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Identifying poses of safe and productive masons using machine learning

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ABSTRACT

This paper presents a framework to classify work poses among groups of masons during the building of a standard wall of concrete masonry units. The experience of the group composed of masonry instructors and master masons averaged five times that of the other groups, their productivity was highest, and the loads on their joints were the lowest. Thus, they were deemed experts in this paper. Inertial measurement units (IMU) and video cameras were used to collect kinematic data of the masons, from which pose clusters were identified. A Support Vector Machine (SVM) algorithm was used to classify masons' poses into expert and inexpert classes based on the relative frequency of poses in the motions used to lay each of 945 masonry units. Two classification scenarios were tested. While both scenarios achieved similar levels of accuracy, 91.23% and 92.04% respectively, the processing time for binary classification was only 13 s compared to 523 s for inter-group multiclass SVM. Like characteristic vibration frequencies in machine diagnostics and system identification, the characteristic poses identified provide insight into differing methods between expert and less experienced masons. For example, results show that experts utilize fewer and more ergonomicaly safe poses, while being more productive, which indicates lower energy expenditure (less wasted motions). The classification method and the poses identified contribute knowledge to help develop affordable mason training systems that utilize IMU and video feedback to improve health and productivity of apprentice masons.

1. Introduction

Work-related musculoskeletal injuries are depleting the construction industry workforce. The quandary with work-related injuries is that they are sometimes a result of normal work. Workers are exposed to musculoskeletal injuries in various ways: multivariate interaction of genetic, morphological, psychological, and biomechanical factors, differential fatigue, cumulative load, or overexertion [1,2]. All of these paths to musculoskeletal injuries are common in construction work. The frequency at which injuries occur in the workplace is measured by the incidence rate. The severity of injury is measured by days away from work due to injury. The incidence rate of musculoskeletal injuries in 2014 was 33.8, requiring an average of 13 days away from work compared to 9 days for all injuries [3]. The leading sources of injury were sprains, strains, or tears.

Construction work is highly physical, which is the basic source of risk for musculoskeletal injuries. The general trend of transforming construction work from a physically demanding environment to a safer less demanding one, using advanced technologies, cannot change this fact for most workers in the near term. Moreover, the worker population is aging. For example, typical of most western countries, > 40% of the Canadian workforce is older than 45 years. For the first time, the number of workers under 24 is less than those aged 55 or more [4]. The economic cost of musculoskeletal injuries in Canada alone was estimated at $25.6 billion CDN in 1994 [5].

Efforts to enhance construction work conditions accelerated in the 1990′s. Organizations such as the National Institute for Occupational Safety and Health (NIOSH), the Center to Protect Workers' Rights (CPWR), and the Construction Industry Institute (CII) presented best practices which include: toolbox meetings, structured hazard analysis processes, drug testing, leadership commitment, and cultural changes for safer environments. Moreover, workers' safety gained significant interest, which was manifested by interventions in workplaces to decrease the number of injuries and to enhance work conditions. Changes were made in craft training and apprenticeship programs as well.

Many construction workers, such as masons, undergo an apprenticeship program to become journeymen. Throughout this program, typically three to four years long, apprentices learn different skills including safety practices, gain experience, and increase productivity. Perhaps as a result, journeymen with more than five years of experience

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with the same employer suffer fewer injuries than less experienced workers [3]. Furthermore, masons with more than five years of experience have significantly higher productivity than less experienced workers [6]. An increased productivity and a lower rate of injuries suggest that experienced workers are adopting safer and more productive work methods. The question of whether these methods were taught to them or gained by experience remains unanswered and is part of the inspiration for this research.

Current training programs in North America focus on providing apprentices with the skills required to complete a task professionally, are hands-on with some theoretical elements, and are typically offered during a series of three annual eight-week long in-school sessions at training centers. These programs also offer safety education aimed at decreasing injury prevalence. However, current statistics indicate that musculoskeletal disorders account for 32% of all labor injury and illness cases [3]. Hence, new methods for in-field behavior monitoring using inertial and image-based motion capture systems have been introduced to the construction field. These methods have also been used in other fields such as gaming, sports training, rehabilitation, and animation. One class of these methods is automated characterization of poses, postures, form and motion (depending on the application) based on a set of rules. Such data analytics and machine learning algorithms hold promise in activity tracking, productivity, and safety analysis.

This paper presents a new approach to the classification of masonry workers' poses as distinguished by combined levels of joint loads and productivity. Biomechanical analysis was conducted on twenty-one masons placing 945 concrete masonry units (CMUs) of 10 kg each. Of these masons a group of five highly trained master craftsmen and instructors with an average of five times more experience than the remaining sixteen masons were found to experience lower levels of joint forces and moments than the remaining masons [6]. Moreover, the analysis showed that these five masons were more productive, as measured by differences in time and space required to complete a controlled task, and their work was of the highest quality. Given their roles, their range of skills and knowledge was broad as well, including stone, brick and concrete masonry in their skill sets. For purposes of brevity, this group is hereafter referred to in this paper as “expert” masons. The experts required significantly less space and time to complete the given task, which translates into less energy expenditure. Hence, this paper describes the implementation of machine learning techniques as well as data analytics to classify workers' poses, defined as relative joint center locations, into expert and inexpert classes. To put it simply, the objective of this study is to identify the poses that characterize a group of people who are most productive and also experience lower loads on their bodies, so that we might gain insight into how they do that and teach those poses to people who are less productive and safe.

It should be noted that this paper uses statistical data on worker injuries obtained from U.S. labor data and Statistics Canada in addition to experimental studies conducted on Canadian masons. The underlying assumption is that the masonry worker demography is similar in the United States and Canada. The International Union of Bricklayers and Allied Craftworkers, which covers Canada and the US, has recognized this essential similarity since its founding in 1865.

2. Background

Literature related to the scope of this paper is presented and analyzed. Also discussed in this section are current practices to reduce injury rates, kinematic data collection methods, and machine learning classification.

2.1. Current practice of injury prevention in construction work

Efforts to decrease the number of injuries among workers include interventions by stakeholders to reduce the impact of musculoskeletal disorder (MSD) injuries on the industry. These interventions include regulatory procedures, such as the NIOSH lifting equation that defines how much weight is considered safe for carrying [7,8]. Another form of intervention to reduce MSDs is job analysis which assesses work conditions for a given job and identifies potential dangers [9–16]. Results of these two types of interventions are often procedural guidelines for work with less exposure to risk factors leading to increased number of work-related injuries.

Yet another type of intervention is to implement physical changes in the work environment by introducing new tools. This type of intervention aims at assessing and reducing workloads on workers' bodies and increasing productivity through the use of robotics [17], as well as analysis of physiological signals such as (EMG, EEG, Heart rate etc.) [18–22], image-based tracking [23–25], or inertial measurements [26–28]. These interventions, while shown to have a positive impact on reducing exposure to risk factors, are not yet widely implemented in workplace [29,30].

Many complications hamper the application of these interventions in the field. Hurdles appear at the sector, institution, and implementation levels. They include peer pressure and lack of competition within the sector, and lack of awareness about musculoskeletal injuries across all three levels [31]. The cost of adopting those interventions, in terms of productivity loss, job quality, or costly maintenance, is another major hurdle [29].

2.2. Data collection methods in construction environments

The use of kinematics and visual data to analyze workers' safety and productivity is on the rise. These technologies allow for in-the-field data collection, thus overcoming the disadvantages of simulated environment studies, which often simplify tasks in ways that affect the outcome of the analysis [32]. Two types of data collection are used: (1) direct angle measurement systems, where body angles are directly measured by a sensor, and (2) indirect angle measurement systems, where post-processing is required to obtain body joint angles.

Direct angle measurement systems, such as electrogoniometers, have been shown to possess high resolution and precision compared to indirect systems [33]. They can be used to measure joint angles in non-structured environments such as construction sites. Results of these systems, obtained with no post-processing, can help monitor awkward postures and unsafe behavior [34,35]. However, major drawbacks of these systems are that they are cumbersome and they measure motion in 2D only [36].

Indirect angle measurement systems use image-based systems, such as depth sensors and stereo cameras, or inertial measurement units to track human motion. The benefit of using indirect methods is that they offer high rates of resolution and precision in tracking whole body motion in 3D. The use of depth sensors, such as the Kinect™ camera, is rapidly increasing in the construction field to track workers' body movements. Applications of this method range from activity classification [37,38] to biomechanical assessment and safety [26,39–41]. Moreover, inertial measurement units (IMUs) have been used to perform full body tracking [42] and to classify activities in construction [43].

2.3. Machine learning applications and data analytics for human tracking and classification

On-site kinematic data collection allows researchers to implement automated systems to track workers' motion for training and safety. The use of machine learning algorithms and data analytics is on the rise for such applications. Machine learning and data mining techniques call for defining features that differentiate and separate actions from each other to create a classifier. The uniqueness of these features determines the accuracy of the classifier. The input to these classifiers is extracted from either IMU or image-based data collection methods.