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EVALUATION OF WEARABLE SENSORS TO QUANTIFY CONSTRUCTION WORKERS MUSCLE FORCE: AN ERGONOMIC ANALYSIS

Shahin Jahanbanifar
Reza Akhavian

School of Engineering
California State University, East Bay
25800 Carlos Bee Blvd.
Hayward, CA 94542, USA

ABSTRACT

Construction industry has one of the highest rates of bodily injuries including serious Work-related Musculoskeletal Disorders (WMSDs). The Occupational Safety and Health Administration (OSHA) identifies force level as a risk indicator associated with WMSDs. Without direct measurement, quantifying the force exerted during a given task performed by workers is difficult, if not impossible. Therefore, an indirect and non-intrusive way of identifying excessive force applied during physical tasks can effectively reduce the risk of WMSD injuries. In this research, a series of physical activities involving pushing and pulling are simulated by the research team in laboratory-scale experiments. The exerted force is measured using a work simulator tool and accelerometer data is collected from a smartphone sensor affixed on the working arm. Artificial Neural Network is trained with the accelerometer data and the force levels. Testing results indicate that the trained model can predict the force level with over 87.5% accuracy.

1 INTRODUCTION

Construction is the second most hazardous industry in the United States with approximately 12 fatal injuries a day (U.S Bureau of Labor Statistics 2018). According to U.S. Bureau of Labor Statistics, private construction had the highest number of fatal injuries in 2015 with 937 reported deaths (OSHA reports 2015). The ratio of workers' fatal injuries per 100,000 full-time workers in construction placed 4th among all industry sectors (U.S Bureau of Labor Statistics 2018). In 2002 estimates showed that fatal and nonfatal injuries in construction cost $11.5 billion (Waehrer et al. 2007). Also, other studies worked on costs of injuries in construction industry using previous studies from 1979 and found a dramatic raise in total cost of construction. 1979 statistics shows 6.5% of total cost and Everett et al. found this ratio between 7.9% to 15% of the total cost of industry (Everett and Frank Jr 1996). Reports from Occupational Safety and Health Administration (OSHA) point out top causes of injuries are; falling from heights, trench collapse, collapsed scaffolding, electric shock, failure to use appropriate protective gear, and repetitive motion injuries respectively (Armstrong et al. 1993; Ahankoob and Charehzehi 2013). Although the first five cases include a higher amount of injuries compared to the last one, there is a gap in the study of repetitive motion damages that affect workers' lifestyle in long-term and also can cause serious damages to their bodies. Repetitive Motion Damages can result in excessive physical stress that can cause Musculoskeletal Disorders (MSDs) which directly disturb muscles, tendons, and nerves (U.S Bureau of Labor Statistics 2018). Figure 1, adopted from U.S Bureau of Labor Statistics shows that the number of days away from work due to MSDs are always more than other nonfatal injuries. Therefore, it reaffirms the importance of keeping workers safe from these types of injuries. There are three main factors to the injuries due to the workers' physical behaviors for which OSHA provided some limitations. These factors, also known as triggers of ergonomic stress, are *Force*, *Repetition*, and *Posture* (Genaidy et al. 1993). Force, as the main component of any physical activity, plays a key role in performing a job-related activity in a safe or unsafe manner.

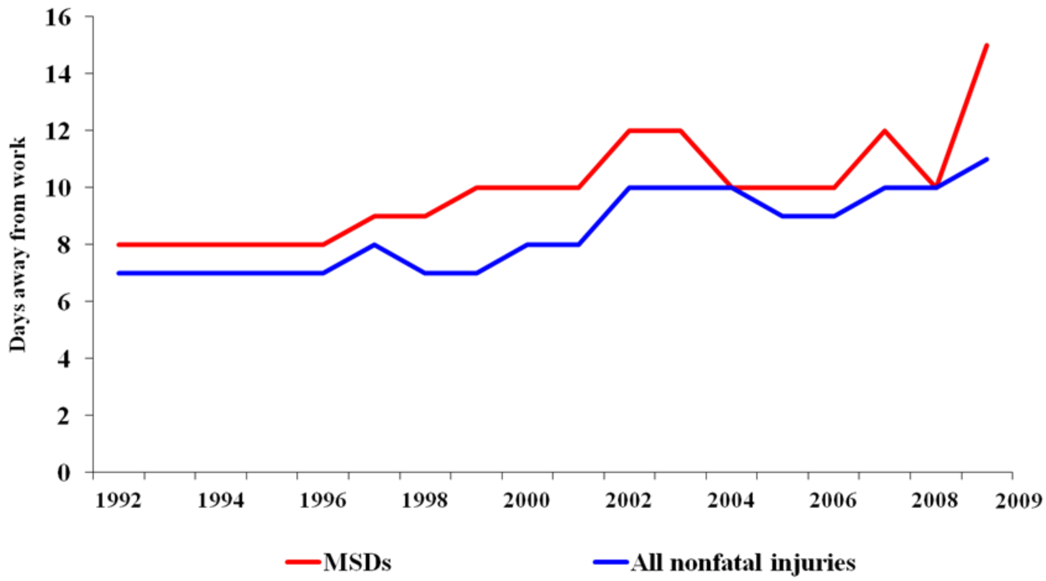

Figure 1: Days away from work, WMSDs vs. all nonfatal injuries 1992-2009.

Any type of job site actions, as simple as using a screwdriver or more sophisticated actions such as vibrating the concrete requires some level of physical effort, which is materialized as the force exerted by the worker to either control the tool or get the task done (Ahankoob and Charehzehi 2013). Construction companies pay a substantial amount of money for expenses directly or indirectly related to their workers' injuries. Records from National Academy of Social Insurance (NASI) show that in 2013 employer costs for workers' compensation were $88.5 billion for 129.6 million covered workers.

Considering the significant effect of MSDs and other related injuries as a result of applying excessive force on workers' productivity and company expenses, this research seeks to develop a framework for quantification of human force using wearable sensors. Specifically, this study focuses on finding a correlation between force and acceleration produced by workers' physical activities such as pushing and pulling.

2 LITERATURE REVIEW

2.1 Work-Related Musculoskeletal Disorders (WMSDs) and Ergonomics in Construction

Previous research indicates that construction labors have the highest rate of WMSDs among all industries (Wang et al. 2016). Researchers suggested reducing of overexertion, as the primary cause of WMSDs, should take place in order to control the risk of injuries. A research team surveyed construction employees to evaluate relationships between worker characteristics, workplace factors, and WMSDs. The total commonness of WMSDs was 39.25% among 1200 male workers between the ages of 18 to 55 (Ekpenyong and Inyang 2014). Another survey in Malaysia showed a prevalence of WMSDs in 66.7% of the construction employees at their elbows, wrists or hands, and ankles or feet (Deros et al. 2015).

Major WMSDs' risk factors were evaluated by (Spielholz et al. 2006) including force requirements. There are many risk factors that can put a construction worker in danger of Work-related musculoskeletal disorders. The first and the most important one as Spielholz and Griffith stated is work postures and movements. The second one is Force of movements which is the focus of this study too. The other factors can be repetition in motions, vibration, temperature, increase pressure and so on and so forth. Also, Canadian Centre for Occupational Health and Safety mentioned the same factors as the risk of injuries in construction (CCOH 2018).

A research team conducted a risk assessment of WMSDs and a review of available techniques. They stated that construction industry needs to continuously work on turning the assessment process into an automated process (Wang et al. 2015). Another comparison study on direct measurement and observation method (vision-based) for upper workplace activities showed a significant correlation between exertion frequency from direct measurement and observation method (Chen et al. 2010). They also found a correlation between effort per minute estimated by Strain Index checklist with the mean power frequency of exertion. They believed findings from observation method could be used in assessing physical works in the workplace.

2.2 Application of Accelerometer Sensors Data Analysis in Construction Safety

To be able to proactively assess the safety of construction workers, monitoring their activities can play a key role. A study team have analyzed construction labor activities using a physiological status monitoring system which contained an accelerometer (Migliaccio et al. 2013). They focused on tracking the workers on site to evaluate their behaviors. This study analyzed ergonomic factors from workers' activities who are handling materials on a repetitive basis with a data fusion approach. This study also tracked and monitored workers' heartbeat during their performance and compared the heartbeat diagram in both situations; doing the work with a correct posture and wrong posture. The final result of this data fusion method which was used in this research shows that there are significant differences in data sets captured from correct performance and the wrong one.

A research team worked on monitoring wrist motion components of the industry workers including position, velocity, and acceleration to evaluate the degree of incidence of hand/wrist cumulative trauma disorders (CTDs) (Schoenmarklin et al. 1994). They indicated that acceleration in the flexion/extension is the best kinematic parameter for evaluation of the low and high incident rates of CTDs. Another group of researchers used IMUs to collect data in order to create a new method of detecting unsafe physical postures using gyroscope data captured from wireless IMUs (Valero et al. 2016). They used motion data such as acceleration to evaluate the motions and characterize the nature of activities. A team of researchers used EMG-based model to evaluate muscle force that affects spinal and lumbar (Jia et al. 2011). The focus of this research is on residential construction and laborers that work with installation of prefabricated walls. The EMG-based neuromuscular modeling is a method that uses muscles neurons to evaluate muscle forces. They figured that the model's ability of prediction is based on the performed tasks. Also, the complexity of the tasks would affect the results of the estimation.

Other studies used both accelerometer and gyroscope data from worker's motions and construction equipment to auto-recognize and categorize construction tasks through activity recognition (Akhavian and Behzadan 2018, 2016; Nath et al. 2017). Such used supervised machine learning algorithms to train computers for classifying unseen activities (i.e. those not presented in the training phase). In other words, the computer should understand the nature of the activity and its category through the collected and labeled data to be able to prepare them for an assessment of the safety level of the activity. In this research, simulated activities were chosen based on the OSHA limitations on pushing and pulling objects by workers. Maximum acceptable weights and forces for different construction operation tasks including lifting, lowering, pulling, pushing, and carrying are prescribed by OSHA and gathered by (Snook and Ciriello 1991). Force limitations for *Pushing* and *Pulling* objects in either horizontal or vertical distance are tabulated in OSHA's manuals so they can be used for evaluations of worker's performances. A research team used acceleration measurements and applied same technique as human activity recognition (HAR) to classify construction activities (Yang et al. 2008). They plotted acceleration data captured from 15 seconds of eight different task performances including; walking, running, scrubbing, standing, working at a PC, vacuuming, brushing teeth, and sitting. Plots show the obvious differences between the acceleration patterns from each activity.

Recent studies in the area of safety in construction have focused on body postures (Xincong et al. 2017; Yan et al. 2017; Golabchi et al. 2016). Xincong and his team used biomechanical methods as a theory to analyze workers' motions . Their evaluation was based on internal (elevated intramuscular strains, torques, and fatigue of muscle) and external (awkward postures and forceful exertions) causes of injuries with the use of the biomechanical structure of the human body and case analysis of typical construction activities. Inertial Measurement Unit (IMU) sensors as one of the most accurate activity recognition tools have helped researchers to collect and transfer data from any moving subjects (Akhavian and Behzadan 2015). The data from these type of sensors can translate into a host of information that can help more thorough analysis of the activity. A research group have worked on monitoring and evaluating the manual material handling (MMH) using whole body kinematics which was captured by IMU sensors (Bastani et al. 2016).

3 RESEARCH TECHNICAL BACKGROUND

Two main data collection means have been employed in this research. Baltimore Therapeutic Equipment (BTE) Simulator II was used to simulate work-related activities that entail *pushing* or *pulling*. BTE simulator II is a machine that is designed for occupational therapy and industrial work hardening clients, and also it replicates daily physical activities and functions using a wide range of attachments and tools. BTE Simulator II measures Force, Power, and also Torque in different types of activities such as extension, abduction, adduction, and so on and so forth. Depends on what tool and how that specific tool is being used, the machine gives the variety of choices to its users to evaluate. This machine can help to simulate any type of physical activities due to its high range of tools and variety of information that it gives the user.

The reason for the particulat focus on *pushing* and *pulling* was the author's field observations as well as previous studies that showed most of the physical activities in a construction site entail some level of *pushing* or *pulling* (Hoozemans et al. 1998). Besides, according to OSHA, there are some health-related limitations on the weight of the objects which is being pulled or pushed, (Snook and Ciriello 1991) and thus a thorough investigation could help in determining the risk level.

The other type of data that was collected in this research was acceleration data using smartphones affixed on a simulated workers' arm as shown in Figure 2. The acceleration data was collected using Sensor Log Application which is available in iTunes App Store. The details of the methodology of this study will be explained further in the Methodology section. The accelerometer data is collected using ubiquitous smartphones. While this is a reliable way of collecting acceleration data for activity recognition according to several past research studies (Kose et al. 2012; Mourcou et al. 2015), investigating this reliability is not within the scope of this study. In fact, experimenting with readily-available ubiquitous means of data collection and model development as opposed to superlative Microelectromechanical systems (MEMS) sensors with demonstrated high-accuracy was intentional to add to the easy implantation of the framework. In a study, it was concluded that among 15 potential locations for wearing an accelerometer, the lower left arm and the upper right arm are the two best locations that yield the highest information gain (Joshua and Varghese 2013). The research team experimented both options and the upper right arm was picked as the most convenient location.

Newton's second law of motion states that the acceleration of an object produced by a net force is directly related to the size of the net force, in the same direction as the net force, and opposite direction related to the mass of the object. As Newton's second law indicates, only two givens are needed to measure the net Force; Mass and Acceleration (Gundlach et al. 2007). There are a huge variety of tools involved in work-related activities that workers use during their daily works and measuring the Mass of these objects and tools are nearly impossible. However, acceleration can be measured in many different ways using different types of equipment. For instance, acceleration data of a worker's motions during any activities can be captured using wearable IMU sensors. Previous works on this technology show the high potential of it in the construction industry as an instrument that can distinguish unsafe behaviors and help companies to reduce the risks of injuries.

4 METHODOLOGY

Data collection phase of this study was conducted in an engineering research lab (i.e. a controlled environment). All the experiments were videotaped to assist in labeling and cross-referencing the collected data and performed activities. A 25 years old male Construction Management graduate student (i.e. the simulated worker) conducted the experiments who provided written informed consent to participate in the study. BTE Simulator II used to simulate construction physical activities includes a series of 21 attachments that can be mounted on its exercise head in multiple positions to facilitate simulation of several activities and movement combinations. The simulator can be connected to a computer that allows selection of the desired resistance and measures performance by quantifying the force exerted, work done, and power output while the task is being performed.

A total number of 10 experiments were conducted each of which with a relatively fixed level of power consumed as reported by the BTE Simulator II. Each experiment lasted for around 20 seconds. An approximation of the net force (F) exerted was achieved using Equation (1)

$$F = \frac{P \times t}{d} \,. \tag{1}$$

In which F is the net force exerted in Newton (kg.m/s^2), P is the power displayed by the BTE Simulator II in Watt (kg.m^2/s^3), "t" is the duration of the experiment in seconds, and "d" is the displacement of the simulated worker's arm in meter. For example, using Equation 1, for a measured power level of 2.5 Watt in one experiment that lasted for 20 seconds with a measured distance of 1 Meter, the force is calculated as 50 Newton.

A smartphone was affixed to the simulated worker's arm with a sports armband to capture acceleration data in three dimensions using its IMU sensors. Sensor Log smartphone application was employed which is a commercially available smartphone app for iOS and Android operating systems. This application reports a variety of signals including Acceleration, Gyroscope data, Core Location, Device Motion, Decibels, Pedometer Data, and Pressure from different sensors of the smartphone. The data collection frequency was set at 35 Hz using the Sensor Log application interface. This ensures collecting enough data for model training as well as capturing all the body movements. The recorded data from this application was extracted in Comma Separated values (CSV) format. Before analyzing the collected data, a data preparation step is required to assure data quality and cleanliness. Toward this goal, the raw data were plotted in Microsoft Excel and cross-referenced against the recorded video. Outliers and redundant data points captured during the transition periods between the experiments were removed. Finally, the prepared data was imported to Python software for the analysis stage.

Artificial Neural Network (ANN) was employed in this study to develop a model trained by the acceleration data as the input and measured forces as the output. The ultimate goal is to prepare a model capable of predicting unseen force levels using acceleration data provided to it. ANN is a machine learning method which works similar to the way brain neurons process information and develops relationships for classification and prediction purposes. The hidden layers of an ANN network collect the input and process them to generate the output (Dongare et al. 2012; Devika and Gupta 2014). Figure 2 depicts a snapshot of the actual experiment as well as the experimental design of the developed methodology.

A total of 10 experiments were conducted with different power (force) values. Approximately 66% of the data was used to train the ANN model. The ANN structure included two hidden layers to make the connection between the input layer (i.e. acceleration data) and the output layer (i.e. net forces). Gradient decent was used as the optimization algorithm within the ANN model training using a feedforward backpropagation method.

5 RESULTS

ANN model training and testing was performed in Python and training and testing results were recorded. In ANN training, the weights of the parameters in the cost function need to be updated and this updating process has to happen more than once since gradient decent is an iterative process. When the dataset is passed through the neural network it is called one epoch.

The result of the model training and testing is shown in Figure 3. After around 2 epochs, an accuracy of slightly higher than 87% was achieved. As the number of epochs increased, the accuracy converged to around 87.5%.

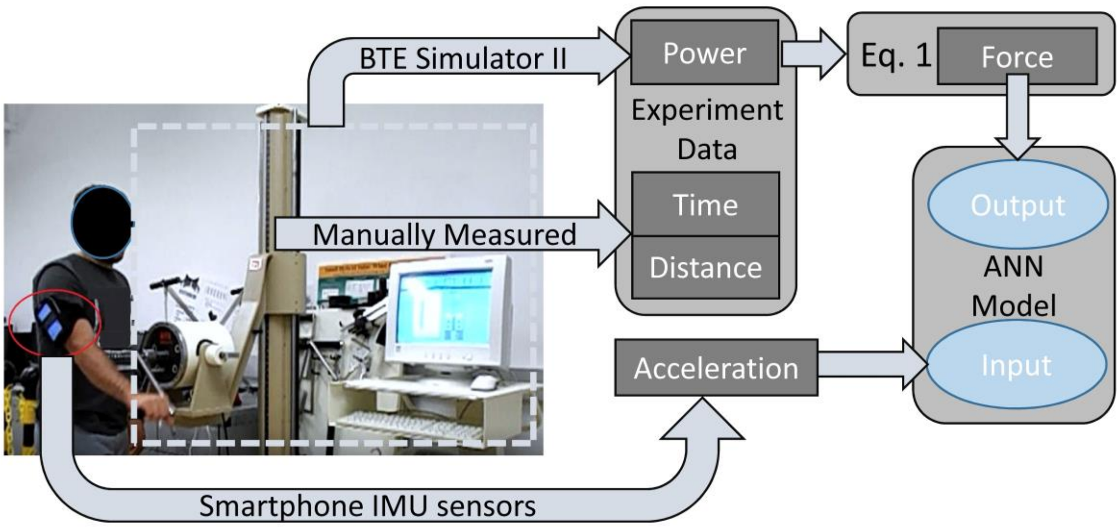

Figure 2: Experimental design of the developed methodology.

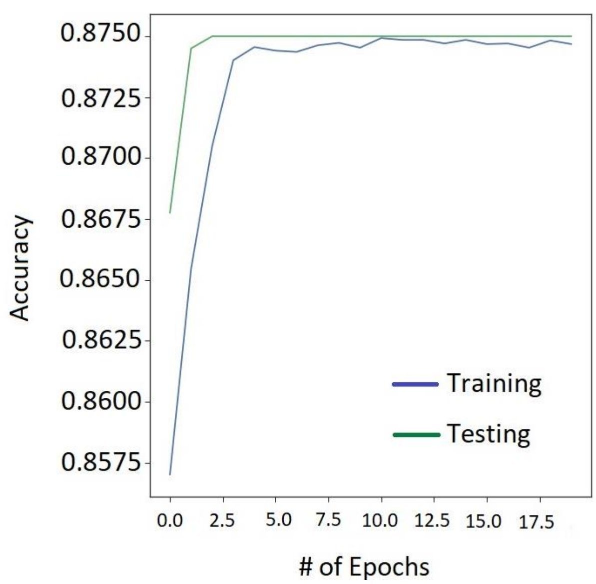

Figure 3: Results extracted from python for ANN.

6 CONCLUSION AND FUTURE WORK

The results of this research study indicate that there is a high correlation between the data collected from wearable accelerometer sensors and the amount of force exerted by human muscles. This study lays the foundation for further evaluation of the ergonomic risk of different attributes of physical activities such as force, repetition, and posture.

One of the limitations of this study is the fact that the experiments were conducted in a controlled environment. Future studies can incorporate real-world data collection to evaluate actual conditions. Moreover, a variety of activities other than pushing and pulling can be subject of future studies and a combination of such motions could lead into a more realistic scenario. Another limitation of the presented study is the administration of experiments with only one human subject performing the activities. This certainly creates bias and takes away from the generalizability of the results. Future work shall focus on user-independent model training and testing. Another limitation of the presented work is the potential generalizability. Limited number of experiments and human subjects takes away from the generalizability of the developed framework to different activities, body postures, and movement habits. As such, future research can explore more variations to increase the generalizability of this framework.

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AUTHOR BIOGRAPHY

SHAHIN JAHANBANIFAR is a graduate student of Construction Management at the California State University, East Bay and the Field Engineer at MGE Underground Inc. Jahanbanifar holds a B.S. degree in Civil Engineering. His email is sjahanbanifar@horizon.csueastbay.edu.

REZA AKHAVIAN is an Assistant Professor of Construction Management in the School of Engineering at the California State University, East Bay and the director of the Data-informed Construction Engineering (DiCE) group. Dr. Akhavian received his Ph.D. and M.S. degrees in Civil Engineering (Construction Engineering and Management) from the University of Central Florida. He also holds a B.S. degree in Civil Engineering from the University of Tehran, Iran. His research focuses on the integrated solutions for the technology-based decision-making in the architecture, engineering, construction, and facility management (AEC/FM) industry. In particular, he has research interests in design and development of methodologies using data-driven modeling and simulation, automation and robotics, wearable system, machine learning, and process mining with applications in construction safety and building smart and sustainable cities. His email is reza.akhavian@csueastbay.edu