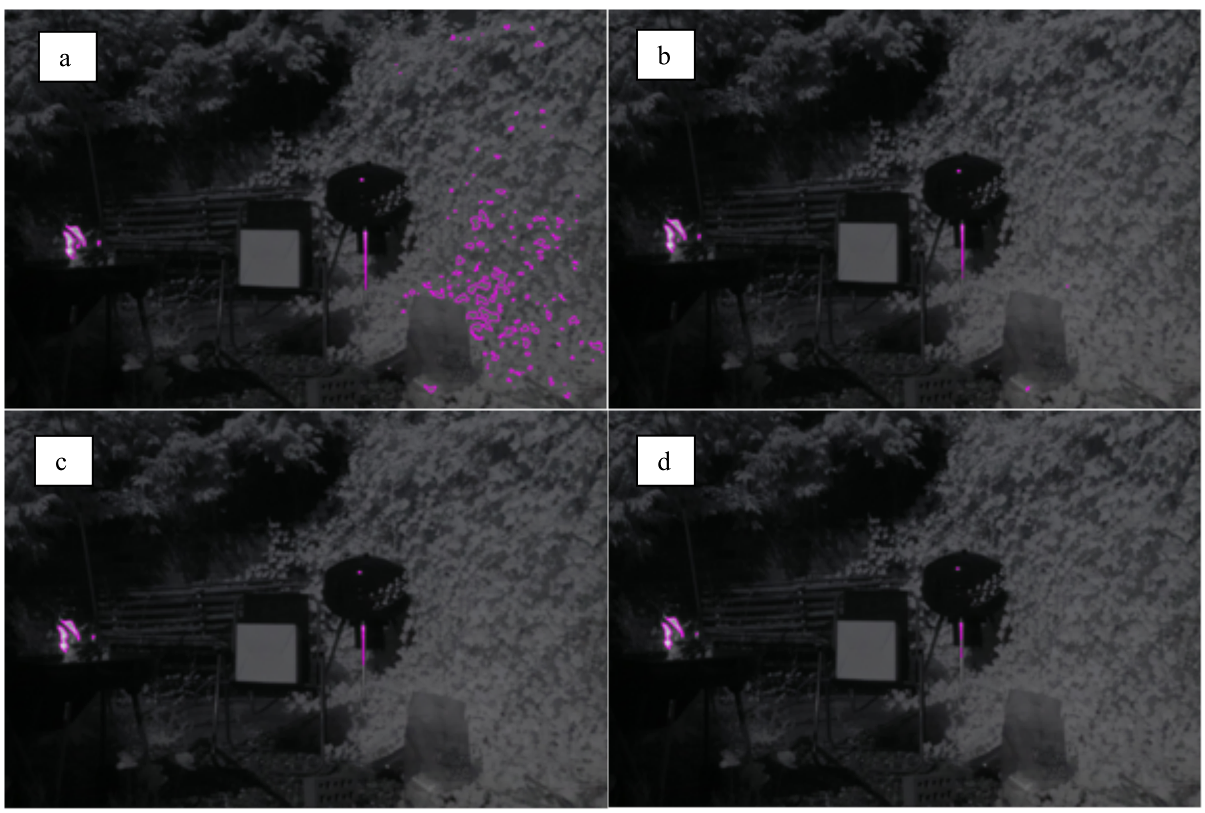

Figure. 6 Thresholding at (a)90; (b)100; (c)110; (d)120

Due to the irregularity of NIR radiation of a flame, the flame region may contain small clusters of blobs. Therefore, an image morphological transformation is employed to merge all blobs into one region. Finally, referring to figure 7, the merged regions will be cropped from the whole scene, which will be subsequently fed into an CNN for fire recognition.

Figure. 7 Dilution and erosion to merge flame blobs into one region

6 Discussion

The segmentation mainly relies on intensities thresholding based on experimental observations. In other words, anything reflects or emits high enough NIR will be selected as candidates. The discrimination between fire and non-fire will be performed by a subsequent CNN model. Comparing to other CNN based models, this method can preserve the fire information because it does not resize the whole image; instead, cropping from the original high-resolution image makes it possible to detect fire at a longer distance or in smaller scale. In addition, the required detection computation is reduced because of one channel image and binary classification. Moreover, the use of NIR imager makes the system immune to fake fires; for instance, fire video on display or fire in advertising posters, which are ubiquitous especially in busy city areas; the display of fire only emits RGB lights to mimic real fire, whereas posters contain pigments that reflect certain wavelength within the visible spectrum to appear as flame.

7 Conclusion

With combined image processing and experimental test, NIR cameras have been demonstrated to have an advantage for fire detection in four main aspects: firstly, the immunity to colour variation and its sensitivity to certain thermal radiation make it more robust to distinguish between actual and fake fire; secondly, the simplified ROI extraction requires less computation, meanwhile to preserve spatial resolution for detection of small and far fire in the scene; then, as fire region is cropped from the original full resolution image, it is possible to infer the fire location and scale through algorithms; finally, the subsequent CNN model for fire recognition is potentially less complicated due to the reduced dimensionality of input data. Nevertheless, a major suggestion can be made towards developing a whole detection system; the training data for CNN model needs to include images of strong NIR reflections, such as sun reflection from building windows, car headlights, pedestrians holding a torch or reflection from the road, etc, as the non-fire training data. Because the segmentation basically relies on thresholding, it is very probable the CNN model will intake crops of the aforementioned scenes. Fortunately, these strong reflections share similar features, which are not diverse so that to render training such model impractical. Future work will be training a CNN model for fire detection as well as the inference of fire location and size. To a greater extent, hot object detection will be developed to detect potential risk of causing fire, which would require further experimental study.

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