Automatic Hardhat Wearing Detection to Enhance Construction Site Safety

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ABSTRACT

Automatic Hardhat Wearing Detection to Enhance Construction Site Safety

Nehad Elsafty

Careers in the construction field are involved with risks and engender a wide range of dangers to which workers and professionals are exposed on a daily basis. Numerous injuries and deaths are reported annually. Injuries and deaths have multiple negative financial, emotional, and psychological consequences on the affected persons and their families. In addition, these accidents increase the time and costs of construction projects. Therefore, construction site safety is a critical issue that needs to be monitored and controlled throughout the construction project timeline by both professionals and contractors. Hardhat wearing is one of the basic safety regulations at construction sites, to which all workers and visitors should adhere all of the time. This study proposes a new automated method to determine if workers and others present on construction sites are wearing hardhats (or not). This method could automatically create alarms for those workers who are not wearing hardhats. The method comprises the following steps. First, video frames captured by fixed cameras on the construction site are used for the detection of human bodies and hardhats. Next, the detected human bodies and hardhats are matched using their geometric and spatial relationships. Those human bodies without their matched hardhats are highlighted to bring them to the attention of the onsite safety inspectors. This method has been tested using real site videos. The safety alert’s precision and recall demonstrates its effectiveness and potential to enhance onsite safety monitoring.

DEDICATION

I dedicate this thesis to my beloved parents and husband for their endless love, affection, support and inspiration in every step of my life.

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I am deeply grateful to my supervisor Dr. Zhenhua Zhu for encouraging, motivating, and supporting me throughout my Master's program. He has contributed to me personally, academically and professionally. Honestly, Dr Zhenhua Zhu has taught me how to conduct efficient research and will always remain an important person in my life who inspired and motivated me. Without his guidance and constant help, this thesis would have been impossible. I would like also to thank my thesis committee members. First, Dr.Moselhi, who helped me to understand the concepts of total project management, which helped me define the breadth of my study, and who guided me in terms of reading materials and research methods. Second, Dr. Amin Hamad, for his valuable support and his meaningful feedback that helped me to choose the research methodology and focus on my research topic.

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Finally, and the most precious to me, I would like to thank my nuclear family, specifically my husband, Hani Badran for his love and support, and my precious children, Remas, Moemen, and Mostafa. I dedicate this thesis to my extended and nuclear families.

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LIST OF ABBREVIATIONS

HOG	Histogram of Oriented Gradients
SVM	Support vector machine
P	Precision
RC	Recall
TP	True positive
TN	True negative
FP	False positive
FN	False negative
P/R curve	Precision-Recall curve
XML	Extensible Mark-up Language
OSHA	Occupational Safety and Health Administration
VHF	Very-High Frequency
RFID	Radio Frequency Identification
GPS	Global Positioning System
UWB	Ultra-Wide Band
WLAN	Wireless Local Areas Networks
RGB	Red, green, and blue

CHAPTER 1. INTRODUCTION

1.1 Problem Statement and Motivation

One of the most dangerous job sectors is the construction field. In Canada, approximately 24 per 1000 workers were injured at construction sites during the year 2008 (Abeid and Arditi 2002, Canada Statistics 2008), and from 2008 to 2010 there were 700 injuries that resulted in death which are 23% of all workplace fatalities during this period (CBC News 2011). In 2009, a total of 7,230 nonfatal head injuries/illnesses involving days away from work were reported from the construction industry, which accounted for approximately 7.8% of the days-away-from-work cases due to nonfatal occupational injuries/illnesses (Bureau Of Labor Statistics 2010).

Specially in Quebec, as reported by Jacques Nadeau of Quebec's Occupational Health and Safety Commission, there are 19 injury cases per day, and this number increase to 26 in the month after holidays (CBC News 2011). Based on a calculation supported by data from the Association of Workers Compensation Boards of Canada, 21.5 per 1000 workers were injured on construction sites inside Quebec in 2008 (Canada Statistics 2011, WorkSafeBC 2014).

It was found that most workers who suffered impact injuries to the head (84%) were not wearing hardhats when performing their normal jobs at their regular worksites. In addition, the Bureau of Labor Statistics noted that "hardhats were worn by only 16% of those workers who sustained head injuries, although two-fifths were required to wear them for certain tasks at specific locations" (OSHA 2014). Wearing hardhats is one of the basic ways to protect construction workers and other persons on construction sites from head injuries.

The Safety Code for the Construction Industry mandates that "any person on a construction site shall wear a certified safety hat in accordance with CSA Standards" (Quebec 2014). A similar guideline or regulation can also be found in the OSHA. It stipulates that “Employees working in areas where there is a possible danger of head injury from impact, or from falling or flying objects, or from electrical shock and burns, shall be protected by protective helmets” (OSHA 2014). It is one of the top priority to confirm that all employees and site visitors wear hardhats all of the time on the construction sites.

Regrettably, the number of easily-preventable injuries is increasing in developing countries. In many cases, there are no specified rules to ensure construction site safety, and even if there are, they are often not respected. For example, many workers whose roles are to load sand or count bricks are not motivated to use safety hardhats (Figure 1-1). For example of the seriousness, in Turkey alone there were around 1,754 death cases in construction sites between the years 2008 and 2012 (Aguilar and Hewage 2013, Idiz 2014). In addition, in Jordan there were 13,843 injured cases reported (Accidents and Jobsite Injuries, 2004). The main causes of these injuries were the non-adherence of the workers to the safety codes and the reluctance in using the personal protective equipment.

Figure 1-1: workers without hardhats.

The social costs of these accidents are very high. Families not only lose a son or husband, these men (and sometimes women) were often major wage earners, sometimes for extended families (especially the case in the developing world). In addition, construction accidents are one of the main causes of delay in a project's progress. For example, in Canada from 2009 to 2010 there were approximately 27,100 time-loss injuries and deaths in construction projects (Canada Statistics 2008). That figure translates into increases in the total direct and indirect cost of the projects affected. In the interest of mitigating the social, human and financial costs of construction site injuries, several governments in the developed countries are evaluating construction site safety regulations.

1.2 Research Goal and Objectives

The research goal is to propose a novel vision-based safety measure to facilitate the safety monitoring work of construction site safety inspectors. This worksite monitoring method is designed to automatically identify whether or not any individual persons, including construction workers, are wearing hardhats within construction sites.

The objective is to create a unique on-time detection method that can detect the hardhats and the correspondent human bodies. The proposed detection method aims: (1) to avoid the previous detection methods' limitations, as the proposed method work as on-time method to detect any persons without hardhats, whatever the color or the shape of the hardhats. In addition, the proposed method does not require the usage of physical tags to be attached to the persons nor the corresponding hardhats to ensure the used of the hardhats as in sensor based detection methods. The proposed method was modified for different construction environments (outdoor, with huge down to dimensions), and (2) help to decrease the number of accidents in the construction site and the total cost of different projects. The goal and objectives of the current research are illustrated in the Figure 1-2.

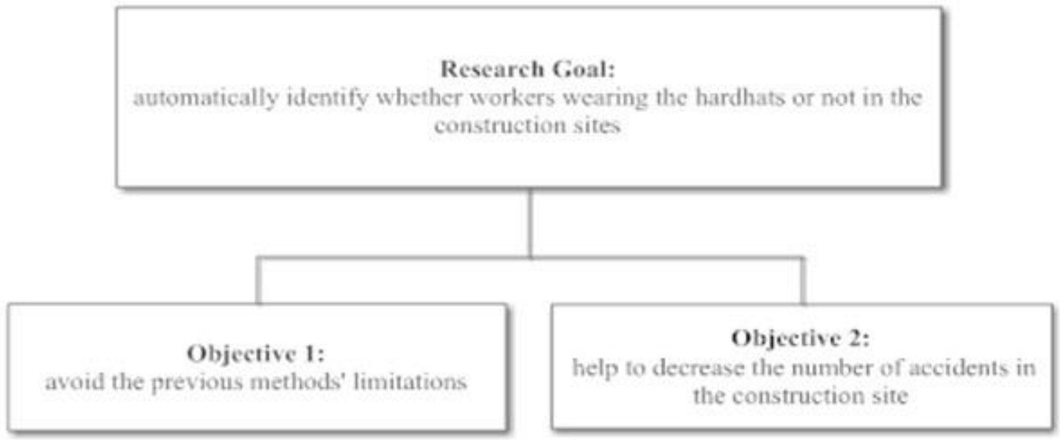


Figure 1-2: research goal and objective.

1.3 Proposed Methodology

The proposed method includes three main steps. First, all the persons in a video frame from an onsite video camera are detected, even if they are not wearing hardhats (human body detection). Second, all the hardhats in that video frame are detected, even if they are not being worn by the people (hardhat detection). Third, matching between the detected persons and their corresponding hardhats is performed (human body and hardhat matching).

Any individual without their matching hardhat could be identified and a safety alert issued to warn the safety inspector. Considering that hardhats may be on the construction site without being worn, the proposed method could not simply count the number of people and the number of hardhats detected in one video frame and subtract the numbers to determine how many are not wearing hardhats. As it is difficult to use the image subtract method to insure that all the counting hardhats were worn by the corresponding human body.

To validate the effectiveness of the proposed method, real onsite videos were tested. This test result showed that multiple people could be accurately monitored without the need for any signal sensors or tags to be physically pre-installed on workers, visitors or hardhats. This method would be suitable to be used at most large-scale construction sites, including those that contain hundreds of employees and other workers. The improvement in construction safety would increase the workers' productivity, improve their morale and reduce project costs. The prevention of one injury or death per day could lead to cost savings of millions of dollars per day.

CHAPTER 2. BACKGROUND

2.1 The Current Practice

Several policies and procedures are created to ensure safety and decrease the number and extent of construction site accidents. For example, in Canada there is the Safety Code for Construction, which provides the general rules to protect the health and the safety of the workers and the subcontractors operating at construction sites (Quebec 2014). In the United States, the Occupational Safety and the Health Administration functions to ensure a suitable healthy and safe environment for all workers, with specific requirements for construction sites (OSHA 2014).

To apply the various safety rules, the contractors for large projects hire qualified individuals (e.g., safety inspectors), who are responsible for applying the safety regulations at construction sites. In Quebec, they are known as construction site health and safety management guarantors. The guarantors identify and address onsite safety issues, if any. They take every measure necessary to ensure that the general contractors comply with a wide range of regulatory requirements as specified in the Safety Code for the Construction Industry (Quebec 2014). Existing regulatory requirements help to establish the safety policies and procedures on a construction site. However, the workers may forget and/or may not exactly follow the requirements due to fatigue, distractions, carelessness, etc., even if they have been educated and trained (Green and Tominack 2012).

Current safety inspection practices still rely heavily on inspectors' manual monitoring and reporting. For example, the inspectors might use construction safety inspection checklists to check the safety issues in the areas of Housekeeping and Facilities, Personal Protective Equipment, Fall Protection, Hand and Power Tools, etc. For safety assurance in the area of Personal Protective Equipment, the inspectors need to make sure that 1) hardhats are being worn; 2) high-visibility vests are being worn where needed; and 3) proper footwear is being worn in material handling areas, among other specifications.

An inspector’s experience and skills play an important role in evaluating the safety inspection performance. A less-skilled safety inspector or even a highly-experienced one may have difficulties in identifying all of the onsite safety issues, especially in a complex worksite (Zhang, Chi et al. 2012). As a result, the safety record of the entire construction industry is still not satisfactory.

2.2 Sensor-Based Onsite Safety Enhancement

Construction site safety is one of the main concerns of researchers and industrial stakeholders. Sensor-based safety alert research has been undertaken to establish appropriate onsite safety alarm systems and procedures. A numbers of studies have investigated the possibility of adding an extra level of proactive safety measures. These studies have focused on the investigation of object locating and tracking methods, including those using radio frequency identification (RFID), the global positioning system (GPS), wireless local areas networks (WLAN), and ultra-wide band (UWB).

In 2007, Ruff suggested several recommendations to evaluate and implement these safety systems on the equipment of surface mining, based on a comparison of these four monitoring methods. Many of the locating and monitoring systems have been produced on a commercial basis. These systems can warn the equipment operators regarding impending collision or other unwanted incidents, thereby contributing to construction site safety (Ruff, Coleman et al. 2011). As a conclusion for his work, Ruff found that these feature may reduce the false alarms, but also has the disadvantage of increasing the potential of collisions with obstacles that are not outfitted with a tag. This is also true for GPS-based systems that require cooperative obstacles(Ruff, Coleman et al. 2011).

In 2010, Teizer et al. investigated the use of a Very-High Frequency (VHF) active Radio Frequency (RF) technique to improve construction site safety. The main findings concluded that VHF active RF technique tracking systems can instantly warn the equipment operators regarding any impeding unwanted incident (e.g., when the equipment get too close to each other or to any other object) (Teizer, Allread et al. 2010).

In 2011, Carbonari et al. implemented a proactive virtual fencing system using UWB technology, demonstrating the ability of such a system to enhance the implementation of safety management guidelines (Carbonari, Giretti et al. 2011).

Chen and Teizer subsequently utilized a new technique, integrating the previously mentioned techniques (real time resource location data from GPS and UWB) into virtual reality applications that monitor the activities at a construction site and consequently enhance its safety (Cheng and Teizer 2013).

Monitoring technologies can be adopted to enhance construction site safety in other ways in addition to using it use for location, tracking, and proximity warning. For example, in 2013, Kelm et al. monitored workers at a construction site using a remote Radio Frequency Identification (RFID) portal. They tracked the workers personal protective equipment and verified if it complied with the safety policies (Kelm, Laußat et al. 2013).

In 2013, Aguilar and Hewage developed an Information Technology (IT) based safety management system. They used wireless high resolution web cameras, gas and particulate matter wireless sensors combined with barcodes and RFID tags installed on construction equipment to provide real-time information access (Aguilar and Hewage 2013).

Despite the lacunae of the current remote locating and tracking techniques, they are currently being used to identify the adherence to construction site safety polices through hardhat detection. The United States Patent provide a full description for the work of (Hudgens et al, 2007). They used a special sensor on the different sectors of the construction site and an electronic circuitry formed as a part of each worker hardhat. The circuitry had each worker personal information. When the workers are on the construction site, a wireless communication link establish between the sensor and the electronic circuitry. The sensors detect the presence of hard hat electronic circuitry. When the circuitry comes within signal range of one or more of the sensors, location information associated with detected electronic circuitry is provided to the monitoring system along with personal information provided by the detected electronic circuitry. As such, personnel wearing hard hats at the construction site may be monitored when they in one of the sectors covered by one or more sensor .The main problems of using this system: first, this system require physical tags or circuitry to be assigned to each worker hardhat. Even though it is promising that the price of these tags or sensors is continuously dropping with massive production, the practical use of the physical tags and sensors would still be a burden for contractors due to its costs, even more onerous if thousands of workers and hardhats must be tagged. Second, the tags or sensors only present an instant tracking of the persons and hardhats in the construction site. They track the presence of the person and of their hardhat inside the construction site, but they cannot identify the safety issues. For example, they cannot determine the use of hardhats and if individuals are appropriately following safety policies; an employee could simply hang up their hardhat inside the construction site and carry out their work bare headed.

Finally, the tracking of individuals and equipment could face resistance from labour unions and civil rights groups, as it may violate privacy issues and negatively affect their health. This concern may also be an issue against installing cameras on construction sites, but cameras have been already been widely used on construction sites as they have proven their worth in terms of the worker safety and the investment in general (Bohn and Teizer 2010).

2.3 Vision-Based Onsite Safety Enhancement

Installing live streaming or time-lapse video cameras on construction sites offers more advantages than installing the RFID, GPS, WLAN, and UWB techniques. Live streaming or time-lapse videos report the built progress of a construction site and the jobsite activities, as they are recorded instantly through fixed cameras. The streaming videos thus contain very useful project site information. This can help general contractors to supervise and manage the construction sites dynamically from a remote site. These videos can also be used to investigate accidents or reported incidents (Abeid and Arditi 2002), safety training and as education resources (Liaw, Lin et al. 2012), monitor a project's as-built progress (Golparvar-Fard, Peña-Mora et al. 2009), analyze the operation productivity of a project (Park, Koch et al. 2011, Rezazadeh Azar and McCabe 2011), and enhance and assure quality (Zhu, German et al. 2011, German, Jeon et al. 2013).

Therefore, it is important to apply a monitoring and alarm system that will help to identify people who are not utilizing safety measures, and initiate an alarm when there is a violation. Tracing individuals without hardhats on a construction site is a problematic issue. First, the three dimensional appearance of people can be changed drastically with the changes of position relative to the camera and its viewing angle. Second, hardhats have different sizes, shapes and colors. Third, the background image may have an impact on the viewing results, as the individuals and hardhats in the image can be displayed with partial occlusions, against a disorganized background, and under different lighting conditions (Ulrich and Steger 2002, Zhang, Chi et al. 2012).

It is now possible to create alarm systems that can be operated and integrated within the live streaming videos, using the advances in the computing and IT State of the art computer workstations can perform the video processing. Computer science visioning and pattern recognition techniques can create the basis with which to integrate an alarm in live streaming videos. For example, Semantic Texton Forests (Shotton, Johnson et al. 2008), a well-known segmentation and classification method, could be used to locate and track the equipment in a construction site (e.g., wheel loaders and trucks) (Jog, Park et al. 2011). Similarly, the Histogram of Oriented Gradients (HOG), which has visual features, can be used to detect the workers and equipment at the construction sites. It learns the features of each object (e.g., using numerous photos of an object in different views and visibility conditions) and then with additional training steps creates a precise model for each object (Park, Koch et al. 2011, Memarzadeh, Golparvar-Fard et al. 2013). In the fixed video cameras, the background pixel function will filter images, using background subtraction algorithms, which will help to identify the moving objects which can undergo real-time classification (Chi and Caldas 2011).

Weerasinghe and Ruwanpura correlated a number of functions to detect hardhat forms (Weerasinghe and Ruwanpura 2009, Weerasinghe and Ruwanpura 2010), utilizing the edge maps of video frames (Weerasinghe and Ruwanpura 2009, Weerasinghe and Ruwanpura 2010). In addition, they used the eccentricity, the blob area, the distance between the blob centroid and the head coordinate, and the distance to the human figure for the prediction of construction hardhats to build a multivariate statistical model (Weerasinghe and Tharindu 2013). This work was designed to monitor construction workers' performance on a construction site; but their experiments were limited to the laboratory (a small space: length: 5m, width: 5m, and height: 3m).

In 2003, Steele et al. installed a stereo camera on the rear of an off-highway dump truck (Steele, Debrunner et al. 2003). This camera helped the driver to identify the possible obstacles in the mining site. The outcomes of this experiment were promising. They subsequently addressed some limitations of the experiment in terms of practical issues (e.g., capture of image, calculation of distance, and fixing the camera on the moving equipment) (Steele, Debrunner et al. 2003). Some recent studies have focused on the use of video cameras to record and investigate workers' unsafe actions that may cause accidents or unwanted incidents (e.g. falling down from a ladder due to leaning too far) (Han, Achar et al. 2013). These studies focused on recording workers' unsafe actions or behaviors by installing monitoring cameras which were installed several meters away from the workers (Han, Achar et al. 2013, Han and Lee 2013).

In 2009 and 2011, Gualdi et al. designed a method to identify workers without hardhats on a construction site to enhance worker safety (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011). They used a pedestrian classifier, which has covariance descriptors, to assign the location of construction workers, and then they employed head and hardhat detectors to monitor the usage of hardhats by construction workers (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011). It was not clear if the safety alarm was accurate for all workers without hardhats. Modeling the contextual information was the main core of their work (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011). This helped them to improve the detection of objects, to outline the limitations of motion-based segmentation and to track the movement in distorted scenes. They learned that white hardhats could disable their detection method (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011). Collectively, there are many limitations in the existing research. T. M. Ruff has recommended using a remote sensing technique to integrate an alarming function with video cameras (Ruff 2007, Ruff, Coleman et al. 2011).

CHAPTER 3. OBJECTIVE SCOPE AND METHODOLOGY

3.1 Introduction

The main objective of this study is to examine the use of computer-vision techniques to record construction worksite activities in order to identify anyone who is not wearing a hardhat, as shown in (Figure 3-1 a and b), and to alert the safety inspector.

(a) (b)

Figure 3-1: Identify workers without hardhats.

The proposed method is illustrated in (Figure 3-2), which shows a complete framework with all the main steps. This method requires the detection of human bodies and the detection of hardhats, a process that is done instantly for each video frame. This detection step uses a software analysis integrated with streaming videos, which is followed by a step that identifies their geometric and spatial relationships in order to find their matches. The human bodies with and those without the corresponding hardhats can thus be identified. The last step, the safety alert, is automatically generated to warn the onsite safety inspector regarding the reported issue (e.g., non-adherence to hardhat use).

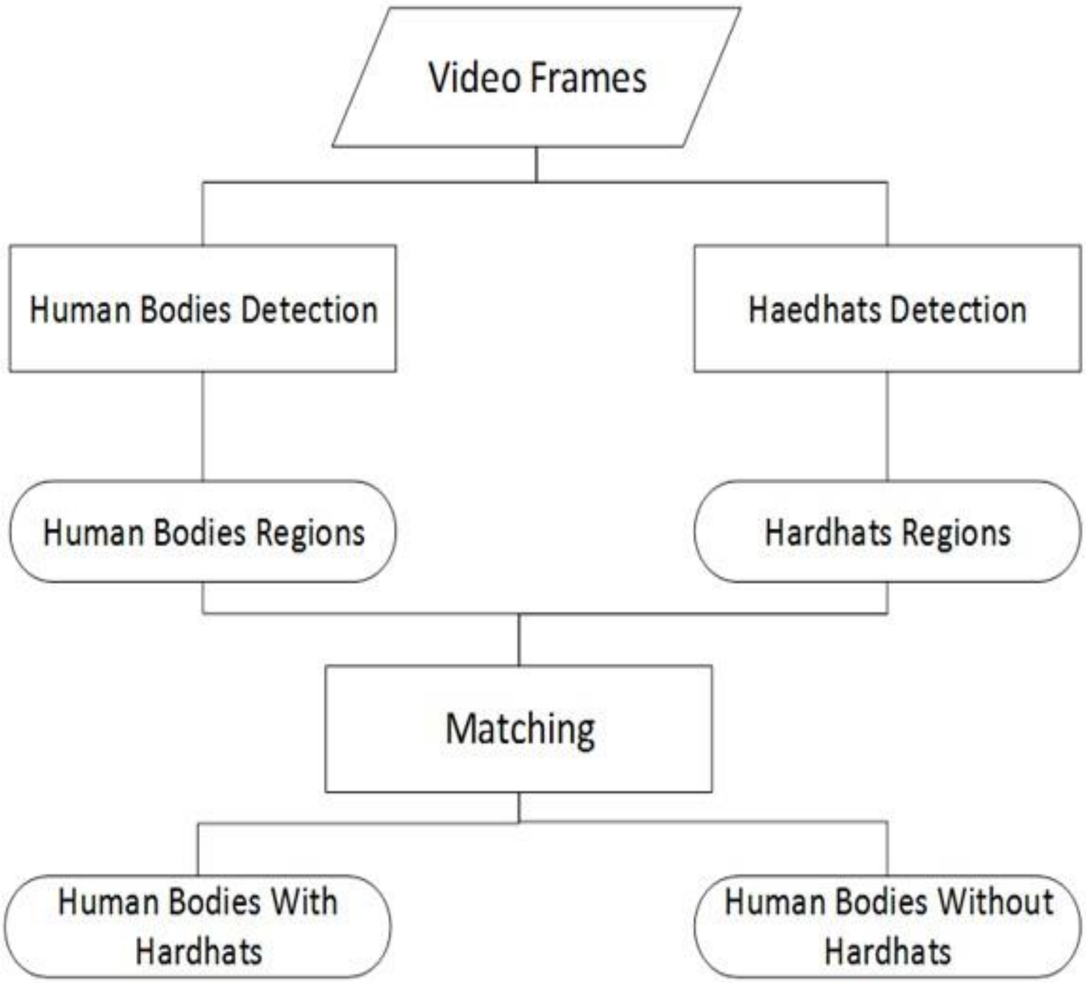


Figure 3-2: The framework of the proposed method.

3.2 Human Body Detection

To detect the human body, two main steps, (1) background subtraction and (2) HOG feature (Dalal and Triggs 2005) were applied. In the first step (background subtraction), foreground blobs corresponding to each object in motion were extracted using the background subtraction, and then the foreground blobs were the main source for human body detection. Background subtraction has two main advantages. First, it reduces the probability of false detections, specifically for human bodies in the background static areas. Second, it restricts the search area to the foreground, which can enhance the computational efficiency involved in searching for sections of human bodies.

In 1995, Macfarlane and Schofield proposed the background subtraction method (McFarlane and Schofield 1995), providing a detailed explanation of the background subtraction method and its efficacy on the restriction of search areas, specifically for detecting construction workers (McFarlane and Schofield 1995, Park, Koch et al. 2011). Their method was adopted in this research project and follows the steps shown in (Figure 3-3). After extracting the moving blobs, morphological operations (e.g., dilation and erosion) were used for further processing of the results. During the dilation process, extra pixels are added to complete the missed component for the moving objects and adjacent moving blobs were merged into one blob. During the erosion the small-sized blobs were ignored. The rest of the foreground blobs were fitted to the smallest possible rectangles around the blobs (see the white rectangles in Figure 3-3). These fitted rectangles were enlarged outwards by 40 pixels, because the template for human body detection adopted in the paper is 64 pixels by 128 pixels. The human body template model also includes margins of 16 pixels from all the borders (Figure 3-4).

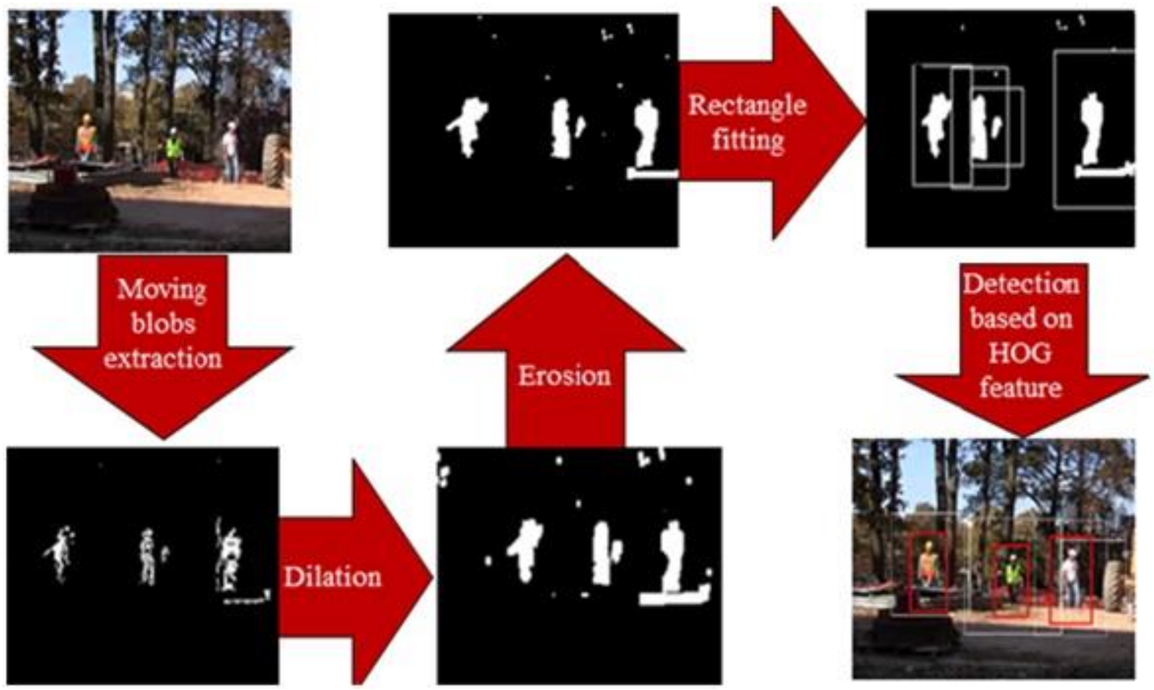


Figure 3-3: Human body detection method.

The background is updated in every frame of the streaming video (McFarlane and Schofield, 1995). This helps to reflect any changes of the illumination conditions and enhances the appearance of the background static objects (McFarlane and Schofield 1995). Therefore, the effect of light conditions changes become negligible. In addition, the effect of light was illustrated as a pre-processing stage for detecting construction workers.

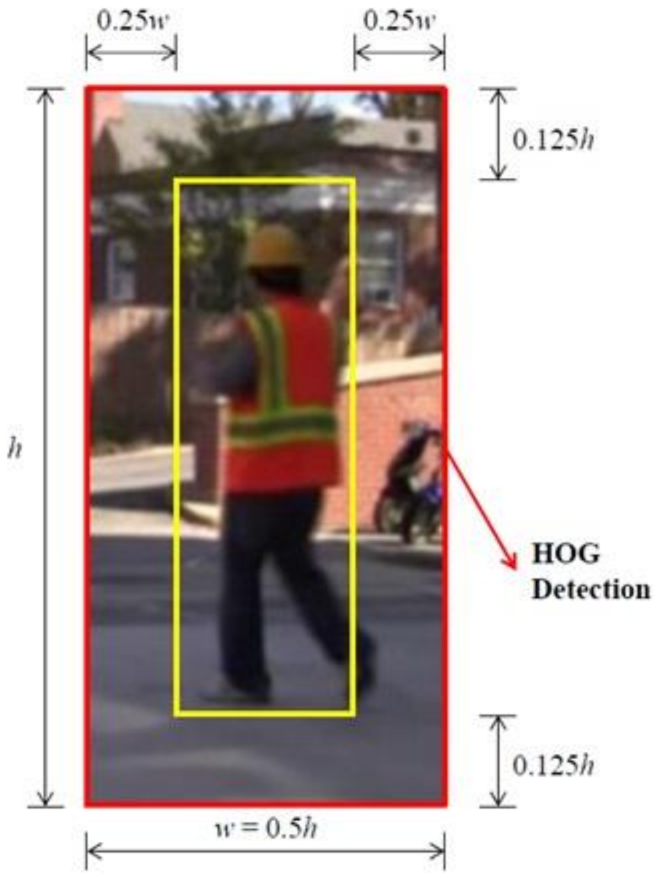


Figure 3-4: Margins around a human object in the HOG feature template.

In the second step, the HOG features detection were applied for the subtracted foreground regions, following the morphological (dilation and erosion) (Figure 3-7). The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image (Dalal and Triggs 2005) (Figure 3-5).

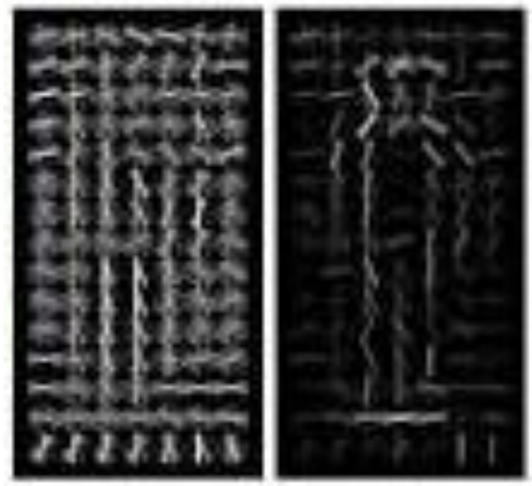


Figure 3-5: HOG for human body.

HOG features work by training the SVM using a big number of images to create the human bodies' detection model. During the image collecting process, around 300 positive images were collected. Those positive images include one or more than one person inside each image. In addition, around 500 negative images were collected. Those negative images include any objects except the human bodies.

The collected positive images had a huge variety. The images were collected from three different construction sites, in different light illuminations, indoor and outdoor, contained different position of the human body, and were taken from different distances as shown in (Figure 3-6). The wide variety of the collected images helped to provide a strong detection model that can detect any human body in any condition.

Figure 3-6: Positive human body images collection.

Figure 3-7: the steps of human body detection.

The HOG features descriptor simply compares the HOG template with HOG features of the images' patches. If the images' patches are greater than the HOG template, they are reduced to the HOB's template size. The template size used in human body detection is 64 pixels by 128 pixels. The proposed method followed this procedure to avoid any drop in its human body detection performance because of the reduction of the resolution when the workers' pictures appear larger than the HOG template size.

The next step was to initiate a training process for the support vector machine (SVM). This helped to reflect all the variations in human body shapes. The HOG detection feature, for each window, was extracted and classified as a human body or non-human body. For example, the foreground was represented by a white rectangle (the result of the background subtraction), while the human bodies were represented by a red rectangle (the result of the HOG feature detection) (Figure 3-8).

Figure 3-8: Example of the HOG-based human body detection in foreground regions.

Even though the color histogram illustration approach may be able to distinguish construction workers from other human bodies (Park and Brilakis 2012), we did not include the color histogram illustration method in our human body detection model. The main reason is that our aim is to create a safety alarm in case anyone is not wearing a hardhat on a construction site (e.g., construction worker, contractor, supervisor, trainee or visitor) (Park and Brilakis 2012).

3.3 Hardhat Detection

Hardhats are usually made of resistant materials (e.g., fiberglass and rigid plastic), and they are produced by many different manufacturers. Hardhats have many different colors (e.g., white, brown, green, blue, orange, red, etc.). These colors may refer to the position of the person wearing it (e.g., managers, engineers, superintendents, laborers, or carpenters). Hardhat design varies from company to company based on the nature of the work and the location of the construction site. Hardhats were therefore identified considering all their colors and forms. This step was simplified by the fact that most hardhats have closely similar shapes, following a (human skull) cap-style, and they have a rigid and smooth surface without any kind of deformations (Figure 3-10).

The HOG hardhat detection features were used as recognition cues. The HOG features detector can effectively provide detailed shape information, and it has proven its utility for shape-based detection in many research studies. As in our human body detection model, hardhat recognition has the following stages. First, construction images with different colors and poses for the hardhats were collected as a training database. The database images were collected from different construction sites and different light conditions. Based on our dataset collection the maximum amount of the brightness in the training images was 120 Lux, and the minimum amount was 107 Lux. as shown in (Figure 3-9). Image (A) is the image captured in the darkest illumination included in our dataset (indoor, unlighted construction site, illumination 107 Lux), while image (B) is the brightest image in the dataset (outdoor, sunny day in the summer, illumination 120 Lux.. The dataset images which used to test the method were randomly collected with an illumination value ranged in between (107 lux-120 lux). The hardhats in the test images wear successful detected regardless the value of the illumination in the images.

Figure 3-9: Darkest image A, and brightest image B with the result of hardhats detection

To calculate the illumination, the value of the red, green, and blue color were used in the following equation. RGB value were calculated using Microsoft Photoshop (Stokes et al, 1996).

$$Illumination = 0.2126R + 0.7152G + 0.0722B \qquad \text{Eq.1.}$$

The hardhats collected images were 300 images. 200 images used to train the model and 100 used to examine the method.Figure 3-10: Hardhat positive image collection. (Figure 3-10) show some examples of the collected dataset images. Next, the annotation of the hardhats in the collecting images were performed. To annotate the hardhats an annotation tool developed by Kor and Scheneider (2007) was used in MATLAB environment. The annotation provide satisfactory answers to the questions like (which image is being annotated, what is the resolution of the image?). In addition, the annotation process provides detailed information about the image source.

When all the images of the hardhats are annotated, the dataset is arranged into two folders. The first folder contains all the images and the second folder contains the corresponding annotation in XLM format files, and the same contents of the image file. All the annotation files were converted to be in the form of boundary polygons format. The boundary polygons format was required in the method of (Felzenszwalb, 2010) to create the final detection model.

In order to generate the bounding box of the hardhat, the polygon information extracted and the polygon point coordination are compared. The maximum and minimum value are obtained from the polygon points. The corners of the top left and bottom right are determined to create the bounding box.

The dataset images and the converted files used to train the recognition model. Based on the method of (Felzenszwalb et al, 2010) a complete learning based system used to train object models. To create the detection model, 800 images were used: 300 images contains positive instances of the hardhat, and 500 images contains negative instances. The positive 300 images were divided into two groups: first group contained 200 images and they were used for the training of the model, and the second group contained 100 images and they were used for testing of the model. The proposed method read the images dataset and their corresponding annotation files to start the training process and create the detection model.

Figure 3-10: Hardhat positive image collection.

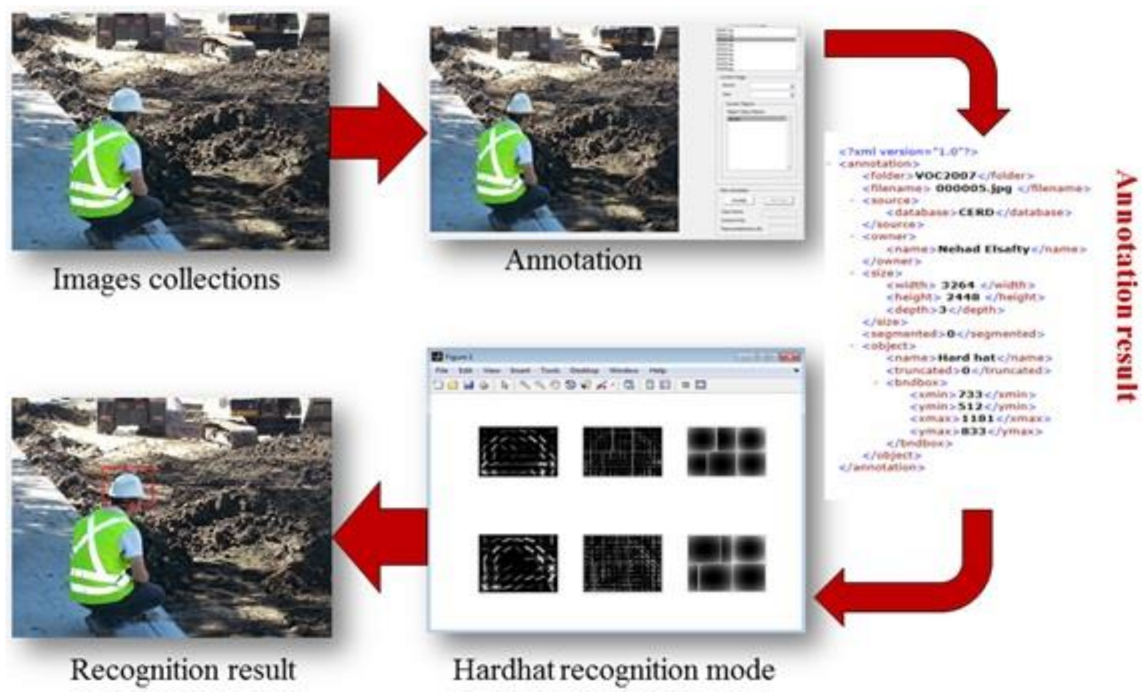


Figure 3-11: Hardhat detection method.

Using the proposed method, hardhats with different colors could be successfully identified, including white hardhats, while the method developed by (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011) could not detect white hardhats.

After the trained of the hardhat detector and created the detection model, the recognition of the hardhat in any image could be performed. First, the method extracted the HOG feature map from the examine images. Second, a sliding detection window use to compere the HOG model feature with the one from the examine image. Third, the method searched for the matched parts in the model HOG and the examine image HOG. Fourth, the matched parts define as a positive detection and get a high value of the color response values. Fourth, the rest of the HOG examine image feature which had not any matched with the model defined as a false detection and get low value of the color response.

Finally, the method create a detection rectangles around the high values color to determine the detecting hardhats in the examine image as shown in (Figure 3-12).

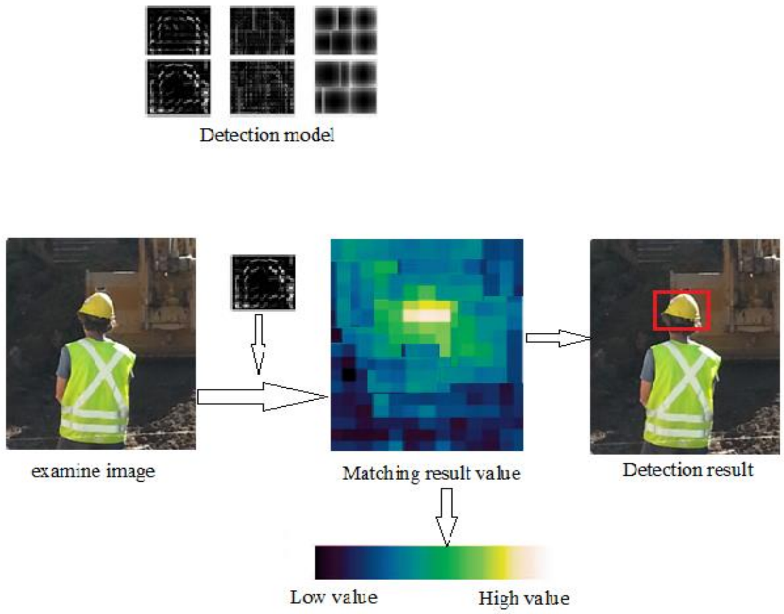


Figure 3-12: image processing for hardhat detection.

3.4 Matching Between the Detected Human Bodies and Hardhats

After detecting the human bodies and the hardhats (Figure 3-13 (a)), the detection process results were the locations and the sizes of the human bodies and the hardhats. It was important to link each hardhat to the corresponding human body to be able to identify people with and without hardhats (Figure 3-13(b)). Three human bodies in (Figure 3-13(b)) are marked with blue color rectangles, identified by the tool that matched them with their correspondent hardhats. Those human bodies without their corresponding hardhats are marked with magenta color rectangles.

(a) (b)

Figure 3-13: Example of the HOG-based detection and matching (a) Human body and hardhat detection. (b) Matching between the detection results.

The matching process would be simple if the detected hardhat and human body regions had their actual shape and size. However, the hardhats' and the human bodies' detected regions were different from reality and they were not perfect. This could change the perspective and dislocate the actual hardhats or human bodies or regions. Therefore, we defined the hardhats' regions to enhance the matching process.

First, the hardhat's positions in relation to the human body regions were divided into region I and region II (Figure 3-14). Region I represents the ideal and common cases when the detected parts human body properly locates in a rectangle enclosing the person (Figure 3-14(a)). The HOG detection feature template for human body parts contains margins of 0.25w and 0.125h for the vertical and horizontal boundaries, respectively (Figure 3-14). The isolated human body location is a dotted rectangle 0.5h×0.75h at the center of the template (Figure 3-14). Consequently, hardhats will locate at the region adjacent to the upper border of the same rectangle. Hence, the detected region will be at the center half of the width and at the top 0.3h of the height in the HOG identification feature template (Figure 3-14 (a)).

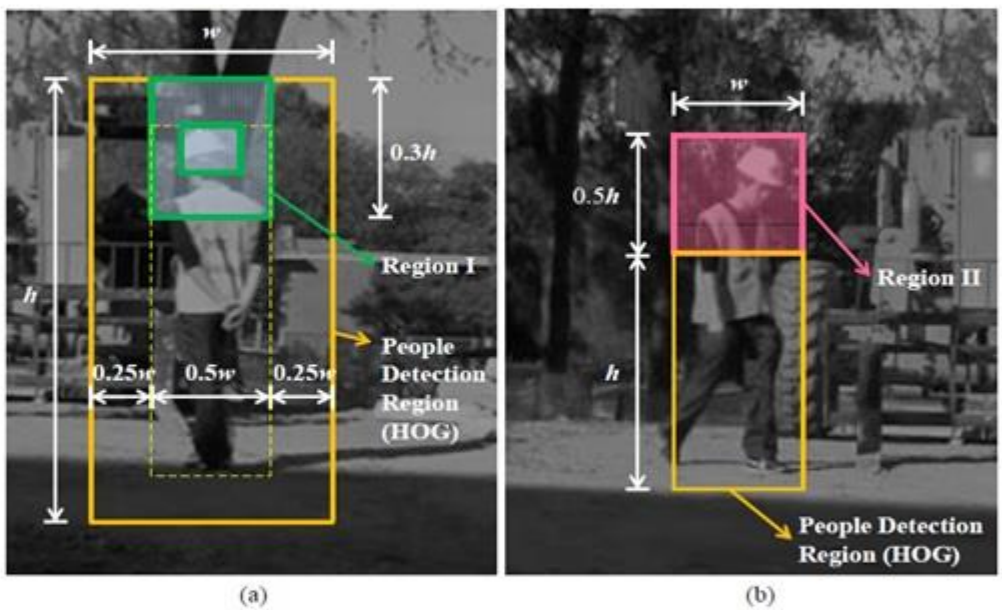
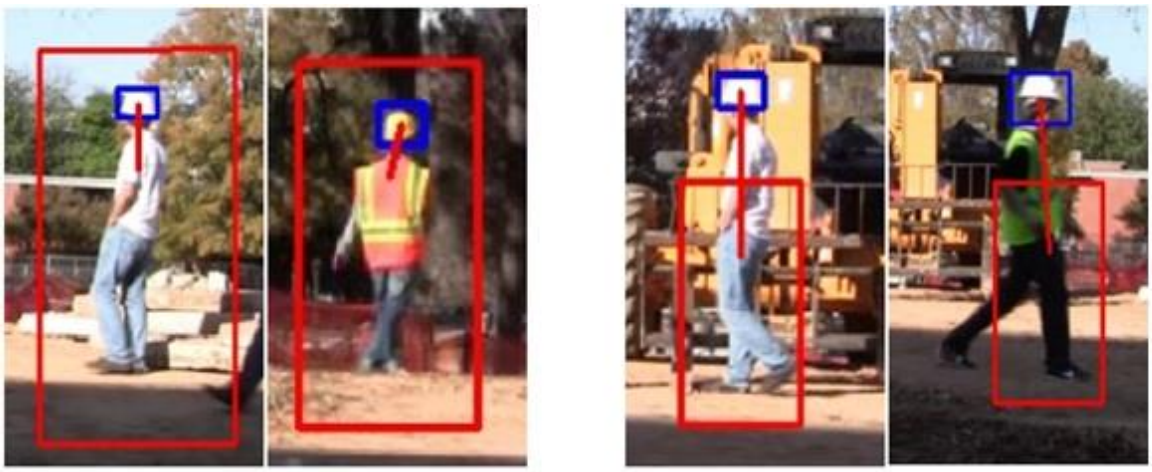


Figure 3-14: Possible hardhat regions. (a) Region I. (b) Region II.

Region II was used for the abnormal cases, when the detected region of the human body is slightly away from the actual person’s location. The identification rectangles in those cases are assigned the lower part of the detected persons (Figure 3-14 (b)). In this case, the hardhats locate at the upper part of the rectangle, and are not included in the human body detection rectangle. For example, hardhats were detected in two Regions I, and II (Figure 3-15). Therefore, Region I, and II were checked to verify if the human body detection accurately identified a person.



(a) (b)

Figure 3-15: Matching between the human body and hardhats. (a) Matching in Region I. (b) Matching in Region II.

Any hardhats that were found in either of the detection regions I or II were considered candidates, with regard to each detection region of the human body. After the verification step, the examined results were filtered to remove the unrelated candidates (Figure 3-16). During the matching process, the priority in results was to Region I over Region II.

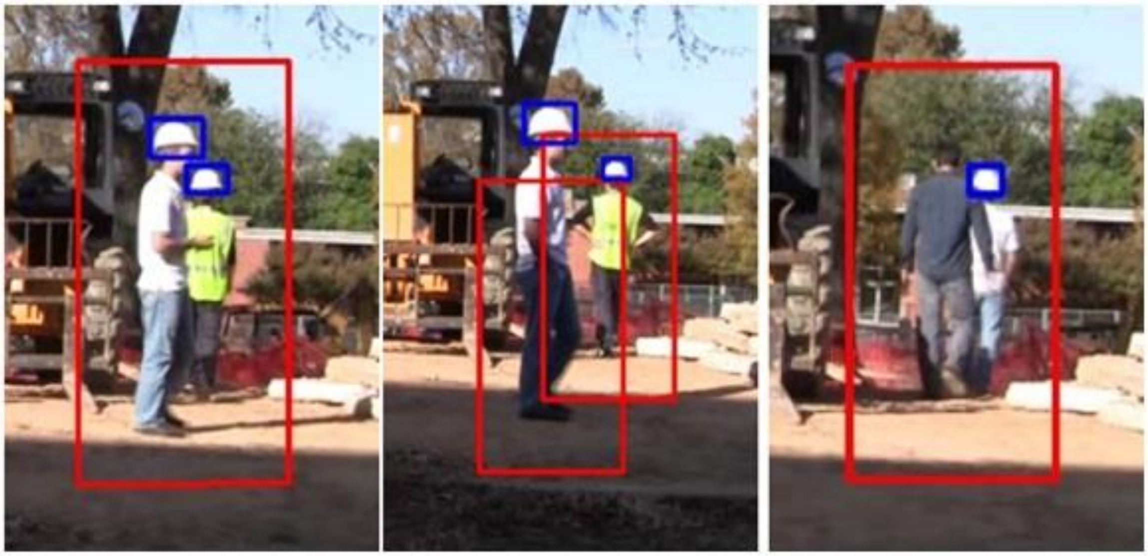


Figure 3-16: Example of rejected result.

CHAPTER 4. IMPLEMENTATION AND RESULT

4.1 Implementation

The proposed method was implemented and each of its three components were tested: human body detection, hardhats detection, and matching the detected human bodies and hardhats. They were then integrated into the Microsoft Visual C++ NET Framework 4.0 environment.

To detect the parts of human bodies, we trained the detection model using the public INRIA person dataset to train the HOG identification features with the parts of human bodies using SVM. The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. HOG features descriptor can be applied for the subtracted foreground regions, following the morphological operations (dilation and erosion). The HOG descriptor is a well-known detection system that is generally used for human body detection (Dalal and Triggs 2005). We used the work of Dalal and Trigg (2005) for training the template as it is a well-known system for the identification of human bodies (Dalal and Triggs 2005). To train the model for hardhat detection, we collected one hundred images from different construction sites in Montreal, Canada. We outlined the hardhats in the images manually as samples for positive training.

The detection and matching system was tested on real construction site videos to confirm their validity. These videos were taken using a HD camcorder (Canon VISXIA HF S100, 8.59 megapixels). To evaluate the method's robustness, only new video frames were used in the evaluation process, not the same ones used for training. These test videos contained many individuals with and without hardhats, from different camera viewpoints in different light conditions, e.g. sunny bright, shady dim areas, and during rain and snow conditions.

For rapid processing, the size of the frames used by the detection process in the test videos were 768 pixels by 432 pixels. The test video was 166 seconds long, with 20 frames per second (fps), and each video contained 3320 frames in total. In the validity tests, 10 frames could be processed per second, which can be considered as almost meeting real-time requirements, as it is very difficult for the workers during 1/10 second to change their situation and takeoff the hardhats. Human body detection was the most time consuming part in the video frame processing. The speed of the detection process was affected by the moving objects in the camera view (e.g., workers and mobile equipment). Moving objects increased the method search space, which in turn reduced the speed of the detection process. Considering the limited resources in our lab, there it would be possible to reduce the detection time with support from Graphics Processing Unit (GPU) computing.

4.2 Evaluate the Performance of the Method

To analyze the effect of the method on the detection of construction workers without hardhats, the performance of three main steps in our proposed detection method (e.g., human body detection, hardhat detection, and issued the safety alert) was evaluated.

The precision and recall were the main determinants to measure the performance as suggested by (Wang, Cheng et al. 2011). The precision is an indication of the true positive accuracy (David L et al, 2008). High precision means many true safety alerts issued by the method to detect workers without hardhats inside the construction site. The recall is an indication of the true positive rate (David L et al, 2008). High recall means that many of the workers without hard hats are correctly detected by the method. The precision and recall were calculated as follows:

$$Precision = TP \ / \ (TP + FP) \qquad \text{Eq. 2}$$

$$Recall = TP/(TP + FN) \qquad \text{Eq. 3}$$

TP, FP, and FN represent the 'True Positive', 'False Positive', and 'False Negative' detections, respectively. The precision of the detection method is determined by the ratio of the number of true detections divided by the total number of detections made by the same method. The recall is the ratio of the numbers of true detections divided by the total number of objects that appear for detection. We summarized the precision and recall ratios for the detection of human bodies and hardhats, and the safety alert issued by the method in the following sections.

4.3 Performance of Human Body Detection

In human body detection, the numbers of correct human bodies' detections are called the True Positives (TP), the numbers of the incorrect human bodies' detections are the False Positives (FP), and the numbers of the human bodies missed, without detection, are the False Negatives (FN) (Figure 4-1). The false positive (FP) results were only 2.0%, as the results of the human body detection tests only had 2.0% that were wrongly detected, and 8.8% were false negative (FN), as 8.8% of the workers who appeared in the test video frames were missed (Table 4-1). The precision has a higher importance than the human body detection recall when the objective is to determine if an individual is wearing a hardhat or not.

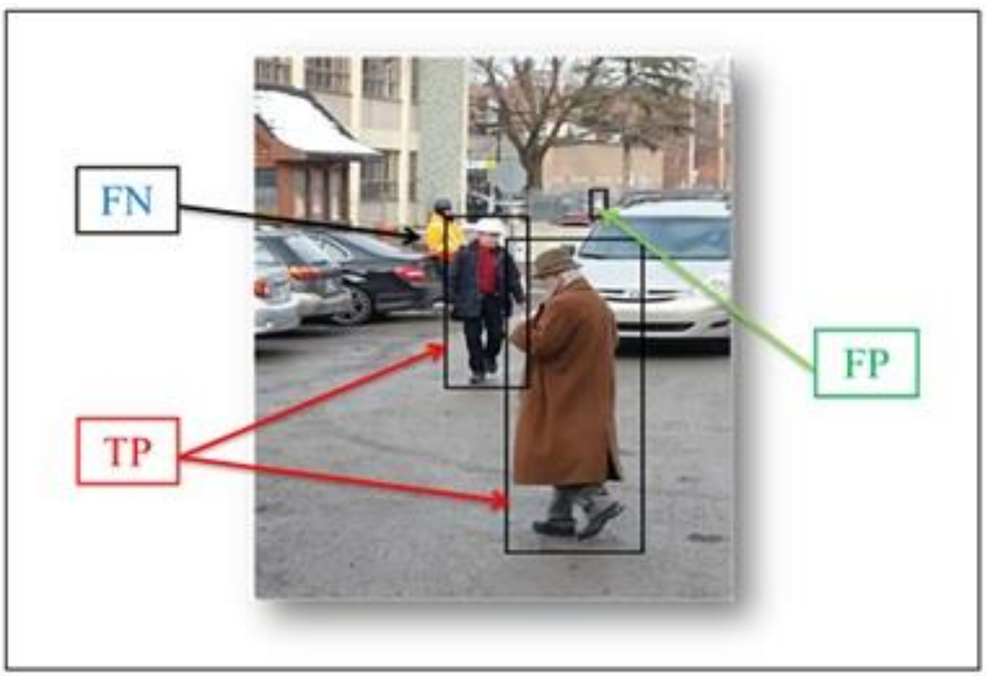


Figure 4-1: TP, FN, and FP for human body detection.

Matric	Human body detection
TP	3026
FP	61
FN	291
Precision%	98.0
Recall%	91.2

Table 4-1: Human body detection result.

If the method can detect a human body every 10 frames, the recall is 10%, but it is still able to identify whether that person is wearing a hardhat once a second. On the other hand, if the precision is reduced, the probability of false alarms will increase. For example, when we have the false identification of a tree branches as a person, this will cause a false alarm, because its accompanying hardhat will not be detected in the region specified for it.

Theoretically, 32 pixels by 96 pixels is the minimum size of the workers which can be detected by the method. This resolution was selected because the HOG template size is 64 pixels by 128 pixels, which consists of a human body region (32 pixels by 96 pixels) and a 16-pixel-wide margin around the human body. Based on the test results, it was found that the proposed method was able to detect people with the size of 27 pixels by 80 pixels through the scaling up of the foreground regions by 20%. In other words, the acceptable size of the human body to be detected by the method in a video frame should be more than 27 pixels by 80 pixels. Using the digital zooming functions of the camcorder in the test video frames this size can be reached easily regardless of the distance between the camera and the person.

(Figure 4-2) shows examples of video frames that are challenging for the proposed method. In these examples, it can be seen that many objects at construction sites, such as tree branches and equipment wheels, might be detected as human bodies by mistake. In addition, occlusions of the field of the camera can also occur, for example, a worker, onsite material or a piece of equipment can occlude the view field of a worker. These occlusions will negatively affect the human body detection performance.

Figure 4-2: Example of challenging detection results.

4.4 Performance of Hardhat Detection

The TP in the hardhat detection is defined as the number of correct detections of hardhats. FP is the number of incorrect hardhat detections, and FN is the number of the undetected hardhats (Figure 4-3). The detection of hardhats does not depend on the results for the detection of human bodies, since those detections are made with different detection templates.

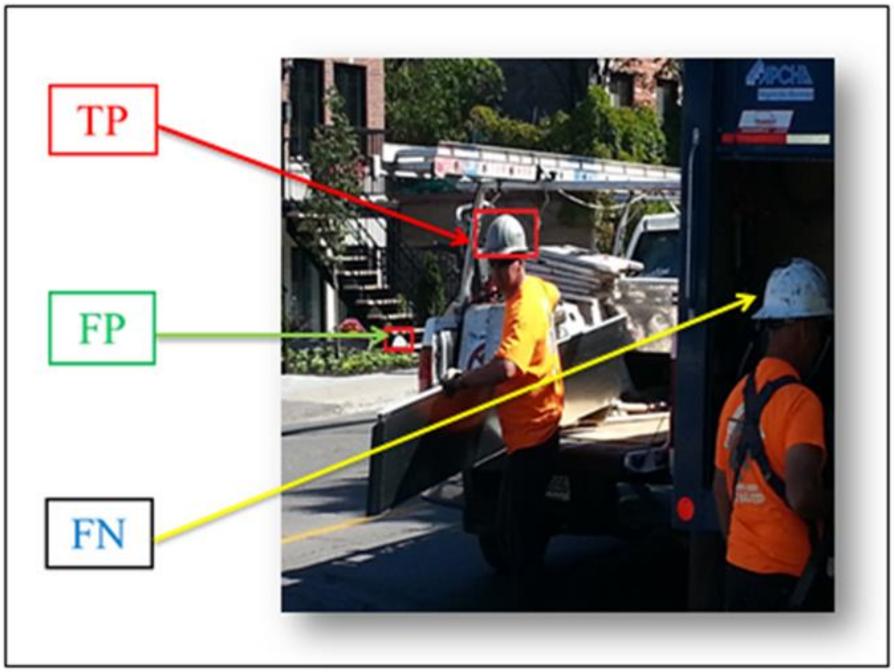


Figure 4-3: TP, FP, and FN for hardhats detection

However, compared with high precision and recall for the detection of human bodies, it is difficult to guarantee both high precision and recall for the detection of hardhat at the same time. As the precision for the hardhat detection increases, the corresponding recall drops significantly, and as the recall for hardhat detection increases, the corresponding precision drops significantly. This may be due to several reasons. First, the differences in the size between the hardhat regions and the human bodies region were huge. Second, the shapes of the hardhats are more uniform compared with the human bodies' shapes in the test scenarios.

` In order to illustrate the effects of hardhat detection results on the final safety alerts issued when a hardhat is not being used, two hardhat detection schemes have been prepared. The first aims to maximize the detection precision even if the detection recall may be low. The second detection scheme aims to maximize a high detection recall even if the detection precision is low. The preparation of these two detection schemes was done by manually changing the threshold in the SVM-based model for hardhat detection. Increasing the threshold increases the detection precision but reduces the detection recall. In contrast, reducing the threshold reduces the detection precision but increases the detection recall. More details about the threshold could be found in the works of (Dalal and Triggs 2005, Felzenszwalb, Girshick et al. 2010).

In the proposed method, the threshold value in the hardhat detection scheme was selected when a higher hardhat detection precision could be achieved from the tests. The corresponding test results indicated that only 0.4% of the hardhat detection results were not correct (high precision), but almost 27.2% of the hardhats were missed (low recall). The threshold value in the second hardhat detection scheme was selected when a higher hardhat detection recall could be achieved from the tests. The corresponding results indicated that almost 38.8% of the hardhat detection results were not correct (low precision), but only 3.2% of the hardhats were missed by the detection (high recall) (Table 4-2).

Matric	**Hardhat detection**	
	Scheme 1	Scheme2
TP	2246	2984
FP	9	1893
FN	838	100
Precision%	99.6	61.2
Recall%	72.8	96.8

Table 4-2: Hardhat detection result.

4.5 Safety alert for not wearing hardhats

When the proposed method identifies that a person is not wearing a hardhat on a construction site, a safety alert will be issued A comparison between the safety alert issued by the proposed method and with the issuing of safety alerts in reality was carried out to identify the value of the TP, FP and FN, as given in (Table 4-3). Specifically, if the safety alert should be issued in reality and a safety alert is issued by the method, then that safety alert is a true positive alert. If the safety alert does not have to be issued in reality but a safety alert is issued by the method, then that safety alert is a false positive. Moreover, if the alert is not issued by the method when a safety alert should be issued in reality, then that safety alert is a false negative alert for the method. When the numbers of TP, FP and FN are estimated, the safety alert precision and recall can be calculated using Eq. 1 and 2.

Category of safety alert	Whether a safety alert should be issued in reality	Whether a safety alert is issued by the proposed method
TP	Yes	Yes
FP	No	Yes
FN	Yes	No

Table 4-3: The definitions of TP, FP, and FN in terms of issuing safety alerts

(Table 4-4) show the result of the method's test under scheme1 and scheme 2 for issuing the safety alert. Under scheme 1 the precision was 53.6% and a recall was 87.7%. In scheme 2 the precision was 94.3% and the recall was 89.4%. The second scheme gives a higher safety alert precision and recall. In order to reach that result, the recall of detecting the hardhat in the second scheme was maximized manually by changing the value of the threshold in the SVM-based model (reducing the threshold increased the recall in the hardhat detection).

Matrix	Scheme 1	Scheme 2
Precision	53.6	94.3
Recall	87.7	89.4

Table 4-4: Precision and Recall for Scheme 1 and Scheme2.

The test videos were 166 seconds long, with 20 frames per second (fps), and each video contained 3320 frames in total. In the validity tests, 10 frames were processed per second, which can be considered as almost meeting real-time requirements, as it is very difficult for the workers during 1/10 second to change their situation and takeoff the hardhats. Human body detection was the most time consuming part in the video frame processing. The speed of the detection process was affected by the moving objects in the camera view (e.g., workers and mobile equipment). Moving objects increased the method search space, which in turn reduced the speed of the detection process. Considering the limited resources in our lab, there it would be possible to reduce the detection time with support from Graphics Processing Unit (GPU) computing.

(Figure 4-4) shows a part of the examination process. Under the scheme (1) the safety alert issued for five time during the examination. Three alerts were false as the assigned workers had the hardhats on head, and tow alert was true as the tow construction workers were without the hardhats during that time. Under scheme (2), the safety alert issued for two times both times were true alert and the workers were without hard hats. That cause the higher recall percentage between scheme (1) and scheme (2).

(a)

(b)

Figure 4-4: The comparison of safety alerts issued under two hardhat detection schemes. (a) Safety alert in scheme I. (b) Safety alert in scheme II.

Figure 4-5: Examples of identifying people with hardhats (red) and without hardhats (magenta).

For example, if ten people are not wearing hardhats on a construction site, under a recall value of 89.3% for scheme2 the proposed method could successfully identify nine of them. (Figure 4-5) shows some examples of the successful detection of individuals without hardhats on a construction site. The overall test results for detecting whether people are wearing hardhats indicated 94.3% precision and 89.4% recall.

4.6 Comparison

The proposed method has been quantitatively compared with the safety helmet detection method proposed by Gualdi. (2009, 2011) (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011) with the same test dataset, as shown in (Table 4-5). Both methods aim at issuing a safety alert to detect any person not wearing a hardhat on a construction site. The precisions and recalls of both methods were calculated and summarized. The values of the precision and recall were significantly improved by the proposed method compared with that of Gualdi et al (2009, 2011).

Matrix	Scheme 2	Gualdi's Method
Precision	94.3	14.3
Recall	89.4	15.8

Table 4-5: Comparison between proposed method (Scheme 2) and Gualdi's method.

For detecting the hardhats in Gualdi's Method, a head detector is employed to obtain the different head position. The head appearance is dominated by a circular shape. The method used the polar image transformation for better result and to generate lighter classifiers that will benefit the detection process with a lower computational load (on average, over the three color spaces, polar classifiers use 23% less weak classifiers). The used of a polar transformation was negatively affected the detection of white hard hats, as the system could not function correctly. The failure of the detection of white hardhats makes the system generate a lot of false alerts when being applied in the construction site. In the proposed method the detection model used only the HOG features without color cues. Therefore, it could detect the hardhats with different colors.

(Figure 4-6) illustrates an example of comparing the safety alerts issued by the method proposed by the authors and the one proposed by (Gualdi et al. 2009, 2011) (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011). In this example, the proposed method successfully identified the man who was not wearing a hardhat, but Gualdi's method failed to identify him. Moreover, the safety alert issued by their method was false, since the person identified as not wearing a hardhat (red box) was actually wearing a hardhat (Gualdi, Prati et al. 2009, Gualdi, Prati et al. 2011).

(a) (b)

Figure 4-6: Comparison of safety alerts issued (a) Proposed method and (b) Gualdi et al.'s method

The neural network could be used also to detect the different objects. Neural network implement the last view based approach of the detected object. It can estimate the orientation of any potential object to recognize it. There were some limitation that makes the neural network not suitable to apply in our method. It is slow for detecting profile objects, which made the system inaccurate and not fast enough for using in other application especially for the real time application (Rowley, 1999).

CHAPTER 5. DISCUSSION AND EXPECTED CONTRIBUTION

Based on the test results of this proposed method, several limitations were noted, limitations that could be improved on the future. First, with the current detection template, the method can only detect people that are standing or walking. Individuals in other positions (e.g. crouching down, bending, and sitting) cannot be detected successfully Those who are bending or sitting can only be detected when they change their posture to being standing. This missed detection problem arose because the detection template adopted for this version of the method was trained using images of standing workers. As a solution, we can extend the detection template by training it with images of workers in different postures. Another solution would be to create different detection models for each posture. The \These two solutions will be investigated for their effectiveness and a more generalized method for detecting construction workers with different postures will be developed in future work.

Second, the proposed method relies on the spatial and geometric relation between the recognition windows of people and hardhats to perform the people-hardhat matching. Closely related to the first problem, the matching process between the hardhats and human bodies gives a negative result when individuals inside the construction site not standing or not walking. If people have other postures, the matching parameters proposed here will have to be correspondingly adapted. For example, if a construction worker is crouching down or bending, the position of the hardhat might be in the left-top area of the worker's recognition region, as illustrated in (Figure 5-1). However, the exact matching parameters cannot be determined until the recognition of construction workers with different postures is implemented.

Figure 5-1: Potential spatial and geometric relationship between a hardhat and a worker not standing or walking

Third, one of the major limitations that affect the performance of the proposed method is occlusion, a problem similar to that of other vision-based methods. If any objects partially or fully occlude a worker, that worker cannot be detected or monitored with the method. The method can detect the workers when they appear clearly in the camera’s view. Installing cameras inside a construction site at a certain height level in order to reduce the chances of occlusions and guarantee the effectiveness of the proposed method could be an effective way to solve this problem. Also, placing multiple cameras would make it possible to cover a larger area of a construction site.

There is another issue, related to the proposed method's use of background subtraction to reduce the video processing time. This step enables the method to only detect moving workers, hence workers without movement are not identified. Static workers were considered as a part of the background and were subtracted during the background subtraction. However, there are opportunities to detect static workers. For example, turning off the background subtractions and considering the whole field of the camera view as the foreground will enable the method to detect static workers, but this will slow the creation of a safety alert. Static workers could also be detected when they first enter a camera's view. Therefore, the integration of the detection and tracking of construction workers will provide another way to continuously monitor workers even if they are static.

The automated recognition of workers without hardhats accomplished through this research work provides an automated and remote way to monitor and control the safety of the workers inside the construction site. In doing so, a matching process performed between each detected hardhat and its corresponding human body. When the hardhats didn't locate in one of the expected regions shown in figure (3-13) the safety alert issued. In some cases the safety alert issued wrongly, as the hardhat didn't located in the exact region. In order to solve this problem other methods will be examined in the future work such as The Artificial Neural Network. The Artificial Neural Network could be used in the matching and detection processes for detecting the workers without hardhats. The ANN could decrees the time of creating the detection models as it use a smaller numbers of training images compared with the used method. Also the ability of detection the workers in difference bosses with different location of the hardhats could be examine using ANN and could give an acceptable result.

CHAPTER 6. CONCLUSION

The construction sector is one of the most dangerous job sectors, and it also employs a large number of people, often with different levels of training. Governments have established safety regulations and procedures to increase construction site safety, but they are not enough. Construction workers may slip up and not always follow the safety requirements due to fatigue, distractions, carelessness, etc. Therefore, it is very important to ensure that these safety regulations and procedures are followed inside any construction site, all of the time.

Currently, it is inspectors who are responsible for verifying safety regulations at construction sites. An inspector monitors and controls the safety at a given site. This thesis proposed a novel, vision-based method to automatically check whether people at construction sites are wearing hardhats. This method is comprised of four parts: human body detection, hardhat detection, matching and then the issuing safety alerts when construction workers are not wearing hardhats. The method is expected to facilitate and automatically monitor the work of construction site safety inspectors. The method has been tested with real site videos. According to the test results, the safety alerts were successfully issued when construction workers were not wearing hardhats with an overall precision of 94.3% and a recall of 89.4%. The second hardhat detection scheme gave a higher safety alert precision and recall, indicating that the worksite safety in terms of hardhat-wearing could be monitored with live streaming or time-lapse videos Maximizing the hardhat detection recall played an important role in improving the precision for issuing safety alerts due to not wearing hardhats.

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