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USE OF UNMANNED AERIAL VEHICLES AND COMPUTER VISION IN CONSTRUCTION SAFETY INSPECTIONS

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Construction is unarguably one of the most dangerous industries whereby many hazardous tasks and conditions exist, which may pose injuries, risks and fatalities to the workers. Hence, safety inspections are continuously carried out to maintain a safe environment. These typically involve safety officers who circulate around the construction site to detect unsafe working conditions, and ensure compliance with health and safety regulations. However, the task of efficiently supervising a large number of workers and consistently identifying all possible violations is still considered manual and tedious. Therefore, this paper takes the initial steps and presents work targeted at automating the safety inspection process using Unmanned Aerial Vehicles (UAVs). These are commonly known as drones and are small, aerial camera-equipped robots capable of rapidly visualizing spacious environments. More specifically, in this study, a UAV system is used to capture real-time videos from a construction site. The videos are then streamed to a central automated system and analyzed using digital image processing techniques to check whether construction workers are wearing personal protective equipment (PPE), in particular hard hats. The components of the proposed system were created and preliminary results highlighted the potential of using camera-equipped UAVs and computer vision to automate safety inspections in construction environments.

Keywords: Hazards, PPE, Automation, Drone, Image processing.

1 INTRODUCTION AND PERTINENT LITERATURE

According to the United States Department of Labor, 874 worker deaths were recorded in the construction sector in 2014, out of which 73 (8.4%) were caused by being struck by objects (OSHA 2016). Hence, inspections have been carried out over the years to check whether workers are wearing personal protective equipment (PPE), in particular hard hats. However, this inspection task is still considered manual and time-consuming (Ham *et al.* 2016). Therefore, the objective of this paper is to improve and automate the construction safety inspections using UAVs or drones. Drones have been recently used on construction sites in many different applications such as: progress monitoring, site monitoring and building inspection (Ham *et al.* 2016). More specifically, Gheisari *et al.* (2014) evaluated the potential applications that unmanned aerial systems (UAS) have for improving safety in construction environments. In this case, safety officers were provided with captured videos from construction sites and the number of hard hats was manually counted.

However, this paper aims at automating this process and identifying workers not wearing hard hats by analyzing captured drone videos using several digital image processing techniques (Chdid *et al*. 2011, Oueiss *et al.* 2012).

2 METHODOLOGY

To achieve the objective identified above, the paper addresses issues in two main task areas: 1) Hardware, and 2) Software and Algorithms.

2.1 System Hardware: UAV Specifications

The UAV used to capture videos from a construction site is a 2.4 GHz Hubsan drone equipped with a camera. It is characterized by a lightweight airframe with nice durability. Its six-axis flight control system with adjustable gyro sensitivity permits stable flights. The drone hovers over the site, and capture videos without affecting construction activities nor disturbing construction workers.

Figure 1. Hubsan drone (Hubsan 2015).

2.2 System Software and Algorithms

The videos captured by the UAV were analyzed using image processing algorithms. More specifically, hard hats were detected using feature detection, extraction, and matching, and the total number of workers was obtained using motion-based multiple object tracking. As such, subtracting the number of hard hats obtained from the number of workers returns the number of workers not wearing hard hats. The following subsections describe both algorithms.

2.2.1 *Feature detection, extraction and matching*

The implemented algorithm detects a hard hat by finding point correspondences between a reference image (image of a single hard hat) and the target image (image of a construction site captured by a drone). According to MathWorks (Matlab 2016), the object detection method works best for objects that display non-repeating texture patterns to allow unique feature matches. Since the helmet is a uniformly-colored object, a sticker was plastered on its top, as shown in Figure 2. This greatly increased the number of features detected by the algorithm as shown in Figure 3.

Subsequently, outliers were removed and the transformation matrix was calculated, using Random Sample Consensus (RANSAC) algorithm (Khoury *et al.* 2015). This helped identifying the hard hat having the best match with the reference image. The number of hard hats was then computed by hiding identified ones from the target image so that the next best match hard hat can be detected in the next iteration of the algorithm. This counting iterative process halts when no more hard hats can be detected in the target image.

Figure 2. Sticker plastered on the hard hat.

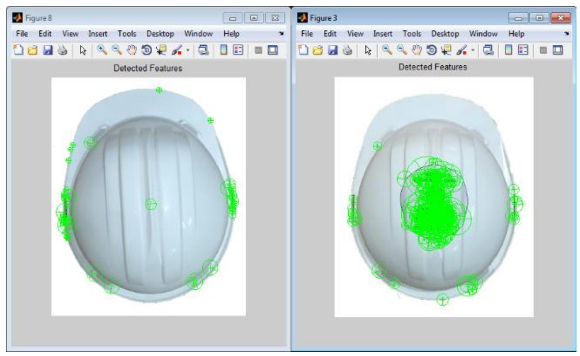

Figure 3. (Left) 49 detected features without sticker and (right) 282 with sticker.

2.2.2 *Motion-based multiple object tracking*

This algorithm performs automatic detection and motion-based tracking of moving objects in a video (Veeraraghavan *et al.* 2006). As a matter of fact, mobile workers were detected using a background subtraction algorithm based on Gaussian mixture models. Morphological operations are applied to the resulting foreground mask to eliminate noise. Finally, blob analysis detects groups of connected pixels, which are likely to correspond to moving objects.

For this algorithm, the motion-based multiple object tracking, to work properly, the drone needs to remain in a fixed location for a period of time.

3 EXPERIMENTS AND RESULTS

In order to demonstrate the feasibility of the aforementioned methods and evaluate their performance, experiments were conducted on a construction site using the drone (Figure 4).

The hard hat counting algorithm was tested on images extracted from the captured video. In the first iteration, 63 matching features were found between the reference and the target image (Figure 5).

The first detected hard hat was then hidden from the target image and in the second iteration, 44 matching features were found between the reference and the new target image (Figure 6).

After the second hard hat was detected then hidden from the target image, no more matching features were detected and the algorithm stopped.

On the other hand, the second algorithm (motion-based multiple object tracking algorithm) was tested on videos captured from the same construction site. Accurate results were obtained while the drone was in a fixed location and expectedly static workers could not be detected (Figure 7).

Figure 4. Drone capturing videos on construction site.

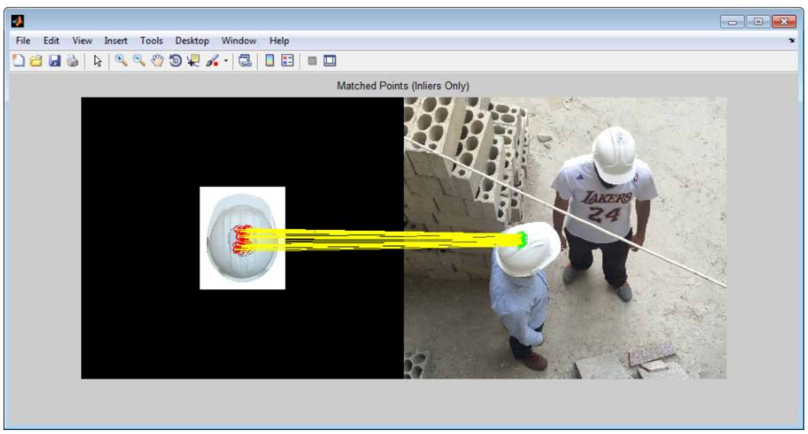

Figure 5. Matching features for the first hard hat.

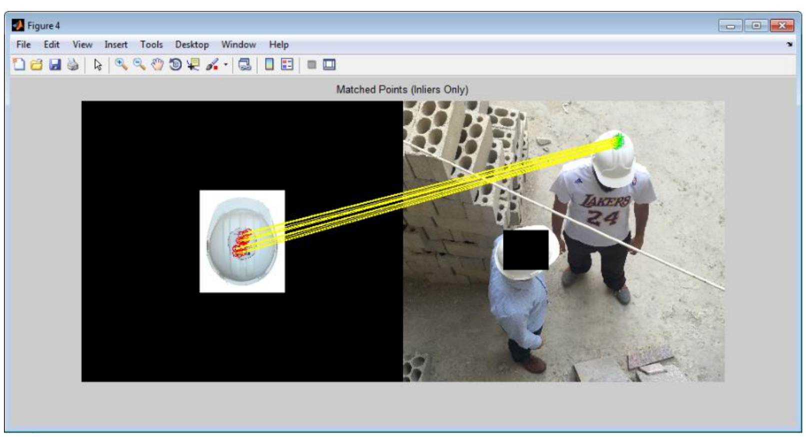

Figure 6. Matching features with the second hard hat.

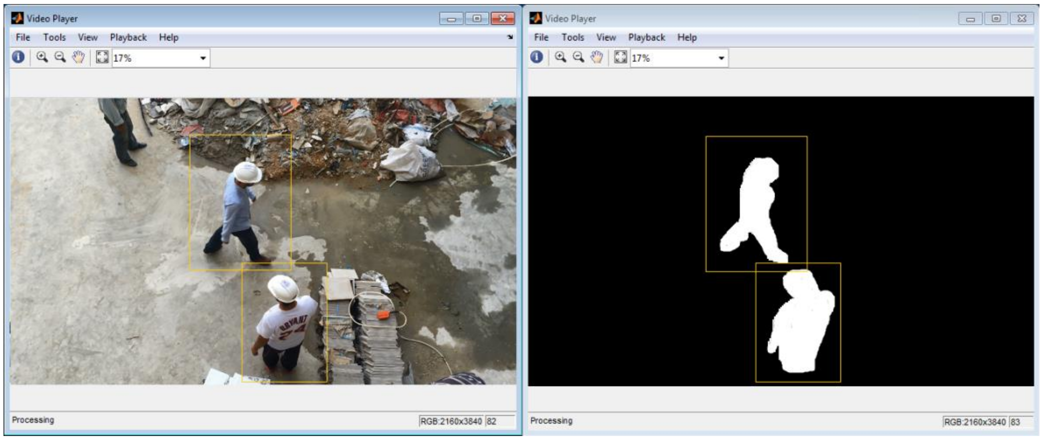

Figure 7. Motion-based multiple object tracking.

4 CONCLUSION

This study focused on creating an intelligent system targeted at automating safety inspections on construction sites, by detecting workers not wearing hard hats. This was achieved by capturing videos using a drone or UAV and analyzing them using digital image processing techniques. More specifically, the number of workers not wearing hard hats was computed by subtracting the number of hard hats detected using feature detection, extraction, and matching from the total number of workers obtained using motion-based multiple object tracking.

One limitation of the proposed approach is that hard hats placed on the ground can be sometimes detected instead of those actually worn by workers. As such, future work will improve the developed algorithms to rapidly and accurately detect the mobile hard hats and workers. Further research will opt for an autonomous drone with better stability and equipped with a higher resolution camera. Additional work is needed as well to determine the exact location of workers not wearing hard hats.

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