ERGONOMIC ANALYSIS OF CONSTRUCTION WORKER'S BODY POSTURES USING WEARABLE MOBILE SENSORS

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ABSTRACT:

Construction jobs are more labor-intensive compared to other industries. As such, construction workers are often required to exceed their natural physical capability to cope with the increasing complexity and challenges in this industry. Over long periods of time, this sustained physical labor causes bodily injuries to the workers which in turn, conveys huge losses to the industry in terms of money, time, and productivity. Various safety and health organizations have established rules and regulations that limit the amount and intensity of workers' physical movements to mitigate work-related bodily injuries. A precursor to enforcing and implementing such regulations and improving the ergonomics conditions on the jobsite is to identify physical risks associated with a particular task. Manually assessing a field activity to identify the ergonomic risks is not trivial and often requires extra effort which may render it to be challenging if not impossible. In this paper, a low-cost ubiquitous approach is presented and validated which deploys built-in smartphone sensors to unobtrusively monitor workers' bodily postures and autonomously identify potential work-related ergonomic risks. Results indicates that measurements of trunk and shoulder flexions of a worker by smartphone sensory data are very close to corresponding measurements by observation. The proposed method is applicable for workers in various occupations who are exposed to WMSDs due to awkward postures. Examples include, but are not limited to industry laborers, carpenters, welders, farmers, health assistants, teachers, and office workers.

Keywords:

Ergonomics, Construction safety; Risk assessment; Posture analysis; Smartphone sensor; Wearable technology.

1 INTRODUCTION

Today's construction projects are becoming more complex and challenging. Construction workers require a wide variety of skills to be able to achieve project goals within specified time, budget, and specifications. Compared to other industries such as manufacturing, construction projects are more labor-intensive. The complexity of tasks often requires workers to go beyond their natural physical limits, or perform repetitive tasks for a long period of time. Over time, such sustained physical demand on workers' bodies may cause health issues and bodily injuries. Work-related injuries of this type are also referred to as Musculoskeletal Disorders (MSDs). Besides their adverse physical implications, MSDs can also lead to significant financial losses. For example, in 2009, direct workers' compensation costs due to MSDs were amounted to more than \$50 billion in the U.S. [1]. To remedy this problem, various health and safety organizations have established rules and guideline to identify the risks associated with performing certain tasks. Such efforts aim at ergonomic design of the workplace to match physical jobs with workers' natural capabilities.

1.1 Work-related Musculoskeletal Disorders (WMSDs)

MSDs are a group of disorders or injuries in a person's inner body parts (e.g. muscles, nerves, tendons, joints, cartilages, and spinal discs) which have relative deformations while he or she moves. Example of MSDs includes Carpal Tunnel Syndrome (CTS), Tendonitis, and Bursitis [2,3]. Work-related Musculoskeletal Disorders (WMSDs) refer to the MSDs due to activities in the workplace associated with physical jobs.

Construction jobs are among the most ergonomically hazardous occupations which involve activities such as manual handling, heavy lifting, body twisting, and frequently working in awkward positions, all being potential causes of WMSDs in workers [4,5]. According to the U.S.

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4 Department of Labor, construction is one of the six occupations where workers suffer from
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6 nonfatal occupational injuries and illnesses [6]. The most common types of WMSDs in
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8 construction are sprain, strain, CTS, tendonitis, and back pain. In the U.S., 32 construction
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10 workers in every 10,000 get injured from a WMSD and take leaves from work [6]. Among all
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12 trades of construction workers, laborers have the highest rate (45 workers in every 10,000) of
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14 getting injured due to WMSDs, with helpers, plumbers, carpenters, and others following [7]. In
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16 2015, the number of days lost due to non-fatal occupational injuries in private construction sites
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18 in the U.S. was 79,890, while WMSDs incident rate per 10,000 workers was 34.6 with 13
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20 median days away from work [8]. According to the European Labor Force Survey (LFS), in
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22 1999, 4.1 million workers were subjected to WMSDs. In the same year, 3,158 in every 100,000
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24 workers in the construction sector suffered from WMSDs, and in 1,292 cases, workers took 14 or
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26 more days of leave of absence from work [9]. According to the Liberty Mutual Workplace Safety
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28 Index, in 2009, WMSDs caused by overexertion resulted in \$12.75 billion in workers'
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30 compensation costs which was 25.4% of all compensation costs [1]. These and similar figures
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32 provide a glimpse into the loss of productivity at construction sites due to WMSDs. This has also
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34 intrigued researchers to explore ways to ergonomically prevent WMSD-related hazards.
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42 According to the Occupational Safety and Health Administration (OSHA), there are eight
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44 risk factors related to WMSDs including force, repetition, awkward postures, static postures,
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46 quick motion, compression or contact stress, vibration, and extreme temperatures [4]. Most
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48 often, awkward postures can be prevented by rearranging the workplace or selecting proper tools
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50 for workers. But different jobs are associated with different types of risks and the challenge is to
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52 identify the correct ergonomic risks associated with a particular job. A thorough job hazards
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54 analysis (JHA) can identify the risks at the workplace, but it may be challenging to carry out the
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56 analysis because of complexity of the job and the manual effort needed to monitor work
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processes [10]. Therefore, the objective of this paper is to present a methodology to facilitate the process of unobtrusively monitoring body postures of workers to autonomously assess and preempt potential risk factors.

2 PREVENTION THROUGH DESIGN (PTD) AND RISK ASSESSMENT

Prevention through Design (PtD) is an initiative taken by the National Institute for Occupational Safety and Health (NIOSH). It encompasses a host of efforts to anticipate and design out ergonomic-related hazards in facilities, work methods, operations, processes, equipment, tools, products, new technologies, and the organization of work [11]. The goal of the PtD initiative is to prevent and control occupational injuries, illnesses, and fatalities. According to NIOSH, this goal can be achieved by: 1) eliminating or reducing potential risks to workers to an acceptable level at the source or as early as possible in a project life cycle, 2) including design, redesign, and retrofit of new and existing work premises, structures, tools, facilities, equipment, machinery, products, substances, work processes, and the organization of work, and 3) enhancing the work environment through enabling the prevention methods in all designs that affect workers and others on the premises.

A proper PtD practice requires prior identification of the risk factors on a jobsite which in turn, necessitates that work-related data be adequately collected, and subsequently used in an integrated risk assessment framework. In general, three different data collection approaches have been practiced for identifying risk factors: 1) self-assessment, where workers are asked to fill out a form to identify the risk levels associated with their tasks, 2) observation, where a job analyst assesses the risk factors by observing the jobsite in real time or via a recorded video, and 3) direct measurement, where instruments are used to measure postures directly [12].

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4 In the self-assessment approach, data are collected on both physical and psychosocial factors
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6 through interviews and questionnaires [13]. This approach has relative advantages of having low
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8 initial cost, being straightforward to use and applicable to wide range of workplace situations
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10 [13]. However, since a large number of samples are required to ensure that collected data are
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12 representative of the group of workers, subsequent costs for analysis and the required skills for
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14 interpreting the findings are generally high [13]. Moreover, researchers have stated that workers'
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16 self-assessments on exposure level are often imprecise, unreliable, and biased [14-16].
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21 Observation-based approach is a simpler method that includes real-time assessment of
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23 exposure factors by systematic evaluation of the workers on the jobsite [17]. Despite being
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25 inexpensive and practical for a wide range of work situations, this method is disruptive in nature,
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27 and is subjected to intra- and inter-observer variability [13]. An advanced method of observation-
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29 based assessment includes analyzing recorded video [18,19] which allows for more exposure
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31 factors to be obtained, but is mostly impractical due to the substantial cost, time, and technical
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33 knowledge required [13].
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38 Unlike the previous two approaches, direct measurement uses tools attached to workers'
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40 bodies to collect data. Examples of this type of approach include but are not limited to using
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42 magneto-resistive angle sensors to measure shoulder flexion [10], Kinect or depth sensors to
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44 analyze posture by detecting position of skeleton joints at high sampling rates [20-22], and
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46 smartphone's built-in accelerometer and gyroscope sensors to measure arm inclination [23].
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48 Previous work in this area has revealed that the direct measurement approach yields the most
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50 valid assessment of risk factors compared to other approaches [24,25]. Building on previous
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52 work from multiple disciplines, in this research, a methodology is designed and validated to
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54 accurately identify a worker's body postures while carrying manual work. Ultimately, the
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56 findings of this research are sought to contribute to the PtD's mission by enabling construction
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researchers and decision-makers to design field activities to eliminate (or significantly reduces) work-related ergonomics issues for construction workers.

2.1 Risk Assessment of Construction Tasks Associated with Awkward Postures

For the purpose of identifying risks associated with awkward postures, generally, postures of different body parts (e.g. trunk, shoulder, and elbow) are measured in terms of degree of bent from the neutral posture. A neutral posture occurs when a worker needs minimum effort for standing (i.e. standing straight with his or her arms down) or sitting, while all joints are aligned and there is minimal physical stress on bones, muscles, nerves, or tendons [26]. The larger the difference between the degree of bent from the neutral posture, the higher the risk of bodily injuries due to awkward posture. Researchers have shown that the degree of bent of different body parts can be partitioned into ranges to minimize observational errors [24, 27,28]. Figure 1 shows how trunk flexion, trunk lateral bend, shoulder flexion, shoulder abduction, and elbow flexion are measured, by measuring the angle deviated from neutral posture, and Table 1 shows suggested posture categories [29].

Figure 1- Trunk Flexion, Trunk Lateral Bend, Shoulder Flexion, Shoulder Abduction, and Elbow Flexion

Table 1- Suggested Category Sizes for Observation-Based Measurement of Trunk Flexion, Trunk Lateral Bend, Shoulder Flexion, Shoulder Abduction, and Elbow Flexion

Ergonomic Risk	Trunk Flexion	Trunk Lateral Bend	Shoulder Flexion	Shoulder Abduction	Elbow Flexion
0°-30°	0°-15°	0°-30°	0°-30°	0°-30°
	30°-60°	15°-30°	30°-60°	30°-60°	30°-60°
	60°-90°	30°-45°	60°-90°	60°-90°	60°-90°
	> 90°		90°-120°	90°-120°	> 90°
			> 120°	> 120°	
High					

3 RESEARCH SCOPE AND OBJECTIVES

As previously stated, sensor-based direct measurement of risk factors presents a great opportunity for precise and unobtrusive ergonomic assessment of construction tasks. Nevertheless, setting up, calibrating, and using a sophisticated sensor network requires expertise that is normally beyond what is expected from most construction workers and field practitioners. Even if such skills are available, the upfront investment as well as the time commitment necessary to purchase, install, and maintain the equipment may be considered a hindering factor [13]. In previous studies, researchers achieved an RMS error of 3° while measuring the knee flexion/extension angles using Inertial Measurement Units (IMUs) [30]. Other studies incorporated IMUs to measure multiple joint angles [31] and gait stability [32]. Since smartphone sensors are technically a class of IMUs, to overcome the implementation challenges, in this research smartphones are used as data collection devices. Moreover, smartphones have advantages of ubiquity, low procurement and maintenance cost, and ease of use. Additionally, smartphones are generally equipped with a large number of sensors (20 on average) that can be

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4 activated on demand to collect various modes of data. However, in this study, only one sensor
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6 (i.e. 3D accelerometer) is ultimately used to demonstrate the potential of mobile devices in
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8 ergonomic assessment. It should be noted that generally accelerometers in IMUs have higher
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10 sensitivity (i.e. range) than the smartphone's accelerometer, but for static postures, smartphone's
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12 built-in inertial sensors are reliable compared to other standard tools [33]. Because in static
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14 postures, gravity acceleration dominates over body acceleration, 3D accelerometer can be used
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16 as inclinometer with the sensitivity of $\pm 1g$ [34]. Since most smartphones have higher sensitivity
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18 (e.g. $\pm 2g$) than the expected range (e.g. $\pm 1g$) for static postures, these devices can precisely
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20 capture data for static posture analysis.
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25 The rest of this paper is organized as follows: The data collection and analysis methodology
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27 is described in detail in Sections 4 and 5. Next, Section 6 reports on the experiments carried out
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29 to test the hypothesis, and evaluate the practicality of using smartphones for ergonomics
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31 assessment of construction tasks. The developed scientific methodology is rooted in novel
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33 computing techniques. It contributes to the existing body of knowledge and practice by
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35 automating the process of ergonomics assessment without interrupting field activities. It also
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37 eliminates the need for extra training required to carry out data collection and analysis tasks.
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43 **4 METHODOLOGY**

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46 Figure 2 shows the overall process that starts with sensory data collection. Details of this process
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48 are described in the following Subsections. In a nutshell, while a worker is performing a task,
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50 sensory data from two smartphones (as shown in Figure 3), one mounted on the worker's upper-
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52 arm and another on the waist, are collected. The collected data are preprocessed for feature
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54 extraction and then the most distinctive features are selected for further analysis.
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Figure 2- Schematic Diagram of Overall Data Processing

Figure 3- Smartphones Mounted on the Worker's Upper-Arm and Waist

4.1 Data Collection

Timestamped data are collected from three built-in smartphone sensors, namely accelerometer gyroscope, and linear accelerometer, in all three axes (i.e. X, Y, and Z). The accelerometer sensor measures the acceleration vector of the device and returns the components of the acceleration in three local Cartesian axes. The gyroscope sensor measures the rotation rate (i.e. angular velocity) of the device by measuring the roll, pitch, and yaw motions of the smartphone about the X, Y, and Z axes, respectively. Similar to accelerometer, the linear accelerometer sensor measures the acceleration of the device, but it excludes the gravity effect on the device.

Figure 4 shows the arrangement of the local Cartesian axes and the rotational angles.

Figure 4- Local Cartesian Axes and Rotational Angles in a Smartphone

4.2 Data Preparation

Collected sensory data contains noise which should be removed before the data can be used for analysis. It is very common for a smartphone sensor to temporarily freeze and stop recording data during a relatively long period of recording. When the sensor recovers from freezing, it records data at a higher rate to compensate for missing data points. This essentially means that the resulting sensory data may not follow a uniform time series. Similar to past work [35,36], in this research, in order to have a continuous and orderly data stream, collected data are processed into 100Hz of uniform time series by removing redundant data and interpolating missing data.

4.3 Feature Extraction

Collecting raw data at a high sampling rate results in a significantly large number of data points that is computationally inefficient to handle. To address this issue, raw time series data needs to

be compressed by being segmented into several windows for feature extraction [37]. In this study, raw data are segmented into 2-second windows (each containing 200 data points) with 50% overlay. Previous research in this area has indicated that data segmentation by overlapping adjacent windows reduces the errors caused by transition state noise [38]. Finally, statistical time-domain features (e.g. mean, maximum, minimum, and interquartile range (IQR)), as shown in Figure 5, are calculated for each window since time-domain features are most commonly used in data mining for activity recognition using smartphones [39].

Figure 5- Extracted Features for Data Analysis

4.4 Feature Selection

Not all extracted features are useful since not all yield distinguishable patterns. For example, it may turn out that the mean of the windows in the X axis does not contain value-adding information and thus can be excluded from computations. In order to identify the most effective features (a.k.a. distinctive features), two feature selection algorithms, namely Correlation-based Feature Selection (CFS) and ReliefF are applied to the dataset. By definition, CFS is an algorithm that uses a correlation-based approach and heuristic search strategy to find the best feature sets containing features that are highly correlated with the classes, yet uncorrelated to each other [40]. ReliefF is a feature selection algorithm that assigns weights to the features and ranks them according to how well their values distinguish between neighboring instances of

same and different classes [41]. Using CFS, first, irrelevant and redundant features are removed, and then the remaining features are ranked using ReliefF. Finally, the best 9 features out of a total of 36 (i.e. 4 features in 3 axes from 3 sensors) are selected for further analysis. Using these algorithms, it was found that the accelerometer sensor's mean, maximum, and minimum features (for all three axes) are the best features for this study. Figure 6 summarizes the selected features for data analysis in this research.

Figure 6- Selected Features for Data Analysis

5 ANALYSIS OF HUMAN POSTURES USING WEARABLE SMARTPHONES

In this Section, a worker's postures while performing a manual screw driving task are analyzed using data from bodily-mounted smartphone sensors. First, the mathematical description of the hypothesis established to measure the worker's trunk and shoulder flexions from the smartphone's accelerometer sensor is presented. Next, predicted postures from data are compared with observation-based measurements to evaluate the accuracy of the developed methods.

5.1 Hypothesis

In general, for ergonomic posture analysis, body postures are determined by angular rotations of different body parts (e.g. trunk flexion, trunk lateral bend, shoulder flexion, shoulder abduction, elbow flexion, neck bent, neck twist, wrist bent, forearm twist, knee angle, ankle posture)

[12,42]. In this research, a body posture is defined as a vector that consists of angular rotations of m different body parts, as shown in Equation 1,

$$T_i = \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \beta_{i3} \\ \dots \\ \beta_{im} \end{bmatrix} \quad \text{Equation 1}$$

where β_{im} is the angular rotation of body part m in posture vector T_i . For example, a posture vector T_1 , consisting of five components, namely trunk flexion (TF), trunk lateral bend (TLB), shoulder flexion (SF), shoulder abduction (SA), and elbow flexion (EF), can be shown as in Equation 2,

$$T_1 = \begin{bmatrix} TF_1 \\ TLB_1 \\ SF_1 \\ SA_1 \end{bmatrix} \quad \text{Equation 2}$$

Using the definition in Equation 1, the neutral posture (T_0) can be expressed as a null vector. As a convention, feature k corresponding to a posture T is shown as $T.feature_k$. It is important to normalize features prior to further processing. Feature normalization can be done by subtracting features obtained from the neutral posture from the corresponding features obtained from posture T . A normalized feature is denoted as $T.feature_k'$ and mathematically expressed by Equation 3,

$$T_i.feature'_k = T_i.feature_k - T_0.feature_k \quad \text{Equation 3}$$

It is thus imperative that the normalized feature vector for the neutral posture be a null (i.e. a zero) vector. Finally, as described in Subsection 4.4, in this research, the feature space is defined by Equation 4, below,

Feature space

$$= \left\{ \begin{array}{l} Accelerometer_X_Avg, Accelerometer_X_Max, Accelerometer_X_Min, \\ Accelerometer_Y_Avg, Accelerometer_Y_Max, Accelerometer_Y_Min, \\ Accelerometer_Z_Avg, Accelerometer_Z_Max, Accelerometer_Z_Min \end{array} \right\}$$

Equation 4

For example, $T_1.Accelerometer_X_Avg'$ refers to the normalized mean of the accelerometer data about the X axis while the worker was in posture T_1 .

Using this convention, if a posture S can be expressed as the weighted sum of n base postures ($T_1, T_2, T_3, \dots, T_n$), as shown in Equation 5 (referred to as posture composition equation) then it is hypothesized that a normalized feature k obtained from sensory data while the worker is in posture S can be expressed as the weighted sum of that same normalized feature k obtained from sensory data corresponding to base postures $T_1, T_2, T_3, \dots, T_n$, as formulated in Equation 5 and Equation 6 (referred to as feature composition equation). Further, the weight of each feature of a base posture, $f(\alpha_i)$ in the feature composition equation is a function of the corresponding weight of the same base postures, α_i in the posture composition equation. In mathematical terms, if,

$$S = \alpha_1 T_1 + \alpha_2 T_2 + \alpha_3 T_3 + \dots + \alpha_n T_n = \sum_{i=1}^n \alpha_i T_i \quad \text{Equation 5}$$

then,

$$\begin{aligned}
S.feature_k' &= f(\alpha_1)T_1.feature_k' + f(\alpha_2)T_2.feature_k' \\
&\quad + f(\alpha_3)T_3.feature_k' + \dots + f(\alpha_n)T_n.feature_k' \\
&= \sum_{i=1}^n f(\alpha_i)T_i.feature_k'
\end{aligned}$$

Equation 6

5.2 Mathematical Analysis of the Hypothesis

In this Subsection, several corollary propositions are developed, based on the hypothesis described in Subsection 5.1, which are further used to discover the relationship between the posture vector and the extracted features. Assume a general posture vector T_i consists of m number of components, denoted with β which is mathematically expressed by Equation 1. Then, from Equation 5, any given posture S can be written as,

$$\begin{aligned}
S &= \alpha_1 T_1 + \alpha_2 T_2 + \dots + \alpha_n T_n = \alpha_1 \begin{bmatrix} \beta_{11} \\ \beta_{12} \\ \beta_{13} \\ \dots \\ \beta_{1m} \end{bmatrix} + \alpha_2 \begin{bmatrix} \beta_{21} \\ \beta_{22} \\ \beta_{23} \\ \dots \\ \beta_{2m} \end{bmatrix} + \dots + \alpha_n \begin{bmatrix} \beta_{n1} \\ \beta_{n2} \\ \beta_{n3} \\ \dots \\ \beta_{nm} \end{bmatrix} \\
&= \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \dots \\ \alpha_m \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} & \dots & \beta_{m1} \\ \beta_{12} & \beta_{22} & \beta_{32} & \dots & \beta_{m2} \\ \beta_{13} & \beta_{23} & \beta_{33} & \dots & \beta_{m3} \\ \dots & \dots & \dots & \dots & \dots \\ \beta_{1m} & \beta_{2m} & \beta_{3m} & \dots & \beta_{mm} \end{bmatrix}
\end{aligned}$$

Equation 7

According to Equation 7, posture S can be expressed as the sum of weighted n base postures T , using n unknown multipliers $(\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n)$ and m independent equations. If $n = m$, then the number of unknowns will be equal to the number of independent equations. Hence, Equation 7 can be solved mathematically to find the unknown values of multipliers, i.e., in matrix form:

$$S = \alpha.T \xrightarrow{\text{solving for } \alpha} \alpha = T^{-1}.S$$

Assume that an arbitrary posture S is identical to any given base posture T_i . Therefore, from Equation 5, $\alpha_i = 1$, and $\alpha_j = 0$ for all $j \neq i$. In this case, features of posture S are identical to features of base posture T_i , and thus, from Equation 6, $f(\alpha_i) = 1$, and $f(\alpha_j) = 0$ for all $j \neq i$. This important observation serves as the basis for establishing key boundary conditions when attempting to find a mathematical relationship between α values and corresponding $f(\alpha)$ values.

From the two boundary conditions, it can be inferred that the mathematical function $f(\alpha)$ can be any of the three types; algebraic, polynomial, or trigonometric, which can be expressed in the general forms of $f(\alpha) = \alpha$, $f(\alpha) = \alpha^m$, and $f(\alpha) = \sin(90\alpha)$, respectively.

All features, either of combined posture (S) or of any base posture (T_i), should be normalized to satisfy both boundary conditions. As stated earlier, normalization is done by subtracting the feature of the neutral posture from the corresponding feature obtained from any given posture.

6 VALIDATION EXPERIMENTS

As mentioned in Section 4, for posture analysis of the manual screw driving task, two smartphones were mounted on a worker's body, one on the upper-arm and another on the waist. Previous research has shown that these two positions produce the most distinctive features for most manual jobs performed by field workers [43,44]. As shown in Figure 7, data were collected from both smartphones for six base body postures. Collected data were then preprocessed and features were extracted. In particular, data collected from the smartphone on the upper arm were used for measuring total flexion (combined effect of trunk and shoulder flexions), while data collected from the smartphone on the waist was used to measure trunk flexion. For the specific task of screw driving, as shown in the postures of Figure 7, trunk flexion involves downward angular movements while shoulder flexion involves upward angular movements. Therefore, the total flexion is measured by subtracting the trunk flexion from the shoulder flexion. Finally, by

combining the results from both smartphones, values for trunk flexion and shoulder flexion were determined individually. Referring to the six postures shown in Figure 7, trunk, shoulder, and total flexions are tabulated in Table 2.

Figure 7- Six Base Postures for the Screw Driving Experiment

Table 2- Observed values for Trunk, Shoulder and Total Flexions of Six Postures

Postures	P_1	P_2	P_3	P_4	P_5	P_6
Trunk Flexion ($^{\circ}$)	0	0	0	0	30	90
Shoulder Flexion ($^{\circ}$)	0	90	120	30	60	90
Total Flexion ($^{\circ}$)	0	90	120	30	30	0

Since all angles are zero for posture P_1 , this posture is considered as the neutral posture (i.e. $T_0 = P_1$). As previously discussed, the number of base postures should be selected as equal to the number of components of a posture vector. In this experiment, each posture vector consists of a single component, which is total flexion for the upper arm-mounted smartphone and trunk flexion for the waist-mounted smartphone. Therefore, one base posture must be selected for analysis in each case. Here, posture P_2 is selected for the upper arm-mounted smartphone, and posture P_6 is selected for the waist-mounted smartphone. Since, P_2 and P_6 both represent an angular vector of 90° , Equation 5 can be rewritten as $P_i = \alpha \cdot 90^\circ$. Equation 6 can be rewritten as,

$$P_i \cdot feature_k = f(\alpha)[P_{90} \cdot feature_k - P_1 \cdot feature_k] + P_1 \cdot feature_k \quad \text{Equation 8}$$

where, $P_{90} = P_2$ and $i = 3, 4, 5, 6$ for the upper arm-mounted smartphone, and $P_{90} = P_6$ and $i = 2, 3, 4, 5$ for the waist-mounted smartphone.

6.1 Developing a General Equation for $P_i \cdot feature_k$

Investigation of extracted features reveals that a trigonometric relationship between α and $f(\alpha)$ yields the most accurate prediction of $P_i \cdot feature_k$. Further investigation reveals that the best trigonometric relation is a sine function for the features (i.e. mean, maximum, and minimum) extracted from accelerometer-X and accelerometer-Z sensors, and a cosine function for the features extracted from accelerometer-Y sensors.

Considering a general form of sine function, i.e., $f(\alpha) = a * \sin(90\alpha) + c$, and applying two boundary conditions, we get $a=1$ and $c=0$. Hence, Equation 8 can be rewritten as,

$$\begin{aligned}
P_i \cdot feature_k &= \sin(90\alpha)[P_{90} \cdot feature_k - P_1 \cdot feature_k] \\
&+ P_1 \cdot feature_k
\end{aligned}
\tag{Equation 9}$$

Similarly, considering a general form of cosine function, i.e., $f(\alpha) = a * \cos(90\alpha) + c$, and applying two boundary conditions, we get $a=-1$ and $c=1$. Hence, Equation 8 can be rewritten as,

$$\begin{aligned}
P_i \cdot feature_k &= \cos(90\alpha)[P_1 \cdot feature_k - P_{90} \cdot feature_k] \\
&+ P_{90} \cdot feature_k
\end{aligned}
\tag{Equation 10}$$

6.2 Prediction of $P_i \cdot feature_k$

Using Equation 9 and Equation 10, features from each posture can be calculated and compared to the features obtained by analyzing smartphones' sensory data. Results are shown in Table 3 and Table 4. In these Tables, the *Experimental Result* column shows the values of extracted features from the actual sensory data, while the values in the *Obtained Result* column show the predicted features using Equation 9 and Equation 10. For each posture, minimum absolute errors are highlighted in Table 3 and Table 4. Table 3 shows that, for all four postures, *Accelerometer-Y-Max* features are predicted with the least error compared to other features. Table 4 also shows that *Accelerometer-Y-Avg* and *Accelerometer-Y-Max* are predicted with least error compared to other features. For both cases (i.e. for the upper arm-mounted smartphone which measures the total flexion, and for waist-mounted smartphone which measures the trunk flexion), predictions for *Accelerometer-Y-Max* features, using Equation 9 and Equation 10 are

the most accurate compared to other features. Therefore, it can be concluded that prediction of total and trunk flexion from the *Accelerometer-Y-Max* data will yield the most accurate results.

Table 3 - Comparison of Results for Upper-arm-mounted Smartphone

Sensor/ Posture		Experimental Result				Obtained Result				Error			
		P_3	P_4	P_5	P_6	P_3	P_4	P_5	P_6	P_3	P_4	P_5	P_6
Acc.X	Avg	-0.803	-0.576	-0.479	-0.214	-0.668	-0.332	-0.332	-0.164	17%	42%	31%	23%
	Min	-0.764	-0.549	-0.446	-0.175	-0.707	-0.46	-0.46	-0.123	7%	16%	-3%	29%
	Max	-0.846	-0.613	-0.514	-0.251	-0.783	-0.538	-0.538	-0.204	7%	12%	-5%	19%
Acc.Y	Avg	0.3617	-0.787	-0.849	-0.942	0.3752	-0.835	-0.835	-0.953	-4%	-6%	2%	-1%
	Min	0.3849	-0.768	-0.831	-0.919	0.4066	-0.816	-0.816	-0.936	-6%	-6%	2%	-2%
	Max	0.3375	-0.806	-0.868	-0.965	0.3418	-0.854	-0.854	-0.971	-1%	-6%	2%	-1%
Acc.Z	Avg	0.5245	0.0909	0.0119	-0.056	0.4893	0.2912	0.2912	0.0207	7%	-220%	-2345%	137%
	Min	0.5549	0.1202	0.0463	-0.02	0.5181	0.3213	0.3213	0.0524	7%	-167%	-594%	359%
	Max	0.4951	0.0624	-0.016	-0.094	0.46	0.2603	0.2603	-0.013	7%	-317%	1703%	87%

Table 4 - Comparison of Results for Waist-mounted Smartphone

Sensor/ Posture		Experimental Result				Obtained Result				Percent Error			
		P_2	P_3	P_4	P_5	P_2	P_3	P_4	P_5	P_2	P_3	P_4	P_5
Acc.X	Avg	-0.208	-0.214	-0.203	-0.454	-0.171	-0.171	-0.171	-0.498	18%	20%	16%	-10%
	Min	-0.198	-0.205	-0.194	-0.445	-0.161	-0.161	-0.161	-0.486	19%	21%	17%	-9%
	Max	-0.22	-0.225	-0.213	-0.463	-0.183	-0.183	-0.183	-0.511	17%	19%	14%	-10%
Acc.Y	Avg	1.0168	1.0287	1.0258	0.9526	1.0239	1.0239	1.0239	0.9665	-1%	0%	0%	-1%
	Min	1.0254	1.0375	1.0336	0.9593	1.0311	1.0311	1.0311	0.9738	-1%	1%	0%	-2%
	Max	1.0084	1.0195	1.0184	0.9462	1.0163	1.0163	1.0163	0.9587	-1%	0%	0%	-1%
Acc.Z	Avg	0.2113	0.1154	0.1697	0.043	0.219	0.219	0.219	0.0165	-4%	-90%	-29%	62%
	Min	0.2175	0.1247	0.1765	0.0514	0.2253	0.2253	0.2253	0.0256	-4%	-81%	-28%	50%
	Max	0.2049	0.1073	0.1632	0.0348	0.212	0.212	0.212	0.0062	-3%	-97%	-30%	82%

6.3 Developing an Equation for Finding P_i from $P_i \cdot feature_k$

Since the *Accelerometer-Y-Max* feature is the most reliable feature for predicting P_i , as established in previous Subsection, substituting $P_i = \alpha \cdot 90^\circ$ and $feature_k = Accelerometer_Y_Max$, Equation 10 can be rewritten as,

$$P_i = \cos^{-1} \left(\frac{P_i \cdot Accelerometer_Y_Max - P_{90} \cdot Accelerometer_Y_Max}{P_1 \cdot Accelerometer_Y_Max - P_{90} \cdot Accelerometer_Y_Max} \right) \quad \text{Equation 11}$$

Where, for the upper arm-mounted smartphone, P_i = total flexion, $P_{90} = P_2$, and $i = 3, 4, 5, 6$, and for the waist-mounted smartphone, P_i = trunk flexion, $P_{90} = P_6$, and $i = 2, 3, 4, 5$.

6.4 Prediction of P_i

Using Equation 11 and sensory data from the upper arm-mounted smartphone, total flexions are measured for four postures and tabulated in Table 5. Similarly, trunk flexions are measured using Equation 11 and sensory data from the waist-mounted smartphone, and listed in Table 6.

Table 5- Prediction of Total Flexions

Postures	P1.Accelerometer_Y_Max	P90.Accelerometer_Y_Max	Pi.Accelerometer_Y_Max	Total Flexion, P_i (°)
P_3	-0.971371297	-0.095891187	0.337469734	120
P_4	-0.971371297	-0.095891187	-0.806222257	36
P_5	-0.971371297	-0.095891187	-0.867731428	28
P_6	-0.971371297	-0.095891187	-0.965261204	7

Table 6- Prediction of Trunk Flexions

Postures	P1.Accelerometer_Y_Max	P90.Accelerometer_Y_Max	Pi.Accelerometer_Y_Max	Trunk Flexion, P_i (°)
P_2	1.016270039	0.586581745	1.008369841	11
P_3	1.016270039	0.586581745	1.019543369	0
P_4	1.016270039	0.586581745	1.018436005	0
P_5	1.016270039	0.586581745	0.946233972	33

In addition to the six initial postures (P_1 through P_6) explained throughout the paper, more experiments were conducted to further assess the robustness and accuracy of the developed formulation in predicting arbitrary body postures of workers involved in manual tasks. In particular, 10 new body postures (P_7 through P_{16}), shown in Figure 8, were analyzed. It should be noted that these 16 body postures were randomly selected to cover all risk categories (ranging from low, to medium, to high) as described in Table 1. Table 7 and Table 8 show calculations of total and trunk flexions of these body postures, respectively.

Figure 8- Ten New Postures for the Screw Driving Experiment

Table 7- Prediction of Total Flexions of New Arbitrary Postures

Posture	P_1 .Accelerometer_Y_Max	P_{90} .Accelerometer_Y_Max	P_i .Accelerometer_Y_Max	Total Flexion, P_i (°)
P_7	-0.93446	-0.07067	-0.6867	45
P_8	-0.93446	-0.07067	-0.93205	4
P_9	-0.93446	-0.07067	-0.60958	51
P_{10}	-0.93446	-0.07067	-0.14265	85
P_{11}	-0.93446	-0.07067	-0.93446	0
P_{12}	-0.93446	-0.07067	-0.57244	54
P_{13}	-0.93446	-0.07067	-0.18295	83
P_{14}	-0.93446	-0.07067	-0.07067	90
P_{15}	-0.93446	-0.07067	-0.56386	55
P_{16}	-0.93446	-0.07067	-0.36909	70

Table 8- Prediction of Trunk Flexions of New Arbitrary Postures

Posture	P_1 .Accelerometer_Y_Max	P_{90} .Accelerometer_Y_Max	P_i .Accelerometer_Y_Max	Trunk Flexion, P_i (°)
P_7	1.041574	0.879573	1.041574	45
P_8	1.041574	0.879573	1.015564	37
P_9	1.041574	0.879573	1.018172	83
P_{10}	1.041574	0.879573	1.000776	127
P_{11}	1.041574	0.879573	1.022249	28
P_{12}	1.041574	0.879573	0.999042	97
P_{13}	1.041574	0.879573	0.994996	127
P_{14}	1.041574	0.879573	1.016283	122
P_{15}	1.041574	0.879573	1.017257	87
P_{16}	1.041574	0.879573	0.879573	160

6.5 Analysis of Results

Shoulder flexion (SF) is measured by subtracting trunk flexion (TF) from the total flexion. Predicted values for TF and SF for postures P_3 , P_4 and P_5 , along with the observation-based measurements are tabulated in Table 9. Similarly, in Table 10, predicted values for TF and SF for the 10 arbitrary body postures (P_7 through P_{16}), along with the observation-based measurements are tabulated. It should be noted that the observation-based measurements were taken by visually inspecting the photos of each experiment, while the predicted (hypothesis-based) measurements were calculated using the methodology laid out in this paper.

Table 9- Predicted vs. Observed Measurements of Trunk Flexion (TF) and Shoulder Flexion (SF)

Posture	Predicted		Observed		Difference = Observed - Predicted	
	TF	SF	TF	SF	TF	SF
P_3	0	120	0	120	0	0
P_4	0	36	0	30	0	-6
P_5	33	61	30	60	-3	-1

Table 10- Predicted vs. Observed Measurements of Arbitrary Postures

Posture	Predicted		Observed		Difference = Observed - Predicted	
	TF	SF	TF	SF	TF	SF
P_7	0	45	0	45	0	0
P_8	33	37	40	40	7	3
P_9	31	83	30	85	-1	2
P_{10}	42	127	35	130	-7	3
P_{11}	28	28	45	40	17	12
P_{12}	42	97	40	100	-2	3
P_{13}	45	127	45	125	0	-2
P_{14}	32	122	25	115	-7	-7
P_{15}	32	87	25	90	-7	3
P_{16}	90	160	90	160	0	0

7 DISCUSSION

As listed in Table 9 and Table 10, with a few exceptions, values calculated from the hypothesis are very close to the observation-based measurements. In particular, for posture P_3 , P_5 , P_7 , P_9 , P_{12} , P_{13} , and P_{16} measurements of trunk and shoulder flexions by both approaches are either

identical or within $\pm 3^\circ$ of the true values. For some postures such as P_{11} , P_{14} , and P_{15} , the difference between predicted and true values is slightly higher. Overall, it is very promising to observe that out of the 13 body postures tabulated in Table 9 and Table 10, the absolute difference in TF and SF is $\leq 7^\circ$ in 12 postures. There is only one posture (P_{11}) for which the difference for both TF and SF is more than 7° . Further inspection of the experiment photos showed that the main reason behind this relatively large error was that the waist-mounted smartphone was not properly secured in this isolated body posture, and as a result, its orientation did not reflect the actual trunk flexion. Nonetheless, results shown in Table 9 and Table 10 are all indicative that the predicted and observed TF and SF values for each body posture are either in the same ergonomic risk level or within one level from each other (as defined in Table 1), which implies that the developed methodology is a reliable tool for ergonomic risk analysis of manual construction tasks.

Table 11 shows the ergonomic risk level of each posture. For the TF of each posture, a risk score, ranging from 1 to 4 is given based on the value falling into the category size described in Table 1. Similarly, for SF, a risk score, ranging from 1 to 5 is given. The total risk score for each posture is then calculated by adding risk scores for TF and SF, resulting in the lowest possible score of 2 and the highest possible score of 9. The risk level of low (L), medium (M) or high (H) is assigned to each posture based on the total risk score being 2 to 3, 4 to 6, and 7 to 9, respectively. Table 11 shows that for 14 out of the 16 postures, risk levels calculated from the hypothesis and observation-based measurements are identical. As shown in this Table, for the specific screw driving task conducted in the validation experiment, postures P_6 , P_{10} , P_{13} , P_{14} , and P_{16} exposed the worker to a high level of ergonomic risk.

Table 11- Risk Level of the Postures (H: high, M: medium, L: low)

Postures	Flexions				Risk Score						Risk Level	
	Predicted		Observed		Predicted			Observed			Predicted	Observed
	TF	SF	TF	SF	TF	SF	TF+SF	TF	SF	TF+SF		
P1	0	0	0	0	1	1	2	1	1	2	L	L
P2	0	90	0	90	1	4	5	1	4	5	M	M
P3	0	120	0	120	1	4	5	1	4	5	M	M
P4	0	36	0	30	1	2	3	1	2	3	L	L
P5	33	61	30	60	2	3	5	2	3	5	M	M
P6	90	90	90	90	3	4	7	3	4	7	H	H
P7	0	45	0	45	1	2	3	1	2	3	L	L
P8	33	37	40	40	2	2	4	2	2	4	M	M
P9	31	83	30	85	2	3	5	2	3	5	M	M
P10	42	127	35	130	2	5	7	2	5	7	H	H
P11	28	28	45	40	1	1	2	2	2	4	L	M
P12	42	97	40	100	2	4	6	2	4	6	M	M
P13	45	127	45	125	2	5	7	2	5	7	H	H
P14	32	122	25	115	2	5	7	1	4	5	H	M
P15	32	87	25	90	2	3	5	1	4	5	M	M
P16	90	160	90	160	3	5	8	3	5	8	H	H

8 SUMMARY AND CONCLUSIONS

Construction works are very labor-intensive and often stipulate the workers to go beyond their natural physical limits to cope up with the increasing complexities and challenges of their assigned tasks. Consequently, workers in this industry are more exposed to WMSDs which can translate into significant amounts of loss in project financial and human resources and negatively impact productivity. To prevent WMSDs, health and safety organizations have been emphasizing

the need to identify hazardous jobsite risks and then ergonomically design the job so that it fits to the workers. An example of such initiative is PtD, taken by NIOSH, to prevent work-related injuries and fatalities by ergonomically designing the work environment. One of the goals of PtD is to identify and eliminate the ergonomic risks at the source and as early as possible. To identify risk levels on a jobsite, self-assessment, observation-based, or instrument-based direct measurement techniques can be used. Previous research has found that direct assessment is more accurate but often requires prior technical knowledge and investment. To overcome these implementation challenges, in this research smartphone sensors were used as measurement tools due to their ubiquity, low procurement and maintenance cost, and ease of use.

Since awkward posture is one of the eight major causes of WMSDs, the research primarily focused on assessing the risk levels associated with awkward postures while performing manual tasks. Generally, assessment of an awkward posture consists of measuring deviation angles of various body-parts, however, the presented research specifically focused on only trunk and shoulder flexions of the workers. In particular, it was hypothesized that if a composite posture could be defined as a weighted composition of base postures, then any feature of that posture would also be a weighted composition of the same corresponding features of the base postures. Furthermore, the weight factors in the feature composition will be functions of corresponding weights for the posture composition. Based on this hypothesis, an equation was developed to measure the components of posture vector from the features of that posture. In other words, an equation to measure trunk and shoulder flexions from the smartphone's sensory data was developed.

For validation of the developed hypothesis, experiment were performed with two smartphones mounted on a worker's body; one on the upper-hand and another on the waist. Data from the smartphones' sensors were collected while the worker was performing a typical

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3 construction task, which was screw driving in this case. Collected data were preprocessed for
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5 feature extraction and the 9 most distinctive features were selected for further analysis. It was
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7 revealed that for the specific experiment designed and carried out in this research, the
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9 *Accelerometer_Y_Max* feature was the best feature for predicting measurement of the flexions.
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11 Therefore, the *Accelerometer_Y_Max* feature was chosen to measure the trunk and shoulder
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13 flexions and it was found that the predicted results based on the hypothesis were in very close
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15 agreement with the observation- based measurements, and could be reliably used to assess the
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17 level of ergonomic risk associated with the manual task conducted by the worker.
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23 It must be noted that although the presented results in this paper primarily focused on posture
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25 analysis for trunk and shoulder flexions in a manual screw driving task, the developed
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27 methodology and analysis techniques can be generalized with minimum modifications to other
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29 types of field activities. Moreover, the proposed method is applicable for workers in various
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31 occupations who are exposed to WMSDs due to awkward postures. Examples include, but are
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33 not limited to industry laborers, carpenters, welders, farmers, health assistants, teachers, and
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35 office workers.
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