The 6th International Conference on Construction Engineering and Project Management (ICCEPM 2015)
Oct. 11 (Sun) ~ 14 (Wed) 2015 • Paradise Hotel Busan • Busan, Korea
www.iccepm2015.org

Vision-Based Identification of Personal Protective Equipment Wearing

Man-Woo Park[1] and Zhenhua Zhu[2]

***Abstract:** Construction is one of the most dangerous job sectors, which reports tens of thousands of time-loss injuries and deaths every year. These disasters incur delays and additional costs to the projects. The safety management needs to be on the top primary tasks throughout the construction to avoid fatal accidents and to foster safe working environments. One of the safety regulations that are frequently violated is the wearing of personal protection equipment (PPE). In order to facilitate monitoring of the compliance of the PPE wearing regulations, this paper proposes a vision based method that automatically identifies whether workers wear hard hats and safety vests. The method involves three modules – human body detection, identification of safety vest wearing, and hard hat detection. First, human bodies are detected in the video frames captured by real-time on-site construction cameras. The detected human bodies are classified into with/without wearing safety vests based on the color features of their upper parts. Finally, hard hats are detected on the nearby regions of the detected human bodies and the locations of the detected hard hats and human bodies are correlated to reveal their corresponding matches. In this way, the proposed method provides any appearance of the workers without wearing hard hats or safety vests. The method has been tested on onsite videos and the results signify its potential to facilitate site safety monitoring.*

***Keywords:** Safety, Personal protective equipment, Hard hat, Safety vest, Image processin*

I. INTRODUCTION

Construction industry is one of the most hazardous industries causing various types of safety accidents. For example, the fatalities of construction industry in Canada were reported to be 700 from 2008 to 2010, which formed about a quarter of all occupational fatalities [1]. When it comes to South Korea, out of all occupational fatalities, construction sector accounted for 26.3% which corresponds to 486 fatalities [2]. The accidents generally entail additional costs and schedule delays which significantly degrade the project performance as well as the business confidence. The total costs caused by the deaths and injuries in construction industry of the U.S. were estimated at $11.5 billion in 2002, which was equivalent to $27,000 per case [3]. Also, it was reported that about 15.6 million working days were lost due to the accidents in construction industry.

In general, it is required to employ site safety inspectors on construction sites who monitor the job sites on a constant alert to check the compliance with safety codes and regulations. One of the most frequently violated regulations in South Korea is the requirement to wear a hard hat and a safety vest. Every worker on construction sites are required to wear appropriate personal protective equipment including hard hats and safety vests. In 2011, inappropriate use of personal protective equipment was listed in major causes of industrial fatalities accounting for 35% of the fatalities [4]. This record suggests that the regulations related to personal protective equipment is frequently violated and the on-site compliance is not monitored well. In order to facilitate the on-site safety monitoring, this paper proposed a vision-based method that automatically detects on-site workers who are not wearing either of hard hats and safety vests. The method basically uses video streams obtained with on-site construction cameras. It locates all human bodies in the camera view, and classifies them into 1) people wearing both hard hats and safety vests, 2) people wearing only hard hats, 3) people wearing only safety vests, and 4) people wearing neither hard hats nor safety vests.

II. BACKGROUND

For decades, research efforts have been made to enhance on-site construction safety. Besides establishing well-organized site safety policies and procedures, various sensing technologies have been tested to automatically identify near-accident events and to proactively apply appropriate safety measures.

Ruff [5] compared various sensing technologies to evaluate proximity warning systems on surface mining equipment. His study reported that remote sensing technologies such as GPS (Global Positioning System) and RFID (Radio Frequency Identification) could be used for warning system that alarm the proximity among construction entities. The proximity warning system can enhance site safety by avoiding impending collisions. Also, Teizer et al. [6] presented in-depth research studies about the RFID-based proximity sensing strategies. Their studies focused on proactive system to warn every worker or equipment operator when a piece of heavy construction

[1] Assistant Professor, 116 Myongji-ro, Cheoin-gu, Yongin, Gyeonggi-do, Republic of Korea, mwpark@mju.ac.kr (*Corresponding Author)
[2] Assistant Professor, 1455 de Maisonneuve West, EV- 6.237, Montreal, Quebec, Canada, zhenhua.zhu@concordia.ca

equipment appears within a certain range of the other equipment or a construction worker.

While a number of safety research studies delved into the proximity sensing methods, few research efforts have been made on the effective way of sensing whether workers wear personal protective equipment on the sites. Also, most of the previous studies are based on radio frequency technologies which require the installation of tags or sensors. The paper aims to propose a sensor-free method to recognize the violation of the safety requirement to wear a hard hat and a safety vest.

III. Proposed Method

FIGURE I
OVERALL FRAMEWORK

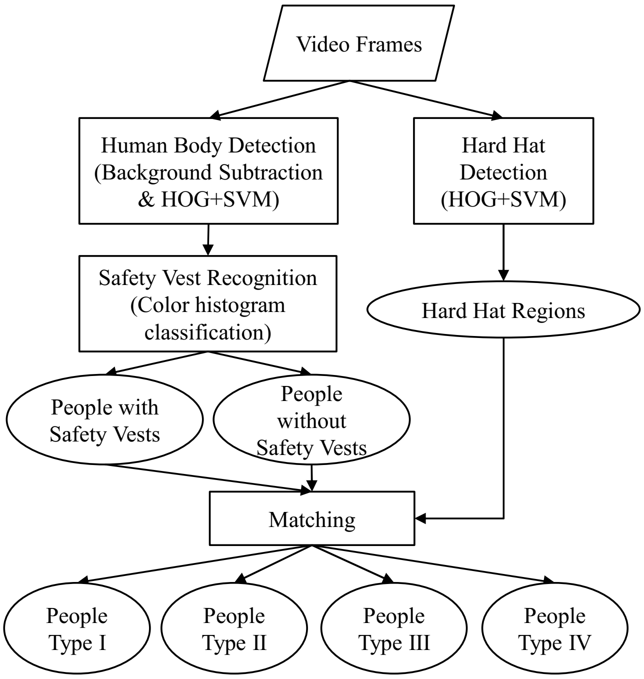


TABLE I
PEOPLE CLASSES

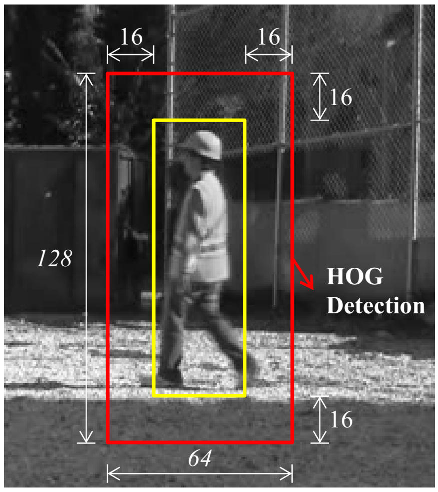
People	Type I	Type II	Type III	Type IV
Wearing Safety Vests	O	O	X	X
Wearing Hard Hats	O	X	O	X

Figure I shows the overall framework of the proposed framework. For every frame of the input video, two detection methods are applied to obtain the regions of human bodies and hard hats. The detected human body regions are classified into two classes - wearing safety vests or not wearing safety vests - based on the color features of the upper half part. The proposed method relates the classified two regions with the hard hat regions to find the corresponding matching pairs. In this way the detected human body regions are finally classified into four distinct classes which are summarized in Table I.

A. *Human Body Detection*

Human bodies are detected based on two features - motion and shape. First, the regions containing moving objects are extracted using background subtraction [7]. From the extracted moving object regions, the shapes of the human bodies in a standing posture are detected using HOG (Histogram of Oriented Gradients) [8] features. In the process of the HOG shape feature detection, the SVM (Support Vector Machine) is used to train the various shapes of standing postures. The background subtraction plays an important role of avoiding false positives of the shape detection and reducing processing time by restricting the candidate regions of the HOG detection. The size of the fundamental HOG shape template is 64 x 128 including 16 pixel width margins around the human body (Figure II).

FIGURE II
THE SIZE OF HOG TEMPLATE FOR HUMAN BODY DETECTION



B. *Classification of Safety Vest Wearing*

The detected human body regions are further processed to distinguish people who are wearing safety vests from people who are not wearing safety vests. Color features are used for the classification since safety vests have distinct fluorescent colors such as yellow-green and orange-red. The color features extracted exclusively from the upper half part of the human body regions. Color histogram is used to characterize the color features and it is constructed based on HSV (Hue, Saturation, Value) color space [9]. The value element is eliminated to create illumination variant feature vectors. The k-nearest neighbors algorithm is used to reflect various colors of safety vests.

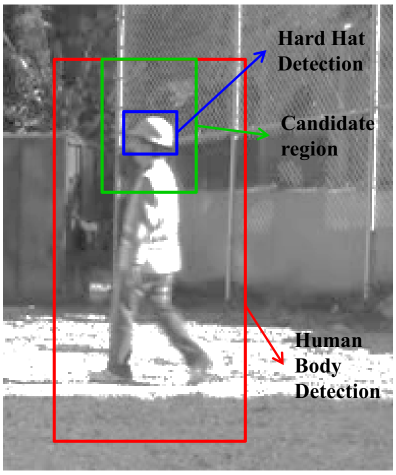
C. *Hardhat Detection*

Parallel to the human body detection, hard hat detection is processed to locate the hard hat regions. It also employs the HOG-based shape detection. The SVM is trained with varied colors and shapes of hard hat images. The threshold parameter of the SVM is tuned to optimize recall performance rather than the precision. Most false positives will be filtered out in the next step that matches human body detection and hard hat detection results.

D. Matching between Human Body and Hardhat Regions

The last step of the proposed framework is matching the hard hat regions with the human body regions. The matching process is based on their relative positions and scales. For each detected human body region, a candidate region (Figure III) of its probable head position and a probable size range of the hard hat are specified. If the candidate region contains a hard hat of which size is within the specified size range, the human body and the hard hat are determined to be the corresponding pair. In this way, the proposed framework determines whether a person wears a hard hat or not. False positives of the hard hat detection are removed in this matching process since hard hat detection regions that do not matched with any human body regions are discarded.

FIGURE III
MATCHING BETWEEN HARD HAT AND HUMAN BODY REGIONS



IV. EXPERIMENTS AND RESULTS

The proposed method was implemented using Microsoft Visual C# in .NET Framework 4.0 environment. As a preliminary experiment, the method was tested on an on-site video in which 5 people are present wearing different combinations of hard hats and safety vests. Figure IV shows three example result frames. In the figure, red, dark red, cyan, and dark cyan rectangles represent Type I, II, III, and IV, respectively. It can be seen that all people in the view are correctly located and classified. The people classified as Type II, III, and IV should be warned to wear missed protective equipment. The performance of the method is evaluated based on precision and recall which are defined as follows.

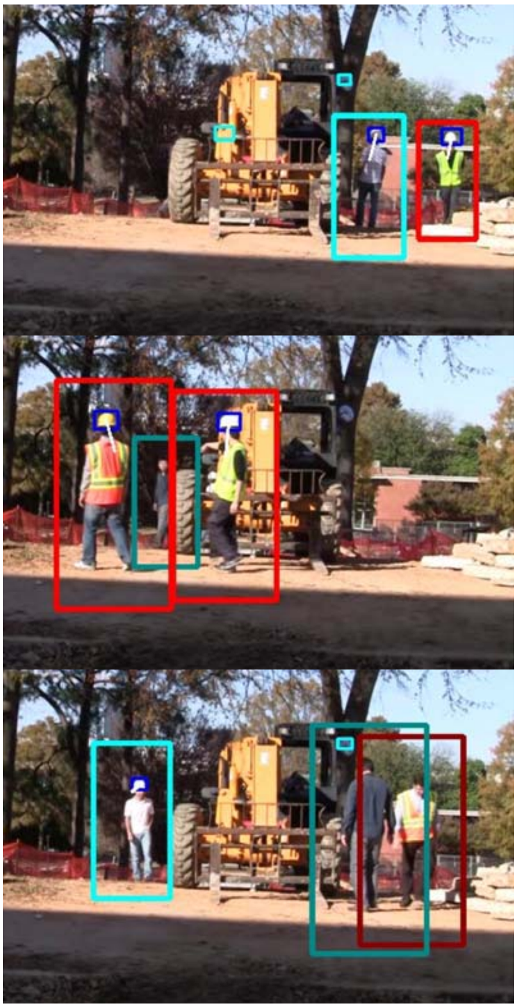
$$\text{Precision} = TP / (TP+FP)$$
$$\text{Recall} = TP / (TP+FN)$$

Here, the definitions of true positive (TP), false positive (FP), false negative (FN), and true negative (TN) are summarized in Table II. The definitions are established on the basis of the main objective which is to identify people who are not wearing either of safety vest or hard hats.

TABLE II
DEFINITION OF TP, FP, FN AND TN

Classified \ Actual	Type II, III, or IV	Type I
Type II, III, or IV	TP (1668)	FP (254)
Type I	FN (36)	TN (994)

FIGURE IV
RESULTS OF IDENTIFYING SAFETY VEST AND HARD HAT WEARING



Accordingly, the proposed method featured the precision of 86.8% and the recall of 97.9%. The recall value indicates the high rate of identifying inappropriate wearing of personal protective equipment. On the other hand, the precision value reveals that 13.2% of the warning alarms are false, which would unnecessarily interrupt the on-site working tasks.

V. CONCLUSION

On-site safety monitoring is one of the critical factors that drive to the successful project. This paper proposed an automated monitoring framework to identify people who are not wearing hard hats or safety vests. The framework uses on-site cameras and detects people in the camera views. Detected people are classified into four types based on the wearing of safety vest and hardhats. The preliminary experiment signifies the potential of the proposed method to facilitate site safety monitoring.

REFERENCE

[1] CBC News, "3 Most dangerous job sectors in Canada", 2012 <http://www.cbc.ca/news/canada/story/2012/04/25/f-dangerous-jobs.html> (June 15, 2015)

[2] Korea Occupational Safety & Health Agency, "Industrial Accidents Records", 2014 <http://www.kosha.or.kr> (June 15, 2015)

[3] G. Waehrer, X. Dong, T. Miller, E. Haile, and Y. Men, "Costs of occupational injuries in construction in the United States", *Journal of Accident Analysis and Prevention*, vol. 39, no. 6, pp. 1258–1266, 2007.

[4] Korea Occupational Safety & Health Agency, "Unsafe Behaviors", 2011 <http://www.kosha.or.kr> (June 15, 2015)

[5] T. Ruff, "Recommendations for evaluating and implementing proximity warning systems on surface mining equipment", *Report of Investigations 9672*, National Institute for Occupational Safety and Health, 2007.

[6] J. Teizer, B. Allread, C. Fullerton, J. Hinze, "Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system", *Automation in Construction*, vol. 19, pp. 630-640, 2010.

[7] N. Mcfarlane and C. Schofield, "Segmentation and tracking of piglets in images", *Mach. Vision Appl.*, vol. 8, no. 3, pp. 187–193, 1995.

[8] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection", *IEEE Computer Society Conf. on Computer Vision and Pattern Recognition*, vol. 1, pp. 886–893, 2005.

[9] M.W. Park, and I. Brilakis, "Construction worker detection in video frames for initializing vision trackers." *Automation in Construction*, vol. 28, pp. 15–25, 2012.