AUTOMATED ON-SITE HAZARD IDENTIFICATION USING DIGITAL AND THERMAL IMAGERY

Mohamad F. Abbas[1], Bahaa Eddine Mneymneh[1], and Hiam Khoury[1]
[1]American University of Beirut, Beirut, Lebanon

Abstract

A major component of construction safety management processes entails identifying potentially on-site hazardous areas. However, traditional methods are manual, labor-intensive, and time-consuming. In an attempt to automate hazard identification, researchers have used digital imagery and computer vision at large but failed to explore thermal imaging analysis. As such, this paper introduces an automated vision-based hazard identification approach using both digital and thermal imagery. Several experiments were conducted and results highlighted the effectiveness of analyzing both digital and thermal images to reduce false positive detections and rapidly identify on-site hazardous areas.

Introduction

The construction sector has always been responsible for a high rate of fatal injuries. As such, regular safety inspections are of paramount importance and help management ensure that safe work practices are being maintained on jobsites. However, current inspection methods still rely on safety officers patrolling the site and identifying unsafe conditions, or on the workers' capabilities in identifying hazards. The former method is manual, labor-intensive, and time-consuming, while the latter approach is considered inadequate and not very dependable. Therefore, there is a need to automate construction safety inspections. Initial research efforts have targeted automating the safety inspection processes and monitoring the site conditions and construction personnel using digital imagery and computer vision (Yang et al. 2010, Brilakis et al. 2011, Park and Brilakis 2012). Other studies have focused on actively detecting PPE-wearing from digital images and videos using computer vision (Shrestha *et al.* 2015, Park et al. 2015, Abbas et al. 2016, Mneymneh et al. 2017, Mneymneh et al. 2018, Mneymneh et al. 2019, Nath et al. 2020, Yang et al. 2020). In a nutshell, extensive work has been done in the past years targeted at automating safety inspection processes while building on recent developments in the field of computer vision (Guo et al. 2021, Maali et al. 2024).

In an attempt to further automate safety inspection processes, several other research efforts evaluated the applicability of Unmanned Aerial Vehicles (UAV) or camera-equipped drones in construction safety (Gheisari et al., 2014, Abbas et al., 2016, Mneymneh et al. 2016, Melo et al. 2017, Kim et al. 2019, Martinez el el. 2020, Maali et al. 2024). Results revealed the importance of adopting drones in safety applications as they can provide safety personnel with real-time visual access to jobsites. However, no prior work has analyzed thermal imagery or coupled it with digital imagery to identify construction hazardous areas. Therefore, the objective of this paper is to enhance construction safety inspections by developing an automated vision-based hazardous identification system using both digital and thermal imagery. As such, real-time images and videos of indoor construction sites are captured using digital and thermal camera-equipped drones or UAVs.

Methodology

The hazardous situations considered in this study were extracted from a previously published survey conducted with construction personnel (Abbas et al. 2018). It was found that the top ranked hazardous situations are unprotected openings, fire, steel grinding, and steel welding. Only fire, steel grinding, and steel welding were considered in this study as the exact location of openings can be obtained from the as-planned drawings. It is worth noting that the routine activities of steel grinding and welding can be safely conducted. However, they may pose risks if adequate precautions are not observed and appropriate protective gear is not utilized. Hence, detecting these activities serves as the initial step towards implementing necessary health and safety measures.

Given the nature of the aforementioned three hazardous scenarios, it was decided to opt for digital imagery analysis using object detection and color-based segmentation as well as thermal imagery analysis. It is worth noting that the latest deep learning vision algorithms commonly used for object detection and segmentation (e.g. Faster RCNN, Mask RCNN, YOLO, etc.) were not adopted in this study, as they require voluminous training data and huge computational power. In this case, simplicity, interpretability, and computational efficiency were prioritized. As such, the chosen vision tools applied on digital imagery were the cascade object detector and RGB-CIE color-based segmentation. Besides, these can be complemented by a thermal imaging analysis to enhance the overall results.

A cascade object detector based on HOG features was used to detect objects having an appearance that does not change significantly (Alionte and Lazar 2015). This technique involves training the detector by creating a database containing images of relevant objects from several angles and views. The detector then uses a cascade classifier to decide whether the window sliding over a certain image contains the object of interest. In this research work, the cascade object detector is used to detect hazardous areas displaying repeating patterns.

On the other hand, the potential hazardous scenarios of fire, grinding, and welding have particular colors that differentiate them from the background. For this reason, color-based image segmentation was used to detect the presence of these hazards. The segmentation was performed using both RGB and CIE LAB color spaces. The acceptable interval of color values that represent each hazard was obtained following several trials and experiments. In other words, hazardous pixels were extracted from real positive images, and their color ranges were identified. If the number of detected hazardous pixels in any image is greater than a significant threshold specified according to the image resolution, then the developed software reveals a hazardous situation detection. This procedure was applied to fire (orange), steel grinding (bright yellow), and to steel welding (bright white).

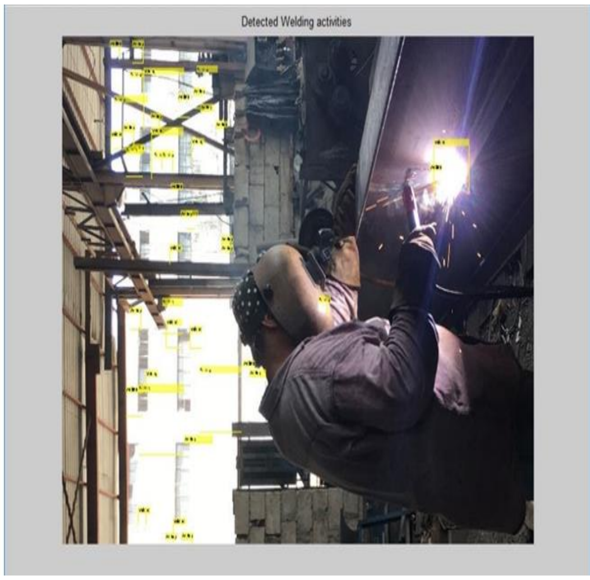
In addition, all considered hazardous scenarios are known to generate high heat when occurring. As such, analysis of thermal images captured by a heat camera was deemed necessary in order to confirm the presence and the detection of high heat hazardous scenarios. In general, heat cameras or thermal imaging cameras are devices that usually detect infrared radiation above 9,000 nanometers and create images of that radiation.

Experiments and Results

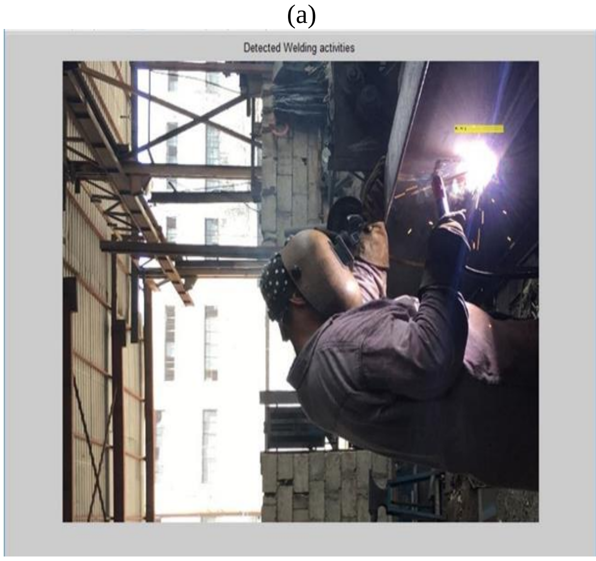
In order to test and demonstrate the feasibility and performance of the three proposed methods, numerous experiments were conducted in several indoor environments under different scenarios. In this case, standard resolution images and videos (640x480p) were captured from different construction sites and construction-like environments using digital and thermal camera-equipped drones.

The first experiment involved training a cascade object detector for the welding activity. The cascade detector is designed to detect objects according mainly to the shape, features, and the contrast difference between the object and its background. Generally, welding is characterized by an approximately circular shape and a white color but may be captured by cameras in other random shapes due to reflectance. When training the detector, it is important to include challenging negative images having shapes similar to welding, including bright windows and light reflections, to reduce the chance of false positive detections. To assess the quality of training images, two detectors were trained, whereby the first was trained with a random set containing non-challenging negative images, and the second was trained with a set of negative images captured from real construction sites and locations where welding activities may occur. Both detectors were trained with a number of stages equal to 7 and a false alarm rate equal to 0.05. Results highlighted the importance of carefully selecting the negative instances to avoid false positive detections, as tests conducted using the first detector revealed a large number of false detections captured in the background (Figure 1a). False negative detections were greatly reduced when using the second detector, as shown in Figure 1b.

One major limitation of the proposed algorithm is that, in case of the presence of objects that reflect sunlight, it may detect this reflection as a welding activity due to the resemblance of shape and shining light between the two. Furthermore, fire and steel grinding have various irregular shapes while the cascade object detector works best when used to detect objects with fixed shapes. Therefore, in order to address the aforementioned limitations, another vision tool was tested which is color-based segmentation.



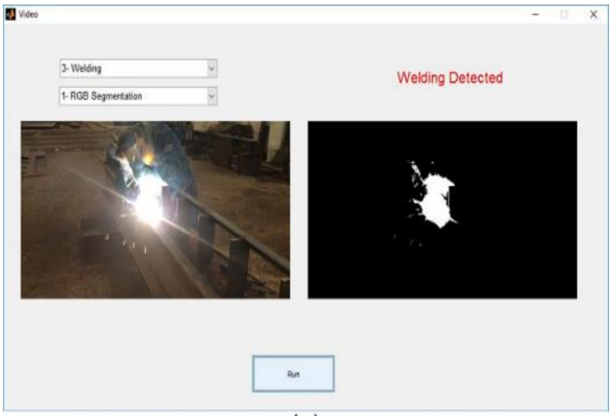
(a)



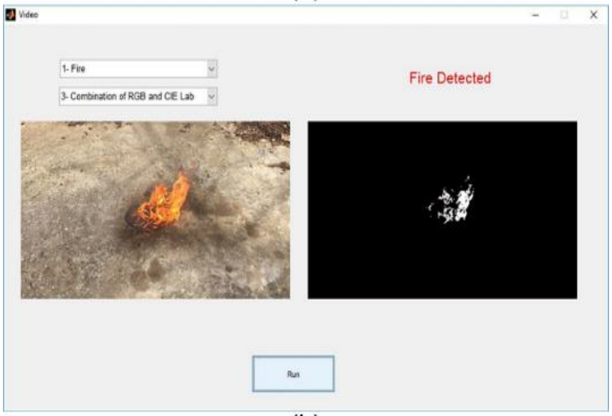
(b)

Figure 1: Cascade object detection examples: (a) welding detection using random training images and (b) welding detection using challenging training images

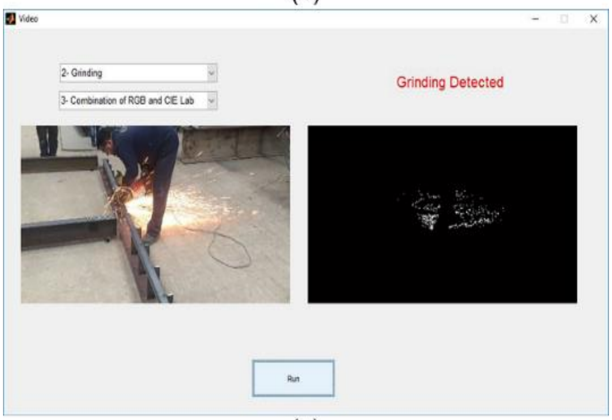
Color-based image segmentation was implemented using the RGB color space, CIE Lab color space, and a combination of both. In this case, the acceptable color ranges need to be pre-defined and calibrated according to the used digital camera for all three color segmentation tools and while considering the three hazardous situations. To test the proposed algorithms, a video-based graphical user interface was implemented whereby the user is first prompted to choose among the three hazardous scenarios then select a particular color segmentation algorithm to test. Figure 2 displays examples of true positive detections for all hazardous cases.



(a)



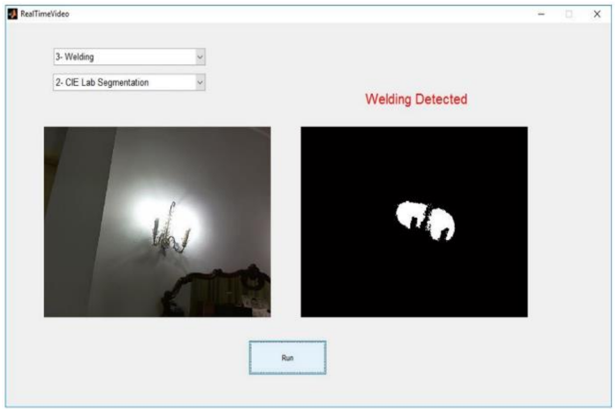
(b)



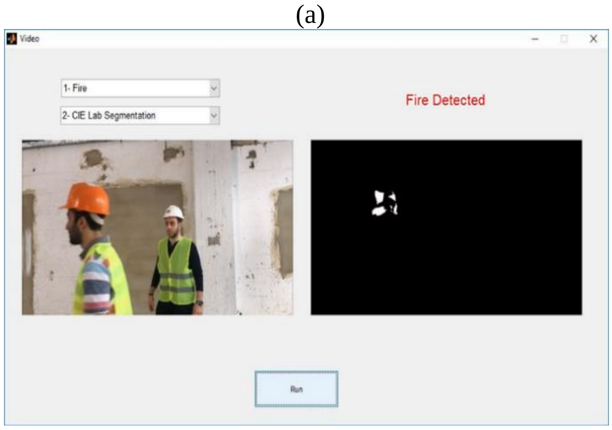
(c)

Figure 2: True positive detections using color-based segmentation: (a) welding, (b) fire, and (c) grinding

Although color-based segmentation was tested on negative images and displayed convenient true negative detections, false positive detections may occur when an object satisfying the algorithm conditions exists. For example, objects displaying a bright white color may be mistakenly classified as welding (Figure 3a) and objects displaying a bright orange color can be wrongly classified as fire (Figure 3b). The same is true for grinding whereby objects displaying a bright yellow color are falsely detected as grinding.



(a)



(b)

Figure 3: Examples of false positive detections using color-based segmentation: (a) welding and (b) fire

One way to enhance the performance of this tool is to benefit from the variation of the shape of the hazardous activities from one frame to another. The intersection of positive pixels in two consecutive frames can be obtained by multiplying their binary matrices. If the ratio of intersected positive pixels over the minimum number of detected positive pixels in both frames is less than a reasonable value, then the change of shape is considered significant and a positive detection occurs. This value was obtained following several trials performed on fire, welding, and grinding videos, and was set equal to 0.4. Experiments conducted highlighted the ability of this frames intersection method in accurately detecting hazardous situations while reducing the occurrence of false positive scenarios (Figures 4, 5, and 6).

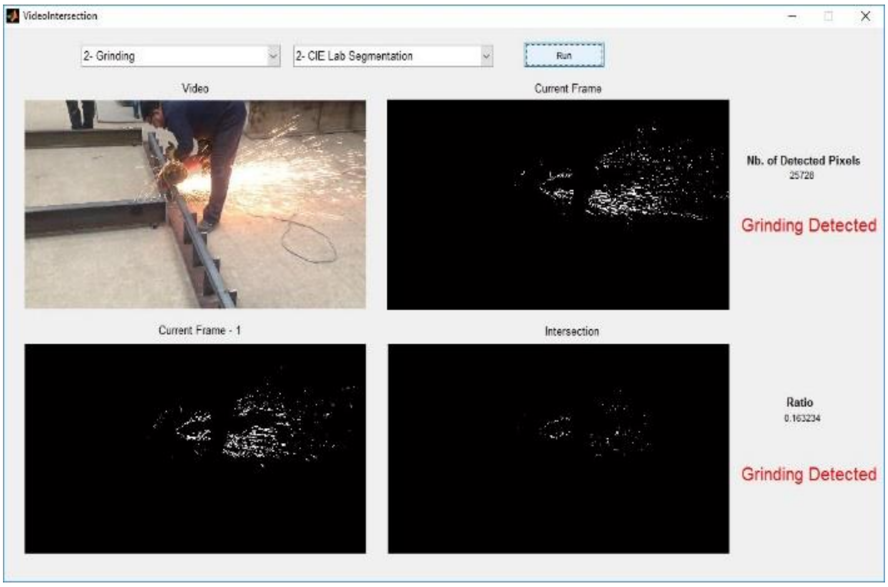


Figure 4: True positive detection of grinding using the frames intersection algorithm

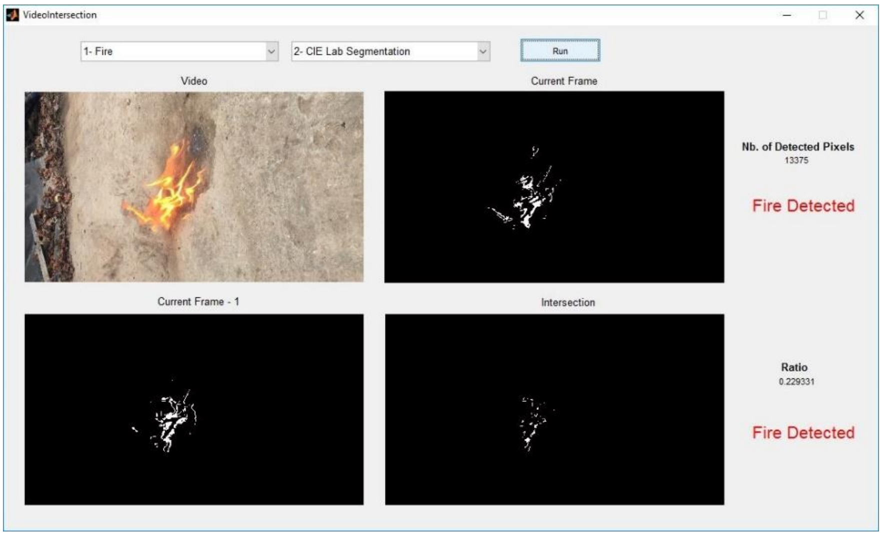


Figure 5: True positive detection of fire using the frames intersection algorithm

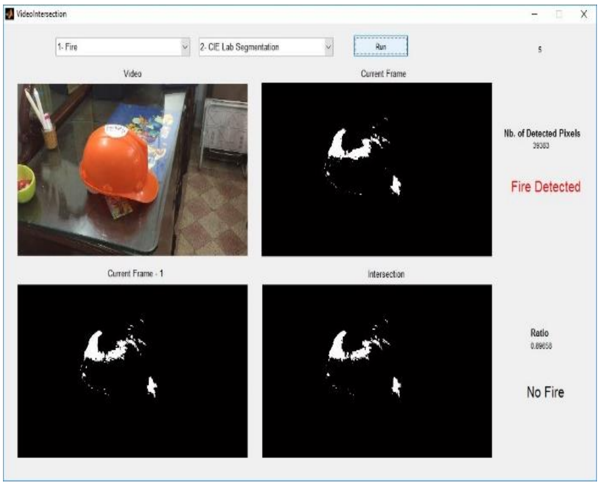


Figure 6: True negative detection of fire using the frames intersection algorithm

Accordingly, this frames intersection tool can potentially reduce false detections resulting from static objects that may have similar color properties of fire (i.e. orange hardhat placed on ground, signs and cones), and are no longer detected as fire since they do not vary remarkably from one frame to another (Figure 6). However, this tool can exhibit some limitations whenever an object having color properties that match one of the pre-defined hazardous situations is actually moving on a construction site (e.g. mobile construction worker wearing an orange hardhat). In this case, the ratio of intersection pixels between two consecutive frames might be lower than the threshold and a false detection may then occur. A false detection can also occur if the camera itself was moving. It was thereby decided to opt for thermal imaging analysis to reduce false positive detections whenever a high heat scenario is not witnessed.

As a matter of fact, the hazardous scenarios of fire, grinding, and welding are known to generate high heat when occurring. Therefore, the analysis of images captured by a thermal imaging camera may then be applied to confirm the presence and detection of high heat hazardous scenarios. Accordingly, several non-processed 14-bit TIFF still images of fire, grinding, and welding scenarios as well as random negative images were captured from several construction sites using the Flir Vue Pro heat camera. These images were then assessed using the software 'Flir ResearchIR' and processed and analyzed later on in order to detect whether the hazardous or high heat scenarios are indeed occurring or not. It was found that the maximum heat values for negative instances did not exceed a value of 9,200 nm (Figure 7), while images containing the three hazardous scenarios (i.e. fire, grinding and welding) displayed high heat values ranging between 12,000 and 16,000 nm (Figure 8).

Figure 7: Heat values for negative images

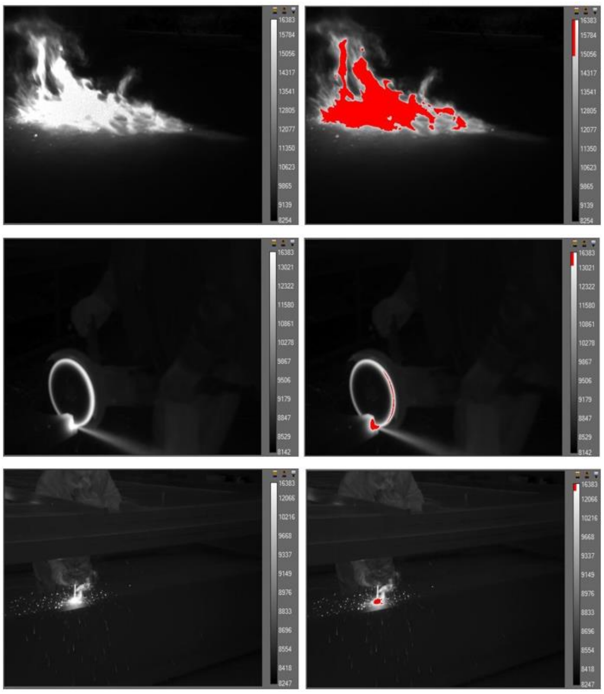


Figure 8: Heat values for positive images

Figure 9 displays an example of a fire thermal image where a high heat was detected.

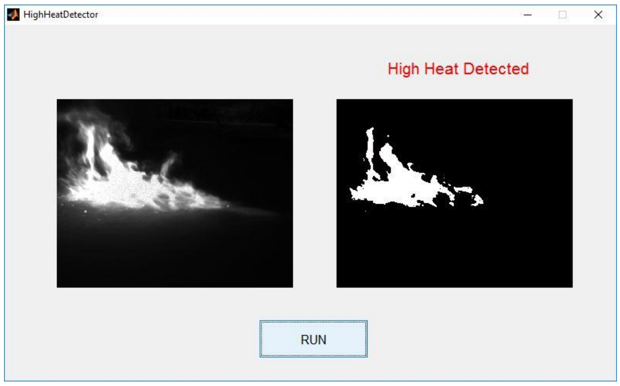


Figure 9: Detection of high heat using thermal imaging

The results in Figures 8 and 9 further highlight the potential of thermal imaging in recognizing high heat-related scenarios on jobsites and can, as such, complement the object detection or color-based segmentation algorithms and reduce false positive detections. For instance, in the case of the indoor light in Figure 3a, only a thermal analysis can confirm a non-welding case since the light with its circular shape and color properties can be mistakenly detected as welding when using the cascade object detector and color segmentation respectively. Similarly, orange objects found on construction sites (e.g. hardhat, cone, sign, etc.) may satisfy the color segmentation algorithm's conditions and can be falsely detected as fire if exposed to certain lighting situations. In this case, capturing and analyzing thermal images of these objects can greatly deny the presence of a high heat scenario and, in turn, eliminate the false positive detection resulting from the color segmentation tool. Figure 10 shows an example of a thermal image captured from a construction site that contains an orange hardhat and displays, as a result, no high heat.

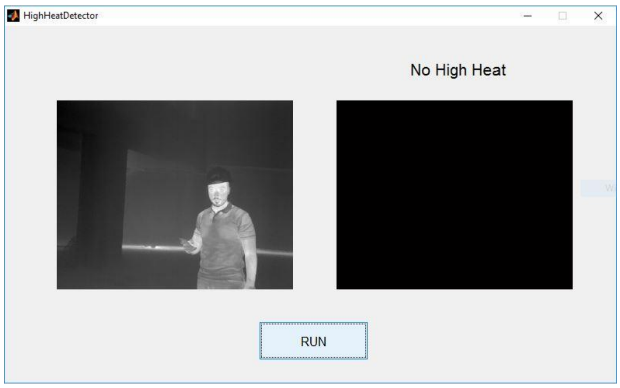


Figure 10: No detection of high heat using thermal imaging

It is worth noting that not only thermal imaging analysis is capable of complementing the two other vision tools but these latter tools can also complement the thermal imaging analysis, as it might be hard to differentiate among the three hazardous scenarios when similar heat values are registered under certain circumstances. Therefore, all three presented tools can complement each other to accurately identify and visualize each of the three hazardous scenarios. Table 1 summarizes the best use for each of the investigated methods for the hazardous scenarios.

Table 1: Summary of Hazardous situations and investigated detection methods

Hazard	Cascade Object Detector	Color Segmentation	Heat Analysis
Welding	Detection	Detection	Reduce False Positive Detections
Grinding	Not Analyzed	Detection	Reduce False Positive Detections
Fire	Not Analyzed	Detection	Reduce False Positive Detections

Conclusion and Future Work

Construction is one of the most dangerous industries whereby many hazardous tasks and conditions occur, which may pose injuries, risks and fatalities to the construction personnel. Thus, safety inspections must be carried out to maintain a safe construction environment. Many research efforts have targeted automating the safety inspection processes using digital imagery but failed to do so using thermal imagery. Hence, this study presented an automated vision-based hazardous identification system using both digital and thermal imagery. The results, obtained from several experiments conducted on construction sites, highlighted the effectiveness of analyzing both digital and thermal images to reduce false positive detections and rapidly identify on-site hazardous areas, in particular fire, grinding and welding scenarios. More specifically, the cascade object detector worked best with certain shapes. Color-based segmentation using RGB or CIE LAB color spaces, coupled with the proposed frames intersection method proved effective in detecting hazardous situations and reducing the number of negative detections. On the other hand, high heat scenarios were accurately identified using thermal imaging, thereby eliminating false positive detections when using the other vision tools.

Future work aims at enhancing and fully automating hazard identification on construction sites. This will be achieved by: (1) detecting a larger set of potential hazardous scenarios besides the three presented ones, (2) acquiring thereby a larger training data set and resorting to deep learning vision tools for analysis, (3) experimenting further with thermal imaging, (4) adjusting the implemented algorithms to read data from the construction tasks' schedule and accordingly detect the associated risks or possible hazardous scenarios, and (5) rapidly locating workers and alerting them of a nearby hazardous area, activity or scenario.

Acknowledgments

The presented work is supported by the AUB's University Research Board (URB). Any opinions, findings, conclusions, and recommendations expressed by the authors in this paper do not necessarily reflect the views of URB.

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