Summer 5-2015

ASSESSING GAIT AND POSTURAL STABILITY OF CONSTRUCTION WORKERS USING WEARABLE WIRELESS SENSOR NETWORKS

Houtan Jebelli
University of Nebraska-Lincoln, jebelli.houtan@huskers.unl.edu

ASSESSING GAIT AND POSTURAL STABILITY OF CONSTRUCTION WORKERS USING WEARABLE WIRELESS SENSOR NETWORKS

by

Houtan Jebelli

A THESIS

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Master of Science

Major: Construction Engineering and Management

Under the Supervision of Professor Changbum R. Ahn

Lincoln, Nebraska

May, 2015

ASSESSING GAIT AND POSTURAL STABILITY OF CONSTRUCTION WORKERS USING WEARABLE WIRELESS SENSOR NETWORKS

Houtan Jebelli, M.S.

University of Nebraska, 2015

Advisor: Changbum R. Ahn

Falling accidents are a leading cause of fatal and nonfatal injuries in the construction industry. This fact demonstrates the need for a comprehensive fall-risk analysis that incorporates the effects of construction workers' physiological characteristics. In this context, the objective of the thesis is to investigate and validate the usefulness of the gait- and postural-stability metrics in assessing construction workers' fall risks. Diverse metrics that assess the capability to keep the body balanced and maintain coordination of body segments during locomotion (gait stability) and stationary postures (postural stability) have been introduced and used in clinical applications. However, their usefulness in the industry settings, in particular construction domain, has not been fully examined. Specifically, the thesis investigates the usefulness of one gait-stability metric and two postural-stability metrics which are computed using kinematic data captured from wearable inertial measurement units (IMUs). The usefulness of the selected metrics is validated by demonstrating their distinguishable powers in characterizing construction tasks with different fall-risk profiles.

This thesis consists of three independent papers that have been published in other venues. The first paper focuses on validating the predictive power of fall risk of the Maximum Lyapunov exponent (Max LE), a gait-stability metric established in clinical settings. The results of the first paper demonstrate that the Max LE is able to distinguish workers' gait stability while doing tasks with different fall-risk profiles. The second paper aims to test the usefulness of two postural-stability metrics that can be calculated from inertial measurement unit (IMU) data—the velocity of the bodily center of pressure (COPv) and the resultant accelerometer (rAcc)—as predictors for measuring construction workers' fall risk in stationary postures. The results showed the distinguishing powers of Acc and COPv in tasks with different fall-risk profiles in stationary postures. The third paper explores the application of the postrual-stability metrics to analyze fall risks of the effects of tool-loading formation on workers' fall risks. The results of the last paper demonstrate the higher risk values associated with tools connected asymmetrically to a full-body safety harness. The postrual- and dyanamic-stability metrics demonstrated in this thesis can be used as the metrics to find tasks and postures that have a higher risk of falling. Knowing the most dangerous locations at construction sites can help the manager provide appropriate fall-prevention systems; these can decrease the hazards at the job sites. Merging the suggested approach with certain alarm systems can provide real-time monitoring, which can assess the fall risk of construction workers.

To my lovely M-O-T-H-E-R, ***Nahid***

M *is for the million things she gave me,*

O *means only that she's growing old,*

T *is for the tears she shed to save me*

H *is for her heart of purest gold;*

E *is for her eyes, with love light shining*

R *means right, and right she'll always be*

MOTHER

A word that means the world to me

Acknowledgements

I am sincerely grateful to my advisor, Dr. Changbum Ahn. Without his daily guidance, comments, persistent monitoring, and patience, I would never have been able to finish this research. I will forever be indebted to Dr. Ahn for his encouraging spirit and all of his support.

A large debt of gratitude also goes to the other two members of my thesis committee, Dr. Terry Stentz and Dr. Asregedew Woldesenbet. I am very grateful to Dr. Stentz for his invaluable feedback and informative ideas, and for expanding my thinking regarding how to improve this thesis. A special thanks is due Dr. Asregedew Woldesenbet for his guidance regarding this thesis and for sitting on my master's committee.

Many thanks go to my dear friends, Kanghyeok Yang and Tim Adams, who helped me collect data for various experiments for my thesis. I would also like to acknowledge Davis Erection Company d.b.a. Topping Out, Inc. of Lincoln, Nebraska, and in particular, Cory Lyons (General Manager, Lincoln Division), for considerable help in collecting data. In addition, I would like to acknowledge Peter Hilsabeck, the coordinator of Civil Engineering Laboratory for his great help on the experimental setup. Finally, I would like to acknowledge the financial support and recognition of this work by the Nebraska Research Initiatives program.

Table of Contents

List of Figures

List of Tables

Chapter 1. Introduction

Overview and the Observed Problem

Based on the available statistics, falling accidents are a significant cause of fatal and nonfatal injuries in the construction industry. In 2013, fatal falls, slips, or trips took the lives of almost 700 workers in the U.S.; 82% of those were falls to a lower level of the building (BLS, 2014). Only 6% of the American workforce works in the construction industry, but their fatal injuries account for 16.5% of all work-related fatalities (BLS, 2011). Falls are a cause of fatal and nonfatal injuries worldwide. Falls account for more than 50% of injuries in China and Hong Kong (Chan et al. 2008; Yung 2009) and are the leading cause of occupational injuries in New Zealand (Bentley et al. 2006). In addition, falls comprise 53% of all of fatal incidents in Taiwan (Chi and Wu 1997; Lin et al. 2011). Most of the falls to a lower level are by workers in the construction trades. Of these trades, ironworkers have the highest fall risk (Teizer, 2013). The probability of fatality in construction is estimated to be approximately 0.5 %, and ironworkers are exposed to a high likelihood of fatalities, 3.11 % (31.1 per 1,000 full-time equivalent staff) (CPWR, 2013).

To effectively implement fall-prevention techniques it is critical to first identify and assess the fall risk associated with the diverse factors impacting construction workers (Sousa et al. 2014). There are many studies that assess safety risks at different levels (Fredericks et al. 2005; Beavers et al. 2009; Hallowell and Gambatese 2009). However, most of these techniques rely on experts' judgments—subject to cognitive biases (Tversky and Kahneman 1974)—or calculate risk by using retrospective data (e.g., accident reports), which do not provide enough information to prevent future accidents (Grabowski et al. 2007). In addition, these techniques often focus on determining risk based upon exposure to various physical objects and frequently ignore the impact of human factors, such as physiological traits and skill capacities. However, previous studies have indicated that individuals with different physiological characteristics have different levels of fall risk; some tend to fall more often than others, even in the same environment (Liu et al. 2012). In addition, there is increasing evidence that physiological characteristics, such as postural balance and gait stability, also significantly affect the fall risk of construction workers (Simeonov et al. 2011).

In summary, there is a clear need for a risk-assessment method that provides a comprehensive analysis of fall risk by incorporating the effects of construction workers' physiological characteristics into the assessment. Stability in the human motion system is defined as the behavior and changes in motion systems a subject experiences when faced with very small perturbations (Reeves et al. 2007). Loss of body balance might have a direct effect on human subjects' fall risk in which increase the human subjects' fall risk. This thesis aims to introduce a method for computing the stability of construction workers using directional kinematic data recorded by IMU sensors attached to construction workers.

Research Objectives

Research Objective 1: Chapter 2

The first objective of this thesis is to study and validate the usefulness of the Max LE as a critical metric for measuring construction workers' gait stability.

Research Question:

- Is maximum Lyapunov exponents (Max LE) able to distinguish tasks with different fall-risk profiles at various construction sites?

Hypothesis:

Max LE is able to measure construction workers' gait stability while doing different tasks with different fall-risk profiles using kinematic time-series data recorded by IMU sensors.

Research Objective 2: Chapter 3

This study aims to test the usefulness of two metrics that can be calculated from Inertial Measurement Units (IMU) data—velocity of the bodily center of pressure (COPv) and the resultant accelerometer (rAcc)—as predictors with which to measure construction workers' fall risk in stationary postures.

Research Questions:

- Can rAcc and COPv distinguish tasks with different fall-risk profiles at the construction sites under study? Are these metrics able to measure construction workers' postural stability?
- What is the correlation coefficient between rAcc, COPv and F-COPv?

Hypothesis:

rAcc and COPv are capable to measure construction workers' postural stability while doing different tasks with different fall-risk profiles can be measured by calculating rAcc and COPv using kinematic time-series data recorded by IMU sensors.

Research Objective 3: Chapter 4

Another objective of this thesis is to use the metrics suggested in the previous chapters to analyze the effects of different intrinsic and extrinsic factors on workers' fall risk. Chapter 4 aims to show the effect of a single extrinsic factor—wearing a full-body safety harness and heavy tool-belt-loading symmetry—on workers' stability.

Research Questions:

- How will workers' tool-belt-loading configuration affect their postural stability?

Hypothesis:

Construction workers' tool-belt-loading configuration will affect their stability.

Significance of the Objectives:

If Max LE, rAcc, and COPv can distinguish construction tasks with different fall-risk profiles, then they can be a predictor of construction workers' fall risk. Using these values can provide a numerical factor that can be used to find the tasks and postures with a higher risk of falling. Finding the most hazardous tasks and postures can lead to using alternative postures or different tasks, rather that those with a high fall risk. Also, the value of the suggested metrics can be used to study the effects of workers' personal characteristics. Some workers may be more capable of doing some tasks with a higher fall risk. Assessing the capability of different workers can help managers use the most competent workers for certain tasks and thereby decrease the risk of falls at a given construction site. Another benefit of the postural and gait stability metrics is determining the locations with a higher fall risk. Measuring the value of the postural-stability metrics continuously can help to find the most hazardous areas. Knowing the most dangerous locations at a given construction site can help the manager to implement appropriate fall-prevention systems for a particular area; these can then decrease hazards at the job sites.

Thesis Organization

Including the current chapter, this thesis includes five chapters. Chapters are prepared in the format of two journal papers and one conference papers. These chapters follow a standard academic format. Each has its own abstract, introduction, objective and methods, literature review, results and analysis, and conclusion. The chapters are as follows:

- **Chapter 2.** The chapter explains the Max LE calculation process in detail. It investigates the ability of Max LE as a gait-stability metric, to characterize the fall-risk profile of ironworkers' tasks. This chapter's paper has been accepted for publication by the ASCE Journal of Computing in Civil Engineering.
- **Chapter 3.** In this chapter, two postural-stability metrics, velocity of the bodily center of pressure (COPv) and the resultant accelerometer (rAcc), are introduced as predictors for measuring construction workers' fall risk in stationary postures. This chapter's paper will be submitted to Elsevier's Safety Science Journal.
- **Chapter 4.** There are several intrinsic and extrinsic factors that affect human gait stability, such as walking speed (Krasovsky et al. 2014; Sloot et al. 2014; Stenum et al. 2014), workers' gears and load (Jebelli et al. 2014; Liu and Lockhart 2013), their age (Brodie et al. 2014; Hsue and Su 2014; Singer et al. 2012), etc. One of the overlooked factors that can increase fall risk is the incorrect use of personal

protective equipment—including safety harnesses and tool belts—since construction workers and their supervisors often do not pay attention to the loading symmetry of heavily loaded tool belts attached to full body fall protection harnesses (Cory Lyons, personal communications, 2014)The research in this chapter demonstrates the application of two of the suggested metrics useful in measuring the effect of workers' gear and load-carrying situations. This chapter's paper has been accepted for presentation at the 2015 International Construction Specialty Conference (ICSC2015).

Chapter 2. Comprehensive Fall Risk Assessment of Construction Workers using Inertial Measurement Units: Validation of the Gait Stability Metric to Assess the Fall Risk of Iron Workers

Abstract

In construction worksites, slips, trips, and falls are major causes of fatal injuries. This fact demonstrates the need for a safety assessment method that provides a comprehensive fall-risk analysis inclusive of the effects of physiological characteristics of construction workers. In this context, this research tests the usefulness of the maximum Lyapunov exponents (Max LE) as a metric to assess construction workers' comprehensive fall risk. Max LE, one of the gait-stability metrics established in clinical settings, estimates how the stability of a construction worker reacts to very small disruptions. In order to validate the use of Max LE, we designed and conducted a laboratory experiment that asked a group of subjects to simulate iron workers' walking tasks on an I-beam. These tasks were designed to showcase various fall-risk profiles: walking with a comfortable walking speed presented a low fall-risk profile; carrying a one-sided load and walking at a faster speed on the I-beam both presented a high fall-risk profile. Inertial Measurement Unit (IMU) sensors were attached to the right ankle of participants' bodies to collect kinematic data for the calculation of Max LE. The results showed that Max LE offers adequate distinguishing power for characterizing the fall risk of various construction workers' tasks and the introduced approach to compute the gait stability from IMU sensor data captured from human bodies could provide the valuable analysis of the safety-related risks present in construction workers' motions.

Key words: Fall risk, gait-stability metrics, quantitative measures, maximum Lyapunov exponents, inertial measurement units

Introduction

The construction industry has always had one of the poorest safety records among all industries. While the construction industry employed only 6% of the American workforce in 2012, the industry accounted for more than 17% of all occupational fatal injuries in that year (BLS 2013). In particular, fall accidents were the leading cause of deaths and injuries in construction projects, accounting for more than 33% of all construction-related accidents (NSC 2013). Statistics indicate that in spite of strengthened workplace guidelines and work practice improvements, the risk related to fall accidents has not decreased throughout the years; in fact, the number of fatal falls to lower levels has increased from 447 in 2007 to 553 in 2011 (BLS 2011).

To effectively implement fall prevention efforts, it is critical to first identify and assess the fall risk associated with the diverse factors impacting construction workers (Sousa et al. 2014). There are many existing studies that assess safety risks at different levels (Fredericks et al. 2005; Beavers et al. 2009; Hallowell and Gambatese 2009). However, most of these techniques rely on either experts' judgments—which are subject to cognitive biases (Tversky and Kahneman 1974)—or depend on retrospective data (e.g., accident reports) to calculate risk, which do not provide enough information or insight to effectively prevent future accidents (Grabowski et al. 2007). In addition, these techniques often focus on determining risk based upon exposure to various physical objects and frequently ignore the impact of human factors, such as physiological traits and skill capacities. However, previous studies indicated that individuals with different physiological characteristics do have different levels of fall risk since some persons tend to fall more often than others, even in the same environment (Liu et al. 2012). Also, there is increasing evidence that physiological characteristics, such as postural balance and gait stability, also significantly affect the fall risk of construction workers (Simeonov et al. 2011). With that said, there is a clear need for a risk-assessment method that provides a comprehensive analysis of fall risk by incorporating the effects of construction workers' physiological characteristics into the assessment.

Gait stability, defined as the capability to keep the body balanced and to maintain coordination of body segments while walking (Iosa et al. 2012; Kavanagh and Menz 2008), has been an important measure in understanding and assessing the fall risk of patients and elderly people with gait disorders (Hamacher et al. 2011). To quantify the gait stability of patients and elderly people, diverse metrics using the kinematic data of human subjects have been proposed and used (Dingwell et al. 2001; Hurmuzlu et al. 1996; Kang and Dingwell 2008), However, the appropriateness and effectiveness of using gait stability measures to assess the fall risk of construction workers—who do not have any gait disorders—have not yet been tested and demonstrated. Therefore, this research aims to introduce a method for computing the gait stability of construction workers using directional kinematic data recorded via inertial measurement unit (IMU) sensors attached to construction workers; subsequently, this research will test the validity of this method as a capable method for measuring construction workers' overall fall risk.

In particular, this research focuses on the computation and validation of maximum Lyapunov exponents (Max LE), which are considered one of the most reliable gait-stability metrics in clinical and healthcare applications. The computation of Max LE provides a way to measure the nuanced changes in a subject's movements by using kinematic data recorded via inertial measurement unit (IMU) sensors attached to human subjects. This research specifically examined whether Max LE can provide sufficient distinguishing power to characterize the fall risk of different iron workers' tasks—iron workers face the highest lifetime risk of fatal workplace injuries (CPWR 2013), making them a prime candidate for this investigation. The discriminating power of Max LE was evaluated by computing and comparing the Max LE of those tasks iron workers perform that manifest different fall-risk profiles. Since stable walking on an I-beam features a low fall-risk profile, this research used the Max LE of stable walking as the baseline task against which to calculate the Max LE of two higher-risk tasks (load carrying and walking at an increased speed). By using IMU data to calculate the Max LE for each of these different tasks, this study evaluates the capacity of Max LE to differentiate the gait stability of iron workers performing assorted tasks on an I-beam.

Research Background

Current Sensing Technology in Assessing Construction Safety

Sensing approaches that use computer vision techniques and diverse sensors have been applied in various safety investigations within the construction industry. A majority of studies based upon the vision-based approaches focus on object identification and location tracking for workers and equipment to study and detect the overlap between workers and corresponding hazards (Brilakis et al. 2011; Chi and Caldas 2011; Park and Brilakis 2012; Teizer and Vela 2009; Weerasinghe and Ruwanpura 2010). Recently, workers' posture and behaviors have been monitored using various types of image processing—including video and Kinect range cameras—to study unsafe-behaviors (Han et al. 2013; Han and Lee 2013), recognize activities (Escorcia et al. 2012), and assess the risk of work-related musculoskeletal disorders caused by workers' postures (Ray and Teizer 2012). However, the precursors of fall accidents (e.g., disruptions in a body's balance control during walking) often do not involve any significant visual difference in workers' physical motions. Therefore, it is still challenging for the vision-based approach to capture information related to subtle disruptions affecting workers' balance systems.

Various sensing devices have also been used to collect information related to safety management in construction. The main focus of sensor-based studies revolves around tracking workers' and other resources' locations. These studies use global positioning systems (GPS), radio frequency identification (RFID), and/or WSNs to identify locations where unsafe events occur (Abderrahim et al. 2005; Wu et al. 2010), to detect and alert workers about their proximity to dangerous situations (Schiffbauer and Mowrey 2008; Teizer et al. 2010), and to visualize data that facilitates safety training (Teizer et al. 2013). In regards to assessing workers' activities and conditions, Cheng et al. (2013) utilized a wearable electrocardiograph sensor, a breathing rate sensor, and a 3-axial accelerometer to capture the heart rate and the thoracic bending angle of construction workers. Also**,** Joshua and Varghese (2011) used accelerometer data to classify the activities of a masonry worker (e.g., fetch and spread mortar, fetch and lay brick, fill joints) for a work-sampling purpose. While these studies have demonstrated the feasibility of utilizing IMU sensor data for workers' posture and motion analysis in construction, previous analyses of IMU sensor data are still limited to recognizing and classifying workers' postures rather than analyzing safety-related risks associated with workers' activities. To this end, this study will open an opportunity to utilize and analyze sensor data captured from construction workers to gauge different levels of fall risks within workers' performed activities, even within a single activity.

Current Fall Prevention in Construction

As there is a high cost associated with injuries and fatalities from construction fall accidents, fall prevention has come to be a major concern on construction sites. Currently, several of the Occupational Health and Safety Administration's (OSHA) regulations specifically address fall hazards in construction sites (OSHA 1999). While these regulations have been partially successful in decreasing fall accidents, researchers report that OSHA's requirements are not sufficient for preventing fall accidents for certain trades who work in dangerous circumstances (Johnson et al. 1998). The persistent frequency of injuries and fatalities from fall accidents indicates that more studies should be done to find a more effective way to decrease the fall risk of construction workers.

Many previous studies focused on prevention through design (PtD), which includes the consideration of construction-site safety during the design process of a construction project (Zhang et al. 2013; Qi et al. 2013; Zhou et al. 2012; Toole 2005; Gambatese et al. 2005). However, the implementation of PtD in practice is still challenging due to many barriers, such as designers' lack of knowledge regarding construction safety, the increased costs for designers, and liability concerns among designers and engineers (Carpenter and Toole 2011). Some studies focused on developing educational programs related to fall prevention (MacCollum 1995; Lingard and Rowlinson 1997; Griffin and Neal 2000; Lingard 2002; Sokas et al. 2009; Wilkins 2011). In spite of the fact that these training programs certainly helped prevent fall accidents in several cases, little evidence supports the usefulness of such educational programs in decreasing fall risk (Rivara and Thompson 2000).

The critical first step toward successfully implementing fall-prevention strategies is to understand the safety risk related to fall accidents for different workers, activities, locations, and situations. However, current practices of safety-risk assessment are mostly based on intuition and subjective judgments (Hallowell and Gambatese 2009). To respond to the qualitative nature of the current practices, there have been several efforts made to systematically quantify relative safety risks at the trade or activity level. For example, Hallowell and Gambatese (2009) quantified the safety risk for concrete formwork construction at the activity level using a frequency and severity rating for each activity to present its total risk; however, such frequency and severity ratings were evaluated according to experts' judgments, which are still subject to cognitive biases. In addition, existing methods for safety-risk assessment are not capable of predicting comprehensive fall risk when multiple extrinsic (e.g., jobsite hazards, hazardous activities) and intrinsic factors (worker-related—e.g., age, experience level, gait traits, physical characteristics) are in play since these techniques define risks based upon the exposure to various physical objects and ignore the impact of intrinsic factors. However, an individual worker's level of fall risk is determined by both intrinsic and extrinsic factors. Thus the need for a comprehensive method to assess construction workers' fall risks remains critical. Obtaining a better understanding of the relationship among these factors will ultimately lead to a better implementation and transformation of existing fall-prevention strategies.

Applications of Gait-Stability Measures

Stability in the human motion system is defined as the behavior and changes in motion systems a subject experiences when faced with very small perturbations (Reeves et al. 2007). Subsequently, gait-stability metrics have been used in clinical and healthcare settings to measure patients' fall risk during walking motions. A large number of gait-stability measurements have been introduced to determine fall risk during different body motions; these measurements include stride interval dynamics (SID), detrended fluctuation analysis (DFA), Hurst rescaled range analysis ($H_{R/S}$), Maximum Floquet Multipliers (Max FM), and Maximum Lyapunov exponents (Max LE). SID measures the time demanded to complete each cycle in a motion system (West and Scafetta 2005). DFA manifests itself as a long-range correlation that can quantify human gait from extended data series (longer than 5 minutes of normal walking); DFA studies the human gait balance by comparing the changes in integrated data series for different strides with the average fluctuation in the overall data (Hausdorff 2005; Peng et al. 1993). $H_{R/S}$ examines fractal properties after integrating a time series and can be used to characterize a time series of motion data when studying a body's stability (Delignlères et al. 2003). Additionally, Max FM builds upon the assumption that the inputted kinematic data represent periodic motions; thus Max FM quantifies the divergence rate of small agitations from one gait cycle to the next. Max FM is based upon the idea that the stability of a system can be calculated by using the discrete moments in successive cycles to determine and thereby measure a body's movement according to its angular velocities (Bruijn et al. 2013).

Max LE quantifies the average logarithmic rate of divergence of a time series data set and provides a measure that can express how a motion system reacts to very small perturbations. Several articles in the clinical literature name Max LE as the most reliable and useful gait stability measure (Bruijn et al. 2009; Dingwell and Martin 2006; Manor and Li 2009; Moraiti et al. 2007; Segal et al. 2008; Yakhdani et al. 2010). For example, Liu and Lockhart (2013) used Max LE to investigate the effect of carrying a load while walking on a treadmill. Also, Qu (2013) conducted research on the physical and cognitive load of soldiers' carrying a backpack; Qu (2013) measured the local dynamic stability of the soldiers' by calculating the maximum Lyaponuv exponent for participants who carried a backpack while walking on a treadmill. Expanding upon this success, this research uses IMU time-series data to calculate the Max LE of iron workers' tasks and examines how Max LE can capture the effects of iron workers' high fall risk–profile tasks on their gait stability.

Methodology

The objective of this research is to validate the usefulness of Max LE for measuring the fall risk of construction workers; in particular, this research applies Max LE to examine the fall-risk profiles of iron workers' assorted walking motions on a steel I-beam. To accomplish this goal, a series of experiments involving human subjects were conducted; these experiments and the calculations performed are described in more detail in the "Subjects and Experimental Protocol" section.

In brief, IMU sensors attached to the right ankle of the participants during each task captured time-series data. Then, the discriminating power of Max LE was evaluated by computing and comparing the Max LE values across different tasks. Statistical tests, such as t-test and an analysis of variance (ANOVA) test, were conducted to examine whether there are statistically significant differences among Max LE values. The significant difference of Max LE values between tasks with different fall-risk profiles could then indicate whether Max LE provides an adequate discriminating power for characterizing the fall risks of different construction tasks.

Subjects and Experimental Protocol

Subjects were instructed to do three different tasks that were assumed to have different fall-risk profiles. The first task was to walk on the installed I-beam with a normal speed; the second task was to walk with normal speed while carrying a load on one side of the body; and the third task was to walk with a higher speed. This research hypothesized that the second and third tasks would have higher fall-risk profiles based on Max LE than the first task.

Eight healthy subjects participated in the experiments. All of the participants reported that they did not have any clinical conditions that could affect their gait, and they all provided basic demographic information before participating in the test. Table 2-1 summarized the anthropometric information provided by the participants. All subjects wore a long sleeve work shirt, a safety harness, and a fitted pair of safety boots in order to minimize the effect of clothing and shoes on the data collection.

Table 2-1. Subjects' Sample Information

Subject Information				
Subject #	**Height**	**Weight (lbs)**	**Shoe Size(US size)**	**Age(years)**
Mean	5ft 11in	177.375	10.375	32.875
Median	5ft 10in	178.5	10.5	28.5
Standard Deviation	6in	21.67	1.40	13.32
Min value	5ft 2in	155	9	23
Max value	6 ft 3in	210	12	65

The experiments required the construction of a 65-foot long I-beam on which subjects were to perform their walking tasks. The I-beam was installed 2 inches off the ground to maintain the test for stability while protecting the subjects' safety. Subjects wore the tri-axial accelerometers (Shimmer 9DOF) on their right pant leg near their ankles. The accelerometer was oriented with X-, Y-, and Z-axes, representing anterior-poster (AP), vertical (VT) and medio-lateral (ML) directions, respectively (See Figure 2-1-c). The sampling rate of the accelerometer data collection was 52 Hz. Additionally, a video camera captured the movements of the subjects. The sensor data was wirelessly collected through a Bluetooth connection.

For Task 1, subjects were asked to walk along the installed I-beam at their normal speed (See Figure 2-1-a); their self-determined comfort speed averaged 5.11 ft/sec. For Task 2, subjects were asked to move side-carrying loads while walking at their normal speed; the subject group's speed during Task 2 averaged 5.06 ft/Sec (See Figure 2-1-b) and their side-carrying load was a one-sided tool bag that contained construction tools weighing 26.5 lbs. Task 3 required subjects to walk with a faster speed on the I-beam; the subject group's average speed of the activity during Task 3 was 7.23 ft/sec.

For each task, subjects were first asked to walk for two minutes without stopping. According to Kang and Gindwell, trial lengths of two minutes can ensure good reliability of local dynamic stability measures (Dingwell and Kang 2007). Subjects were also asked to stop for ten seconds before they started each task for accelerometer calibration. At the beginning of each experiment, the experiment instructor hit the sensor to mark a peak in the recorded data and to record the exact starting point of the walking data. Between different tasks, the subjects were given at least a two-minute break to minimize carry-over effects and to avoid the confounding effects caused by fatigue.

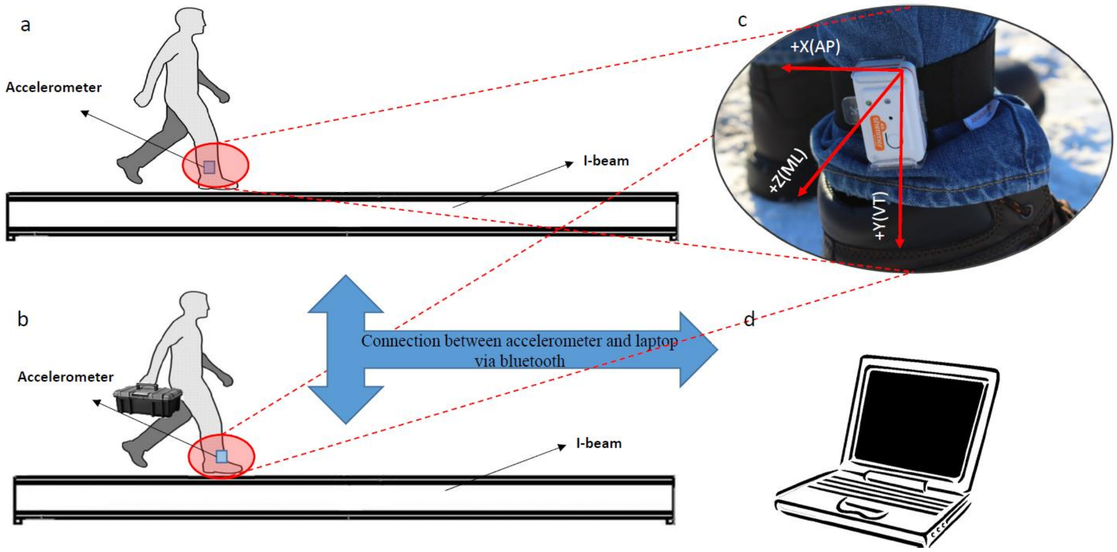

Figure 2-1. Illustration of Experimental Setup: (a) First test experiment (walking on installed I-beam in self-normal speed; (b) Second test experiment (carrying one-sided load); (c) The IMU sensors' direction that attached to the right ankle of the subjects; (d) The IMU sensors were connected to the laptop via Bluetooth connection

Max LE Calculation

In a dynamic system—such as a worker's body during walking motions—stability can be defined as the ability of the system to maintain a desired trajectory despite the presence of small kinematic disruptions. In order to measure this stability, we needed to first create the state space as a graphical depiction of the data. This state space visualized the kinematic data gathered from the IMU sensors documenting the test subjects' movements. Figure 2-2-a shows the steps to prepare the data for state space reconstruction and Max LE calculation. Data for two minutes of the experiment were used to create the state space (6144 data points), and then the data related to the first 65 feet of walking motion were extracted for performing the Max LE calculation.

To quantify the stability of the dynamic system, we calculated the system's reaction to kinematic disturbances by calculating the Lyapunov exponents of the system. Within a state space, two close trajectories in each direction will diverge at a rate represented by the Lyaponuv exponent. Considering that a Lyapunov exponent may be calculated for every dimension of a studied state space (Rosenstein et al. 1993), for an *n*-dimension state space, *n* Lyapunov exponents may be calculated. The maximum Lyapunov exponent will thereby show the highest divergence rate for the studied system. The highest divergence rate indicates the greatest amount of instability.

To find the Lyapunov exponent, it was necessary to find the rate of change in the distance between two proximal data points in the state space. This process demanded knowing the initial separation between the two data points and then calculating the rate of this separation's change. Since the separation rate can vary according to different coordinate and state spaces, the calculation of Max LE first required the selection of a proper state space with enough dimensions to appropriately capture the dynamics of the analysis system. Several techniques have been introduced for reconstructing a state space, such as derivative coordinates (Packard et al. 1980; Takens 1981), principal components (Broomhead and King 1986) and method of delays (Takens 1981). This paper uses Taken theorem (Takens 1981) for constructing the state space; this theorem posits that state space can be constructed based upon the delay in scalar time series data. Figure 2-2-b shows the required steps to construct a proper state space. Time delay and embedding dimension are two parameters that we needed first to create a proper state space; these two parameter calculation are discussed in detail in the "State Space Reconstruction" section. After creating the proper state space, the Max LE value for each subject could be calculated using the recorded body motion in different dimensions (see Figure 2-2-b).

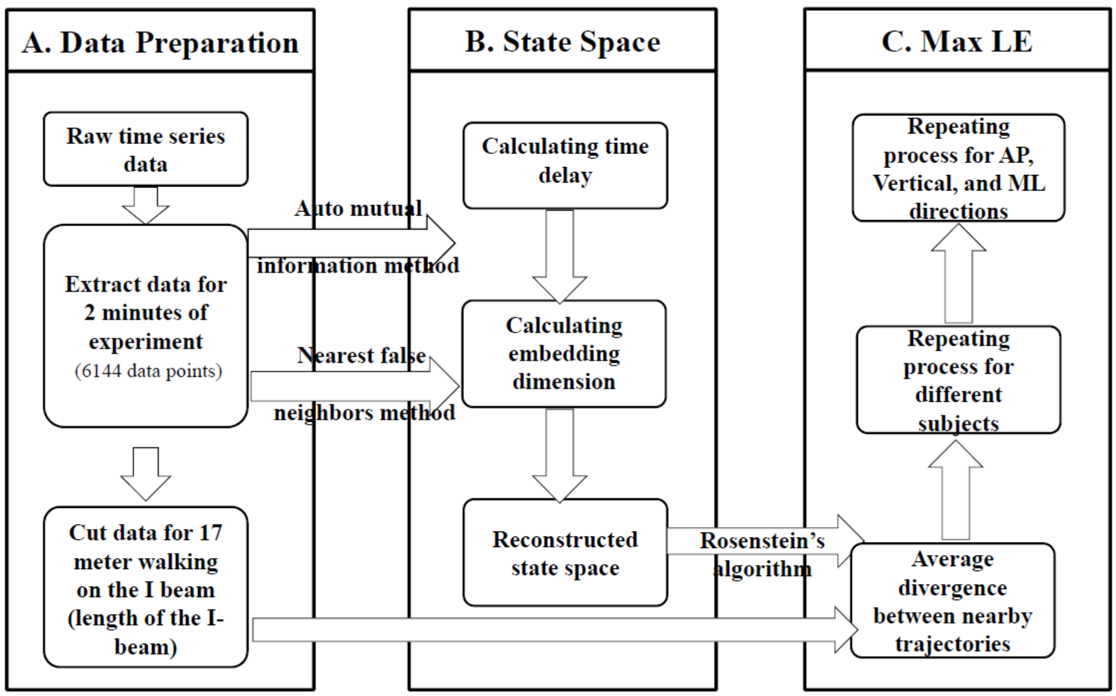

Figure 2-2. Max LE Calculation Process.

State Space Reconstruction

State space reconstruction can be executed by finding a dynamic attractor with enough dimensions to capture the behavior of the studied system. Since an attractor is "a minimal, invariant set to which any neighboring trajectory will be drawn" (Strogatz 1998), it acts as a convergence point for the fluctuating data. Successful state space reconstructions will graphically portray the changes in the variables of a studied system.

The "original state space" is the state space that would have been created using the sensor data for the three different directions without considering any time delay. It is reasonable to select kinematic time historical data as the input for state space reconstruction (Bruijn et al. 2010; Gates and Dingwell 2009; Takens 1981). However, such a selection would create a burden on the calculation process and may cause some errors in showing the motion of the studied system. For this reason, there is value in using alternative methods to develop a state space reconstruction.

In this paper the Delay Coordinates method was used for state space reconstruction. According to this method, the attractor y is represented by Equation 1:

$$y(n) = \big(x(n), x(n+T), x(n+2T), \ldots x(n+(d_e-1)T)\big) \qquad (1)$$

where x(n) are the coordinates in the phase space (Eckmann and Ruelle 1985; Parker and Chua 1990), T is the time delay, and d_e is an embedding dimension. In this paper, x(n) uses the time historic data from our experiment. In general, time delay is the lag time that shows the relationship between the input and output of the attractor y(n), and the embedding dimension corresponds to the necessary dimension needed for the state space to clearly show the studied system's movement.

Choosing an appropriate time delay (T) and embedding dimension (d_e) is an important step toward defining a proper state space. There are three basic methods for selecting an appropriate embedding dimension: (i) computing some invariant on the attractor, (ii) singular value decomposition, and (iii) the method of false nearest neighbors (Broomhead and King 1986; Grassberger 2007; Kennel et al. 1992; Takens 1981). The most popular method for determining the embedding dimension seems to be the method of false nearest neighbors (FNN) (Kennel et al. 1992); since false neighbors are the points that would be projected from the original state space but that would not belong to a delay state space

(Kennel et al. 1992), FNN finds the embedding dimension that minimizes the number of false nearest neighbors.

Due to their nature, false nearest neighbors are sets of points that are very close together at the dimension d_E=k but not at d_E=k+1. The total percentage of false neighbors may be calculated by repeating the mapping process of consecutive points from the original state space to the delayed state space. The total percentages of the false neighbors calculated vary according to the different embedding dimension—which subsequently means that the embedding dimension with the lowest percentage of false neighbors is the preferred embedding dimension for the state space. Considering the size of our data set and the type of our time historic data, FNN analysis was performed using values of R_{tol}=17 and A_{tol}=2—as recommended by Kennel et al. (1992)—where R_{tol} is the tolerance threshold and A_{tol} is the loneliness tolerance threshold; these two criteria control the number of false nearest neighbors in the FNN algorithm (Kennel et al. 1992). A data sample with 6144 data points was used to calculate the embedding dimension. The calculated embedding dimensions are shown in Table 2-2.

Another parameter needed to reconstruct a state space is time delay (T). For a small number of noise-free data, T can be selected almost arbitrarily without a significant impact on the result (Takens 1981). However, previous studies indicated that the quality of the result can be improved by selecting an exact number for T (Roux et al. 1983). Experimenters and theorists mentioned that there are not any specific criteria for choosing the best T (Eckmann and Ruelle 1985).

In this paper, the value of time delay was determined by selecting the first local minimum of the average mutual information (AMI). According to AMI, the time delay will be selected when the time in the mutual information function reaches its first minimum (Abarbanel and Kennel 1993; Abarbanel 1996; Rosenstein et al. 1993).

Table 2-2. Summary of Gait Parameters in Different Experiments. (NS*=Normal speed, L*=Carrying one-sided load situation, FS*= Faster speed, ST*=the number of strides, d_e=embedding dimension, AP=Anterio-posterior, VT=Vertical, ML=Medio-lateral)

		Subject 1			**Subject 2**			**Subject 3**			**Subject 4**		
		AP	**VT**	**ML**	**AP**	**VT**	**ML**	**AP**	**VT**	**ML**	**AP**	**VT**	**ML**
NS*	ST*	18	18	18	18	18	18	17	17	17	18	18	18
	d_e	4	4	4	5	3	3	6	3	3	4	5	4
L*	ST*	18	18	18	17	17	17	16	16	16	21	21	21
	d_e	5	3	3	6	3	3	7	6	4	4	4	4
FS*	ST*	14	14	14	19	19	19	14	14	14	15	15	15
	d_e	5	3	4	5	3	3	6	5	4	4	3	3

		Subject 5			**Subject 6**			**Subject 7**			**Subject 8**		
		AP	**VT**	**ML**	**AP**	**VT**	**ML**	**AP**	**VT**	**ML**	**AP**	**VT**	**ML**
NS*	ST*	18	18	18	18	18	18	17	17	17	18	18	18
	d_e	5	5	5	4	4	5	4	4	4	5	6	5
L*	ST*	18	18	18	18	18	18	17	17	17	17	17	17
	d_e	6	5	5	5	5	4	5	4	6	5	4	5
FS*	ST*	20	20	20	14	14	14	16	16	16	13	13	13
	d_e	5	5	6	5	5	8	5	5	9	9	5	5

Lyapunov Exponent Analysis

After constructing a proper state space (See Figure 2-3-b), the system's sensitivity to very small disturbances was quantified by calculating the Lyapunov exponent (Rosenstein et al. 1993). Calculating the maximum Lyapunov exponent (Max LE) is rather straightforward. In this research, we used the Rosenstein algorithm (Rosenstein et al. 1993) to calculate the

Max LE. This algorithm measures the Euclidian distance between all probable combinations of data points in the time series data set (Rosenstein et al. 1993) (see Figure 2-3-c). Equation 2 shows the Euclidean distance between very close data points of time series data for each direction at time *t*. Calculating all of the Lyapunov exponents from experimental data is very difficult and time consuming. In order to simplify the calculation, Equation 3 was used to calculate the divergence between different points in the studied system. Two randomly selected initial trajectories of subsequent points from the state space should diverge at the largest Lyapunov exponent (Rosenstein et al. 1993).

$$d_t = D_0 e^{\lambda_1 t + \lambda_2 t + \ldots\ldots + \lambda_n t} \qquad (2)$$

$$d_t = D_0 e^{\lambda_{MAX} t} \qquad (3)$$

Where D_0 is the average distance between trajectories at t=0, and d_t is the average Euclidean distance between initially neighboring trajectories at time t.

λ_{MAX} is calculated as the slope of the curve generated by Equation number 4 (England and Granata 2007) (See Figure 2-3-d).

$$y(i) = \frac{1}{\Delta t} < ln\, d_j(i) > \qquad (4)$$

Where Δt is the sampling frequency, $d_j(i)$ is the distance between the jth pair of nearest neighbors at the time *i*, $< \cdots >$ denotes the average of the contents (Rosenstein et al. 1993), and Max LE is calculated as the slope of the curve generated by y(*i*). In this research, the Max LE was calculated for each of the three directions: the anterior-posterior (AP), medial-lateral (ML) and vertical axes (VT). Figure 2-3 shows schematic illustration of state space construction and Max LE calculation

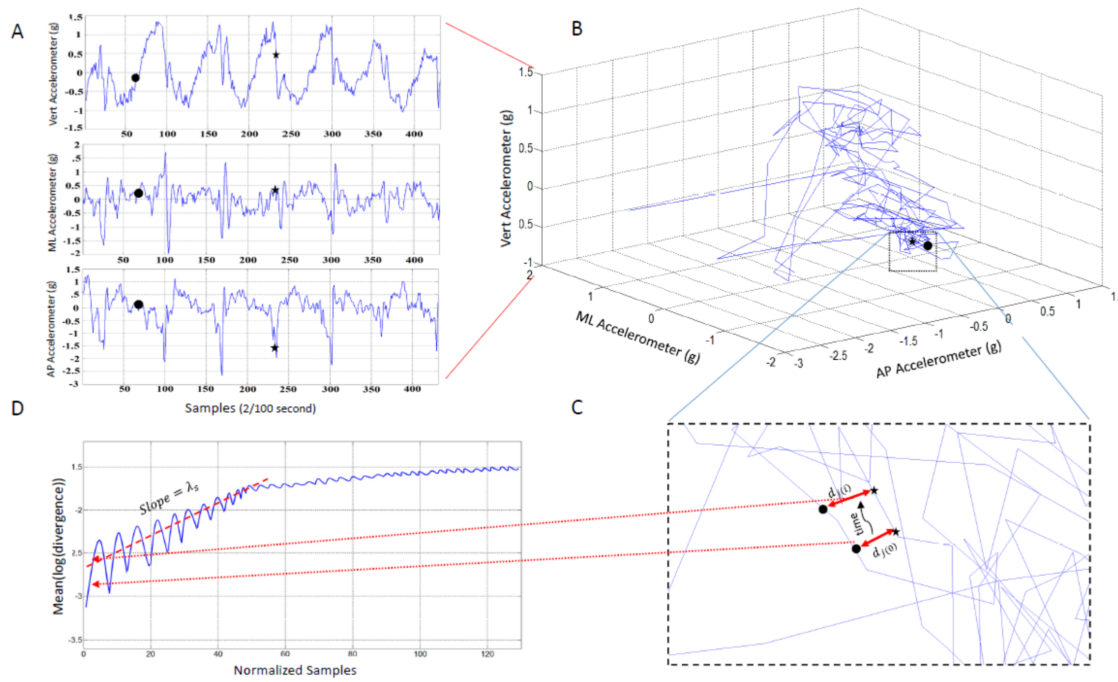

Figure 2-3. Schematic Illustration of State Space Construction and Max LE Calculation. (A) The time series data—which is captured by IMU sensors—define the system's state (Vertical accelerometer, ML accelerometer, AP accelerometer); (B) system trajectory formed by system's state; (C) a zoomed-in area of a system trajectory. Local divergence is computed by measuring the Euclidean distance between the subsequent points; (D) λ were calculated from the slope of the mean log divergence curve. (Figure illustration idea obtained from Schooten et al. 2013)

The data for the first 65 feet of the subject's movements was used to establish the state space for their task. After establishing the state space, the remaining data was used to calculate the Max LE for each task. A MATLAB program was used for all of the computations (ver 8.1.0.604, The Math Works Inc., USA).

Statistical Analysis

T-test analyses were conducted for Max LE values between Task 1 (walking with a normal speed) and Task 2 (walking with a side-carrying load) and between Task 1 and Task 3 (walking with a higher speed). For each comparison among the different tasks, t-tests were conducted for the three different directions. In addition, to compare and contrast the three tasks, ANOVA tests were performed for Max LE values that were calculated for each of the three directions. The Max LE value for the three different tasks in the three different direction were used for statistical analysis, so a total of 9 data sets of Max LE values calculated from IMU time series data were used for statistical analysis. Each data set size included the Max LE values for eight of the different subjects. 6144 data points from the accelerometers were used for calculating one Max LE value and constructing the appropriate state space. The alpha level for the t-test and ANOVA test was set at $\alpha=0.05$.

Results

Figure 2-4 summarizes mean and standard deviation (SD) values for the Max LE values of the three tasks in each of the three directions. Task 2 and 3 have higher Max LE values than Task 1 in all three directions, and the biggest difference is found in the VT direction between Task 1 (mean=0.145, SD=0.0285) and Task 3 (mean=0.4723, SD=0.286).

Table 2-3 summarizes the results of the t-test between Task 1 and 2. These results confirm a significant difference in Max LE values for the ML and VT directions—with an alpha level of 0.05—but fail to confirm a significant difference in the AP direction. Table 2-4 summarizes the results of the t-test between Task 1 and 3. While the p-values in the AP and ML directions are higher than the alpha level, the results still confirm a significant difference in the Max LE values for the VT direction, with the p-value of 0.026. Also, it is worth noting that the p-value in the ML direction (0.072) is marginally significant, though the difference is not significant at the 0.05-level. The ANOVA test results also indicate a significant difference between the Max LE values for the three tasks in the VT direction, with a p-value of 0.0095 (See Table 2-5).

Table 2-3. Summary Results from the T-test Analysis between Task 1 and Task 2

	Anterior-posterior direction		**Vertical direction**		**Medio lateral direction**	
	Normal	**With Load**	**Normal**	**With Load**	**Normal**	**With Load**
Mean	0.144588	0.162525	0.145013	0.472338	0.171338	0.25675
Variance	0.001136	0.003747	0.000813	0.081933	0.001228	0.007555
P(T<=t) two-tail	0.479781		0.006189		0.021908	
t Critical two-tail	2.144787		2.144787		2.144787	

Table 2-4. Summary Results from the T-test Analysis between Task 1 and Task 3

	Anterior-posterior direction		**Vertical direction**		**Medio lateral direction**	
	Normal	**Faster**	**Normal**	**Faster**	**Normal**	**Faster**
Mean	0.145838	0.202129	0.145013	0.304657	0.171338	0.287371
Variance	0.001021	0.011294	0.000813	0.031692	0.001228	0.027004
P(T<=t) two-tail	0.17552		0.025938		0.072175	
t Critical two-tail	2.160369		2.160369		2.160369	

Table 2-5. Summary of ANOVA Tests' P-value

Source of variation	p-value
Anterior-posterior direction	**0.13**
Vertical direction	**0.009552**
Medial lateral direction	**0.08**

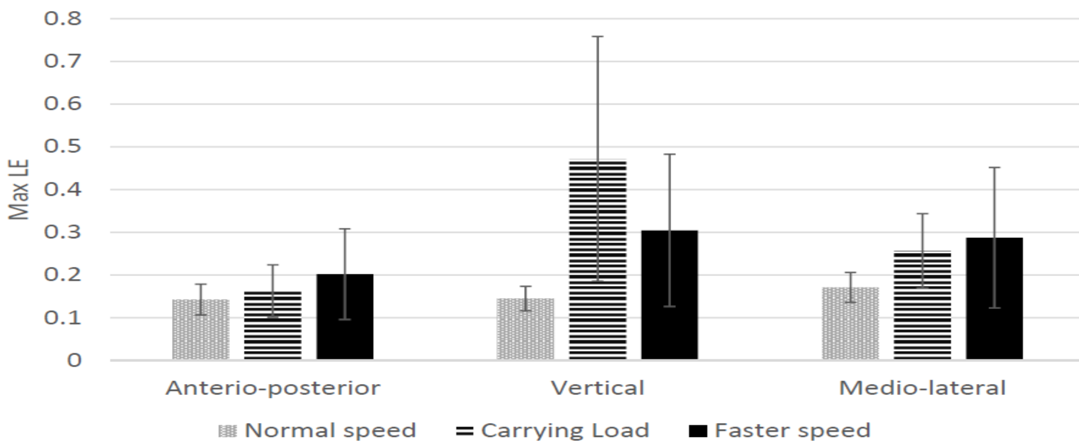

Figure 2-4. Different Tasks' and Different Directions' Means and Standard Deviations of Max LE.

Discussion

The ultimate goal of this research was to validate the usefulness of Max LE as a measure for construction workers' fall risk while they perform different tasks with different fall-risk profiles. Since the usefulness of Max LE has been demonstrated in characterizing the fall risks of patients and elderly people who have a clinical issue in their walking stability, the application of this metric to measure the fall risks of clinically healthy workers in a construction context seems a valuable development. Toward this end, this research investigates whether Max LE can differentiate iron workers' walking tasks when it is assumed that those tasks have different fall-risk profiles.

Carrying a side load and walking with a faster speed on an I-beam were chosen as the tasks with high fall-risk profiles compared to normal walking task on an I-beam. Carrying physical loads is believed to adversely affect gait stability of the construction workers and to possibly increase the fall risk of workers. In particular, carrying a one-sided load (uneven load) could create a significant adverse effect on workers' gait stability by changing their body's center of gravity. Also, it could be an external factor leading to imminent fatigue, which causes a higher fall risk among workers (Qu 2013). Increased walking speed is also known as a negative factor on workers' gait stability—when workers try to walk faster, they usually pay less attention to the location of their feet on the I-beam, which possibly causes decreased stability. Simultaneously, walking with a high speed usually increases workers' fatigue, especially while workers wear a safety harness (additional load).

The results from the experiment strongly showed the capability of Max LE in differentiating these tasks that are believed to have different fall risk profiles. The results showed a visible difference in the mean of Max LE values between low fall-risk tasks (normal walking) and high fall-risk tasks (carry a side load and high speed walking) in all of the three directions. In addition, the statistical tests confirmed a significant difference in the VT direction. The reason why the biggest differences of Max LE values for any comparison among the three tasks were found in the VT direction can be explained by the physical conditions of walking on an I-beam. While walking on I-beam, the worker's feet move along the flange of the beam. The narrow width of the beam's flange causes less variability of movement trajectories in the AP and ML directions; however, movement in the VT direction will not be affected by the flange's width. Also, the experiments' demands that subjects maintain a constant walking speed may cause less variability in the Max LE values for the AP direction.

In addition, a large variability of Max LE values across the experiment's subjects may be seen. For example, the lowest Max LE value for the AP direction during "walking with normal speed" was found to be 0.10 in one subject, while another subject showed 0.1984 in the AP direction under identical experimental settings. This divergence can be related to different physiological characteristics of subjects, such as their age, weight, height, shoe size, their style of walking, and their ability to carry loads and walk with different speeds. Also, this difference can be associated with subjects' past experiences in similar conditions, their perceptions about the safety of the experiment's setting, their history of fall accidents, and even their daily physical and mental conditions.

While the experiment results cannot provide reliable insight into any relationship between physiological characteristics and Max LE values due to the limited number of subjects, several interesting findings contradicted our common beliefs in the relationship between gait stability and physiological and demographic characteristics of workers. For example, it is generally believed that increasing age will have a negative effect on the gait stability of workers. One of the subjects in this research was 65 years old, which was much older than other subjects (the average age of the subjects was 28.5 years), but his Max LE values were found to be lower than the average of all other subjects. This result may be due to the fact that he had a much lower walking speed than others and he was observed to pay more attention on his movement patterns and gait during the experiments. For another example, a highly experienced iron worker was expected to show a higher stability in walking tasks on the I-beam. However, the subject who had an extensive work experience in iron work showed relatively high Max LE values compared to other subjects. It was found that he walked very fast with very short and fast strides while performing the tasks, which may explain his high Max LE values. These findings support the notion that no one physiological or demographic characteristic can be the determinative factor of Max LE values and fall risks.

It is challenging to compare Max LE values of this research with the results from previous studies, since the scale of Max LE values is highly affected by various factors, such as the chosen calculation method, subjects' physiological characteristics, and the experiment's setup. Still, we saw that the Max LE values found in this research are in a reasonable range compared with previous studies that used the Rosenstein algorithm for calculating Max LE. Therefore, the general trend of Max LE values in this research are in accord with the theoretical model, though the external and internal forces in the experiment's setup—such as carrying a load and increasing walking speed—did cause large variability within the Max LE values.

Several limitations still exist in this research. First, the carried load in the experiment had a fixed weight and its impact on subjects' gait stability varied depending upon the subjects' weight and strength. Second, the walking speed in the experiment was not controlled strictly and some variability of walking speed exists among subjects. Since the walking speed itself has a high impact on the Max LE values, such variability in the walking speed may cause some noise in the results of this research.

Contributions and Potential Applications

The main contribution of this paper in the area of computing in civil engineering is to introduce and validate a new method that allows researchers to determine construction workers' comprehensive safety risk by analyzing IMU sensor data captured from construction workers' body motions. While previous relevant studies focused on demonstrating the feasibility of using sensor data to recognize and classify workers' postures and motions, the introduced approach uses IMU sensor data to analyze overall safety-related risks in workers' motions by measuring and comparing the changes in walking patterns during consecutive strides.

In addition, the introduced method for analyzing fall risks using IMU sensor data is expected to provide new insights into understanding and analyzing the fall risks of construction workers. Since this method directly assesses how a worker's motion system reacts to various disruptions caused by diverse extrinsic factors, it will allow managers and researchers to assess the risk of a safety hazard based on workers' responses to the hazard rather than on the physical properties of the hazard. This will allow safety managers to gain a better understanding of how workers react to jobsite hazards and to mitigate the risks of such hazards in a more efficient and effective way. Furthermore, the results from existing safety risk–analysis methods are often criticized since they are mostly based on retrospective (e.g., past accident report) or subjective (e.g., experts' judgments) data. The introduced method will be able to provide more objective results since sensor data directly captures workers' physical responses to a given environment in real-time.

There are numerous potential applications for this research. First it can be used as a risk analysis tool in the pre-construction phase of construction projects. There are numerous extrinsic factors in construction sites that can affect workers' fall risks (e.g., working environment, effects of workers' gears, physical and cognitive tasks), and the suggested approach can be used for a detailed analysis of the effects of extrinsic factors on construction workers' gait stability. Although existing safety risk assessment methods provide knowledge on the effects of extrinsic factors, it is nearly impossible to calculate in an objective way the risks associated with diverse extrinsic factors that have varying degrees of potential severity. Using IMU sensors and Max LE, teams will be able to discern a project's built-in risk before construction starts; such preemptive analysis will help designers plan with safety in mind. The applications and benefits of using this method as a risk analysis tool in the pre-construction phase should all be readily available since the technological requirements (e.g., required number of the sensor units, wireless communication coverage) for this type of applications will foreseeably not be significant, though there are more rigorous experimental designs and executions required in the short-run for reliable results.

Another future application of the introduced method is a real-time monitoring tool to detect fall-prone workers and invisible jobsite fall hazards. Continuous monitoring of gait stability through sensors attached to workers will allow for the characterizing of workers who have higher fall risks due to various reasons (e.g., fatigue, inappropriate work task) and will empower safety managers to take proper actions to prevent fall accidents. With these continuous monitoring applications in mind, sensor units should be designed to have the following features: 1) light-weight and small-sized sensor units; 2) robust communication solutions for harsh and dynamic construction environments; and 3) on-board processing capability to compute the gait stability metric from raw sensor data. Also, since this approach will require the deployment of multiple sensor units, the economic feasibility of the sensor units should be considered. However, the trend in sensors' cost and the technological developments of wireless communication technologies implies an opportunity of the deployment of a real-time monitoring tool in the near future.

Conclusion

This research investigated the ability of Max LE, a gait stability metric, to characterize the fall-risk profile of iron workers' tasks. The experiment results garnered from eight human subjects with various physiological characteristics showed a statistically significant difference in the Max LE values between a low fall-risk walking task and high fall-risk walking tasks. These results indicate that Max LE could provide adequate discriminating power for distinguishing high fall-risk tasks. This outcome highlights numerous opportunities to utilize Max LE for various applications in construction safety management and is expected to contribute to opening new areas of research in construction safety management by introducing a reliable measure for quantifying the fall risk of construction workers with different tasks in different locations.

Chapter 3. Comprehensive Fall Risk Assessment of Construction Workers using Inertial Measurement Units: Validation of the Postural Stability Metric to Assess the Fall Risk of Iron workers

Abstract

Falling accidents are a leading cause of fatal and nonfatal injuries in the construction industry. The loss of bodily balance is a primary factor in falling. Bodily stability can be analyzed by studying dynamic and postural stability. It is clear there is no method of comprehensive fall-risk analysis for workers' fall risk in stationary postures. This study aims to test the usefulness of two metrics that can be calculated from IMU data—velocity of the bodily center of pressure (COPv) and the resultant accelerometer (rAcc)—as predictors with which to measure workers' fall risk in stationary postures. To validate the usefulness of these two metrics, we designed and conducted a laboratory experiment that shows tasks in a stationary posture with various fall-risk profiles: staying in standing and squatting positions in four different situations (i.e. wearing a full-body harness, loaded and unloaded, with a symmetric or asymmetric shape and holding a tool box that weighed up to 12 kilograms). The capacity of postural stability metrics was tested to distinguish the fall risk of construction workers doing different tasks. Also, to validate the value of the IMU-based metrics, I-COPv and rAcc, postural stability was measured by calculating COPv from force plate (F-COPv). Force plate, or platform, is considered a reliable tool for measuring the postural stability of subjects in different situations. The correlation between the suggested IMU-based metrics and F-COPv was calculated. The results demonstrated a significant difference in I-COPv and rAcc values across different postures and tasks. Also, considerable correlations were seen in COPv calculated from both force

plate and IMU sensors and the rAcc while the subjects were in different positions and situations.

Keywords: Construction falls, quantitative measurement, postural stability, Inertial Measurement Units, IMU sensors, Force Plate

Introduction

The construction industry has been considered one of the most dangerous of all industries; it has the largest number of fatal and nonfatal occupational injuries (Im et al. 2009). Among the fatal injuries in the industry, more than 30% are from falling. This number includes falls to lower levels and on the same level (NSC 2013). Many construction workers are prone to falling accidents due to the greater elevation of their workplaces. In particular, ironworkers have the highest lifetime risk of fatal accidents among the construction trades (CPWR 2013).

In order to prevent fall accidents, it is critical to quantifiably and systematically assess the risk of falling for construction workers (Sousa et al. 2014). Our previous research applied a dynamic stability measurement for ironworkers for assessing potential falling accident risk, as based on locomotion data captured from the IMU (Jebelli et al. 2014). Such a dynamic stability measurement is very useful in analyzing safety-related risks inherent in workers' motions while doing tasks that require kinematic movement, such as walking on an I-beam and carrying a load. However, in real construction work, there are other type of tasks that may affect the stability of subjects in stationary postures (such as working on a scaffold and welding or making repairs at high elevations). The ability of human subjects to withstand force or stress without being distorted, dislodged, or damaged in stationary postures is defined as postural stability. According to Hsiao and Simeonov (2001), postural instability is one of the most common factors related to injuries from falling. Didomenico (2010) investigated construction workers' postural stability in different postures using self-report. He found that non-erect postures, including bending over at the waist, squatting, and kneeling forward, have a high level of instability. However, these studies were limited to the use of subjective survey data, which is subject to cognitive bias (Tversky and Kahneman 1974). A comprehensive method for fall-risk analysis, one that can measure workers' stability in stationary postures, can provide important insights into fall-risk assessment of construction workers.

Given this context, this paper aims to introduce and validate a method to assess construction workers' postural stability in a quantifiable and objective way. In particular, it will examine the usefulness of two postrual stability metrics, velocity of the bodily center of pressure (COPv) and the resultant accelerometer (rAcc). As predictors with which to measure workers' fall risk in stationary postures, these can be calculated from IMU data. IMU sensors are light, portable devices, and this data can be applied in the workplace. At a reasonable cost, IMU sensors can easily be attached to the worker's body without diminishing performance, so IMU sensors can be easily implemented at construction sites and be reliable monitoring devices. They can be an appropriate replacement for traditional devices that assess postural stability, such as force platforms, if the results are compatible with results from existing devices. Average velocity of the center of pressure (COPv) and resultant accelerometer (rAcc) will be investigated as two metrics that can measure postural stability. COPv is calculated by summing the distance between each consecutive point of the body's center of pressure and dividing this by the total data-collection time (Hufschmidt et al. 1980), and rAcc is calculated from the root square of different components of the accelerometer in three different dimensions (Mayagoitia et al. 2002). Higher COPv and rAcc values show higher instability for the test subjects. Usually, force plate has been used to measure the COPv of human subjects. The reaction of the momentum and force caused by bodily motion will be the input data with which to calculate the bodily center of pressure using force plate (Clair and Riach 1996; Karlsson and Frykberg 2000; Soangra and E Lockhart 2013). In the clinical domain, some methods are suggested for calculating COPv using inertial measurement units (I-COPv); these come from calculating the body motions captured from different directions by accelerometers (Brumagne et al. 2008; Liu et al. 2012; Mayagoitia et al. 2002). But there has been no attempt to use these metrics to measure construction workers' stability in actual construction domains.

To validate the use of two IMU-based metrics with the power to distinguish construction tasks with different fall-risk profiles, subjects were asked to do four tasks with different risk profiles in two postures, standing and squatting. First, the velocity of the center of pressure (COPv) of the subjects was calculated using force plate (F-COPv) for each of the tasks to determine the rank order of risk of falling associated with different tasks. F-COPv was considered a baseline from which to compare the values of I-COPv and rAcc. Then, postural stability was calculated from data obtained from IMU (I-COPv and rAcc), and the correlation between the calculated F-COPv and I-COPv was studied.

Demonstrating the feasibility of these IMU-based metrics to measure worker stability in different postures can lead to a way to assess the overall risk of falling. These values can be used to provide a numerical factor that can be assigned to tasks and postures with a higher risk of falling. Also, the value of the suggested metrics can be used to study the workers' personal characteristics. Some workers might be more capable of doing some tasks with a higher falling risk. Knowing the most dangerous locations at the construction sites can help the construction site supervisors provide appropriate fall-prevention systems for that particular area, which can decrease the hazards at job sites. Also, it can be a feasible criterion with which to assess the effects of different extrinsic and intrinsic factors related to workers' stability in stationary postures. Finding the most relevant factors that affect workers' stability can lead to control or removal of hazardous elements. In addition, a given method can be used as a monitoring tool to study the effects of different factors that affect workers' fall risk at job sites. Merging this suggested approach with various alarm systems can provide a real-time monitoring system, one that can measure and monitor the fall risk of workers in stationary postures. It can warn workers when their postural stability metric is higher than the value representing a safe range for different tasks and conditions.

Research Background

Current Fall-Prevention in Construction

OSHA has delineated that falls are the leading hazard resulting in fatalities in the construction industry (OSHA 2011). Because of the high rate of fall hazard at construction sites, OSHA regulations specifically address these hazards (OSHA 29CFR 1926.500 to 1926.503). However, while these regulations have been successful in preventing some falling accidents, Johnson et al. (1998) reported that OSHA's requirements are not sufficient to prevent falling accidents for certain trades that work in dangerous circumstances. OSHA regulations cannot address falls related to physical characteristics of the workers. For example, one of the main factors delineated as contributing to falls is the heavy physical requirements of construction activities. According to Dzeng (2014), due to these physical requirements, construction workers are more prone to fatigue, distraction, drowsiness, muscle pain, and loss of balance; these factors increase the risk of impaired performance, safety hazards, and falling accidents. OSHA regulations cannot address the falls caused by this kind of fatigue and/or worker exhaustion.

Examining research well respected in the industry on falls in the construction sector shows that there are viable solutions for combating and reducing falling hazards. Evidence from Lee (2009) demonstrates the importance of safety training on balance and posture stability and that the physiological status of construction workers can influence the risk of loss of balance and falls. The implementation of specific fall-protection training programs is another proven way to prevent construction falls. A study done by Kaskutas (2013) shows that many inexperienced workers are exposed to falling hazards and are not prepared to handle these situations. It has also been shown that fall protection is applied inconsistently and safety mentoring from experienced workers is often inadequate. Kaskutas (2013) introduced a training method focused on the management side, emphasizing the communication of falling hazards and protection with construction crews. The training done during the research proved effective in increasing the use of fall protection, improving safety behaviors, and enhancing on-the-job training and safety communication, as well as aiding mentorship skills for prevention of construction falls. This research suggested training programs and behavior-based techniques were effective in most cases—based on observations of hazard occurance before and after the program. The method suggested in this study can measure the effectiveness of various training programs before the hazards occur. Workers' stability can be measured before and after training programs suggested by metrics in this study. Comparing the amount of changes in these metrics can gauge the effectiveness of the training programs.

In addition, another methodology shown to be effective in improving job-site safety has been called the *behavior-based* approach by Lingard and Rowlinson (1998). This approach consists of instilling safety-management techniques that focus on inspiring individual workers to improve their safety performance through goal setting and performance feedback. Studies by Duff et al. (1994) have shown that behavior-based safety-management techniques can improve safety in the construction industry. According to Lingard and Rowlinson (1998), behavior-based techniques aim to improve individual worker-performance measurements through goal setting and performance feedback. Latham and Yukl, (1976) show that when used as a motivational technique, goal setting was found to improve many aspects of work performance. A comprehensive set of fall-risk analysis tools is necessary to study the improvement in worker stability after applying such behavior-based approaches

In a study by Dzeng et al. (2014), accelerometers in smartphones were used to detect possible falls and fall portents. A smartphone is a commonly carried device, and the research used multiple experiments to test their accuracy in detecting falls and fall portents. The research showed that use of accelerometers is a feasible way to detect possible fall situations and take action to prevent falls. An approach by Dzeng et al. (2014) was only able to detect workers' falls after they occurred. However, it can be useful if merged with a warning module that informs the site manager or others about taking action to help or rescue the worker; still, it didn't suggest a method that can assess workers' fall risk while doing tasks with different risk profiles before the falls occur.

In this study, we will introduce the use of IMU sensors as cheap and small devices that are feasible fpr use in construction sites. Also, suggested metrics can be used to measure the fall risk of different tasks and working conditions to assess workers' stability before actual falls occur.

Postural-Stability Measures in Clinical Applications

Postural stability in the clinical domain can be defined as the equilibrium of the postural control system associated with maintaining balance during standing motions (Horak 1987). An individual level of fall risk in the clinical domain would be calculated by measuring the physical characteristics of the subjects, such as musculoskeletal and sensory function, and even the emotional status of subjects, such as caution or a fear of falling stemming from a previous accident. Any of these can affect postural stability (Perell et al. 2001; Winter et al. 1990). To assess this stability, several measurements and methods have been used in the clinical domain, such as the sensory organization test (SOT), the average velocity of center of pressure (COPv), root mean square (RMS), center of pressure (COP) range, mean power frequency (MPF), median power frequency (MedPF), sway area, intraclass correlation coefficient (ICCs) and maximum displacement (anterior-posterior and mediolateral).

The SOT test results in an outcome called the *equilibrium score* (ES). ES reflects the effect of different parameters that can affect postural stability, such as visual, proprioceptive and vestibular systems (Chaudhry, Hans et al. 2004). The average velocity of the center of pressure is the sum of total displacement vectors of the bodily center of pressure divided by total sampling time. Higher COPv means higher instability and greater risk of falling (Norris et al. 2005). Maximum displacement calculation is the maximum distance between consecutive points on the COP trajectory (Norris et al. 2005). This metric can be useful for assessing sudden instability such as falls or trips.

Previous researchers mostly have used traditional devices to assess postural stability, such as force plates and motion-analysis systems (Clair and Riach 1996; Dickstein et al. 2003; Dieën et al. 2010; Hellebrandt and Braun 1939; Karlsson and Frykberg 2000; Karlsson and Lanshammar 1997; McGraw et al. 2000; Önell 2000; Prieto et al. 1996). Hellebrandt and Braun (1939) measured subjects' age-related postural stability. Their subjects were +from ages 3 to 86 years. In their research, they measured the largest magnitude of sway for very young and very old subjects. Boman and Jalavisto (1953) measured the postural stability of subjects in younger and older subjects using an overhead camera. Their research reported a higher postural instability for these subjects. Prieto et al. (1996) assessed postural stability metrics using COP-related measurements, such as the mean distance of the bodily center of pressure and RMS distance while subjects were standing on a force plate under two different conditions (eyes open and closed). They compared the postural stability of the young adult group and the elderly group. They found that the COPv was the only measure that showed age-related changes under different conditions. Lafond et al. (2004) found that COPv is the most reliable measure compared with other postural stability measurements.

Although a force plate performed accaptably well in taking accurate measures and providing reliable data for calculating COPv, this device usually presents some difficulties, even for use in the clinical domain, because of its high cost, large size and weight. IMUs would be an ideal replacement for force plates if they could measure postural stability as accurately as a force plate (Seimetz, et al. 2012). IMUs are inexpensive, easy to transport and can be used while subjects perform various tasks without disturbing them. A few authors have used IMUs to measure bodily balance in the clinical domain (Brumagne et al. 2008; Liu et al. 2012; Soangra and E Lockhart 2013). In this research, IMU is used to measure the physiological information of needed for calculating I-COPv and rAcc.

Experimental Design and Methodology

This study is designed to validate the usefulness of I-COPv and rAcc as metrics that can distinguish tasks and postures with different risks of falling. To study the distiguishing power of I-COPv and rAcc, we designed and conducted a laboratory experiment that shows tasks in a stationary posture with various fall-risk profiles.

An IMU sensor was attached to the waistline of the subjects. The fall risks of workers in various postures and conditions were calculated by measuring F-COPv from a force plate. The F-COPv results identified the tasks and postures with different fall-risk profiles. Then, the distinguishing power of I-COPv and rAcc was evaluated by comparing these values across different experimental tasks. Statistical tests, such as t-tests and analysis-of-variance (ANOVA) tests, were conducted to determine significant differences among the I-COPv and rAcc values. Spearman's rank-correlation ratio was calculated to find the correlation between force plate-based measures (F-COPv) and the IMU measures (I-COPv and rAcc).

Subjects

Ten healthy people participated in this research. Subjects were selected from a wide range of ages to ensure that we could obtain broad differences in postural stability. All of the subjects were reported to have no clinical conditions or disabilities, no visible gait asymmetries, and no drugs or alcohol in their systems that could affect their ability to stand or walk. Subjects with corrected vision wore their glasses or contact lenses. Table 2-1 summarizes the demographic information on the subjects.

Table 3-1. Subject Sample Information

	Height	**Weight** (lb)	**Shoe Size** (US size)	**Age** (years)
Mean	6ft	192	12.75	30.80
Median	6ft	195	10	28.50
Standard Deviation	2.8in	20.31	1.03	7.13
Min value	5ft 10in	161	9	24
Max value	6ft 1in	220	12	47

Capturing Data Using Force Plate and IMU sensors

For task 1, subjects were asked to stand on the force plate (AMTI force plate) for 30 seconds and to sit or squat for another 30 seconds while wearing full-body harnesses (see Figures 3-1-a and 1-e). For task 2, subjects performed the same set of actions, but this time wearing a full-body harness loaded with common ironworkers' tools—such as a full-body fall-protection harness and tool-belt bag, a sledge hammer, a finish construction wrench, erection wrenches, a pry bar, and pinch bars—in the way recommended by an expert ironworker. The tools were loaded in a symmetrical manner while the participant was in a comfortable position with arms hanging by his or her side (See Figure 3-1-b and 1-f). For task 3, subjects wore a harness while it was loaded with certain tools in an inappropriate manner (asymmetrical loading). All the tools, including a 5-lb. sledge hammer, a finish construction wrench, erection wrenches, a pry bar, and pinch bars, were connected to the left side of the workers' full-body harness (see Figures 3-1-c and 1-g). For task 4, test subjects were asked to repeat the first test while their harness was not loaded with any tools and they were holding a tool box weighing up to 18 lbs. (see Figures 3-1-d and 1-h). During all of these tasks, a tri-axial accelerometer (Shimmer 9DOF) sensor was attached to their waistline to capture time-series data for calculating rAcc, as this location represents the whole-body center of mass (Liu et al. 2012). The sampling data-collection rate of the acceleration was 52 Hz and the force plate data-collection rate was 50 Hz. The accelerometer was oriented by X, Y, and Z axes, representing anterior-poster (AP), mediolateral (ML) and vertical (VT) directions. A force and motion platform was used to capture center-of-pressure data (see Figure 3-1-j). To minimize the effect of clothing on data collection, subjects were asked to wear a work shirt, a safety harness, and a pair of safety shoes. Visual inputs can strongly influence postural stability during both standing (Jeka et al. 2004; Tanaka et al. 2000) and walking (Warren et al. 2001). To provide the same visual environment for all of the subjects, a wide white screen that covered the subjects' purview was placed in front of the force plate. The force plate was located near the white screen, which was attached to the wall. This white screen limited the vision of the participants, and subjects were instructed to look straight ahead at the screen.

Between two consecutive trials, the subjects were given at least a 2-minute break to minimize carryover effects and to avoid confounding effects caused by fatigue. At the beginning of each test, subjects were asked to jump for 3 seconds to synchronize the force plate and IMU data. IMU sensors were attached to the waist line at 57% of the subjects' height for males and 55% for females, the actual location of the body's center of gravity (Mayagoitia et al. 2002). At least 5 minutes of rest between different stages was used to avoid confounding effects caused by fatigue. Subjects were informed of the procedures of the experiment prior to it. A period of 2 minutes was allowed before actual data collection to let the subjects familiarize themselves with standing on the force plate. For all of the standing and squatting positions, subjects were asked to look forward and to not move their heads. To minimize the ordinal effect of doing the tests, half the subjects completed the standing and squatting portions without holding a load and the other half completed those portions while holding one. For each test, the IMU sensor’s height was measured using a flat tape measure. Figure 3-1 summarizes the experimental tasks performed in this research paper.

Calculation of Postural Stability Metrics

In this experiment, as per the calculations below, IMUs and a force plate were used to measure postural stability. The IMU-based COPv is shown with the I-COPv symbol. Also, the force plate-based COPv is shown with F-COPv. The calculation process for F-COPv and I-COPv is illustrated in Figure 3-2.

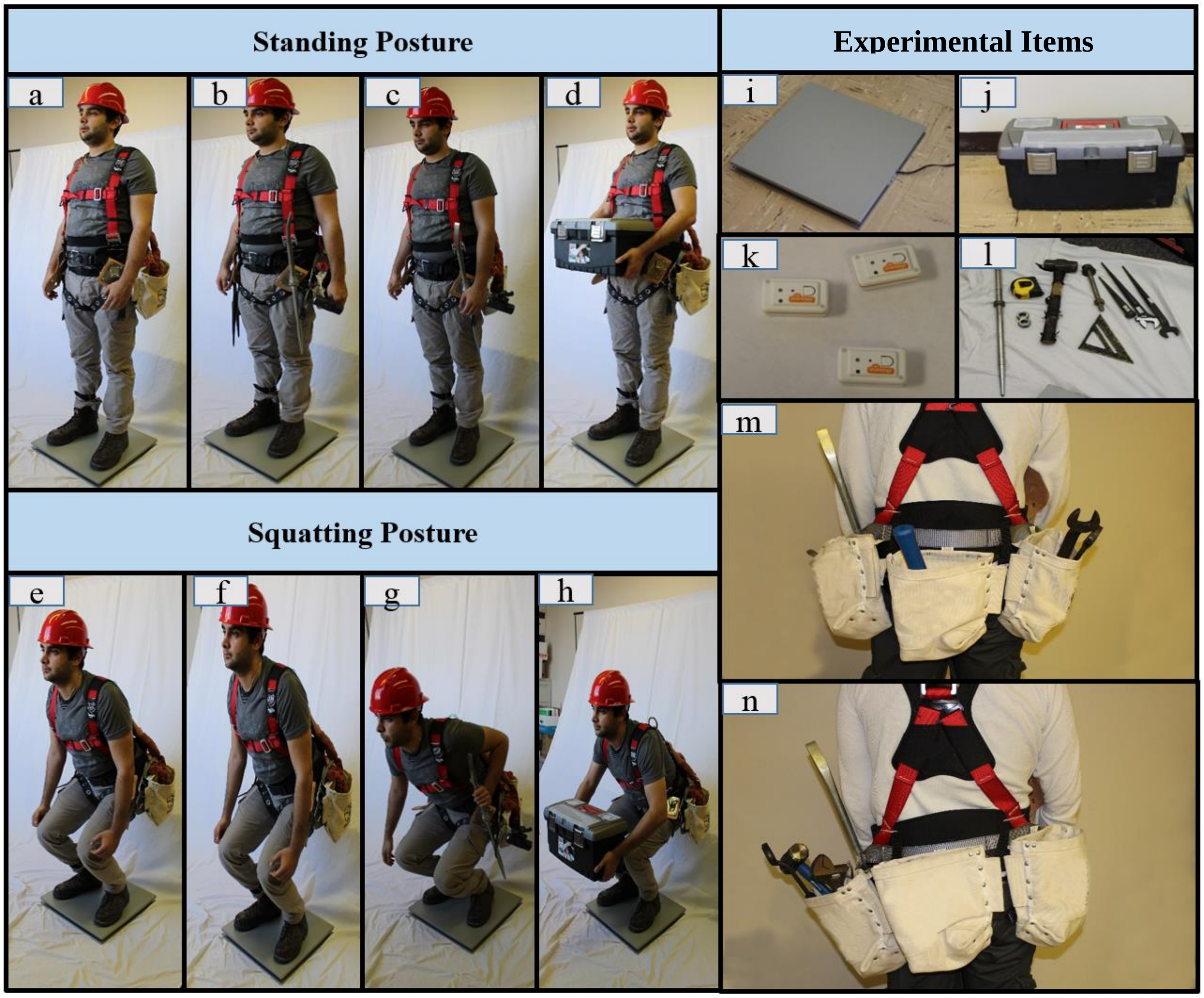

Figure 3-1. Experimental Setup and Various Experiments: (a,e) task 1: standing-squatting while wearing a full body harness; (b,f) task 2: standing-squatting while wearing a full-body harness with a load attached symmetrically; (c,g) task 3: standing-squatting while wearing a full body harness with a load attached symmetrically; (d,h) task 4: standing-squatting while wearing a full body harness with a load attached in an asymmetrical way; (i) force plate; (j) tool box; (k) inertial measurement units (IMUs); (l) attached tools (full-body fall-protection harness and tool-belt bag, 5 lb. sledge hammer, finish construction wrench, erection wrenches, pry bar, and pinch bars).; (m) symmetrical load configuration; (n) asymmetrical load configuration

Calculation of F-COPv

F-COPv was calculated from the momentum and forces from the force plate in three different directions. For each subject, the x and y coordinates of the center of pressure were calculated using the following equations (Hufschmidt et al. 1980):

$$x_i = \frac{-hF_{x_i} - M_{y_i}}{F_{z_i}} \qquad \text{Equation 1}$$

$$y_i = \frac{-hF_{y_i} - M_{x_i}}{F_{z_i}} \qquad \text{Equation 2}$$

where F and M are the moment and force measured from the force plate, h is the thickness of the material cover of the force plate—in case the force plate was covered with any material—which in this research was assumed to be zero. The planar trajectory of the COP over the test interim is commonly referred to as a *stabilogram.* X and Y coordinates were used to plot this stabilogram. The COPv was calculated by summing the distance between each consecutive point of the COP and dividing this by the total data-collection time (T) using the following formula (Hufschmidt et al. 1980):

$$COPv = \frac{\sum\sqrt{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}}{\mathrm{T}} \qquad \text{Equation 3}$$

Calculation of rAcc and I-COPv

rAcc was calculated from the root square of different components of the accelerometer in three different dimensions from the entire dataset (6,144 data points) (Mayagoitia et al. 2002). Calculation of rAcc is straightforward using the following equation:

$$rAcc = \sum\left(\sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}\right) \qquad \text{Equation 4}$$

where ax, a_y, a_z are the acceleration measurements from the IMUs.

To calculate the I-COPv, first we need to measure the sway path of the accelerometer. This was calculated using the equation provided in Mayagoitia et al. (2002). Then we need to measure the magnitude of the resultant (A) for each point using equation 5.

$$A_i = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2} \qquad \text{Equation 5}$$

where a_x, a_y, and a_z are the acceleration measurements from the IMUs.

After finding the magnitude of the resultant for each point, the directional cosine of the accelerometer (see Figure 3-2) was defined using equation 6.

$$\cos\alpha = \frac{a_{zi}}{A}, \cos\beta = \frac{a_{xi}}{A}, \cos\gamma = \frac{a_{yi}}{A} \qquad \text{Equation 6}$$

where $\cos\alpha, \cos\beta, \cos\gamma$ are the directional cosine and α, β, γ are the angles between the components of the acceleration and the resultant.

Having the value of the directional cosine, we then calculate the projected location of each point using equation 7.

$$d_{xi} = D * \cos\beta$$

$$d_{yi} = D * \cos\gamma \qquad \text{Equation 7}$$

$$d_z = D * \cos\alpha$$

where D is the magnitude of the displacement vector and d_z is the height of the sensor from the floor (see Figure 3-2).

In the group of equations 7, D has an unknown value, and d_z is a known parameter, the height of the sensor from the floor, measured during the experiments for each subject. By knowing d_z , we can easily find D and calculate d_x and d_y for each point by multiplying D by their directional cosine. After calculating d_x and d_y, we can plot the stabilogram again based on the data captured by the IMUs. We can also consider d_x and d_y as the input for equations 1 and 3 and calculate I-COPv. IMU data were low-pass filtered with a cutoff frequency of 10 Hz to remove noise from the system during data collection; also a high-pass filter with a cutoff frequency of 0.1 Hz was used to remove the slow drift in the COP related to spontaneous sway. The cutoff frequencies were selected, as is consistent with a cutoff frequency used by other researchers, by using the accelerometer for data collection (Mayagoitia et al. 2002; Önell 2000). All of the calculations were performed using custom software written in MATLAB (ver 8.1.0.604, The Math Works Inc., USA).

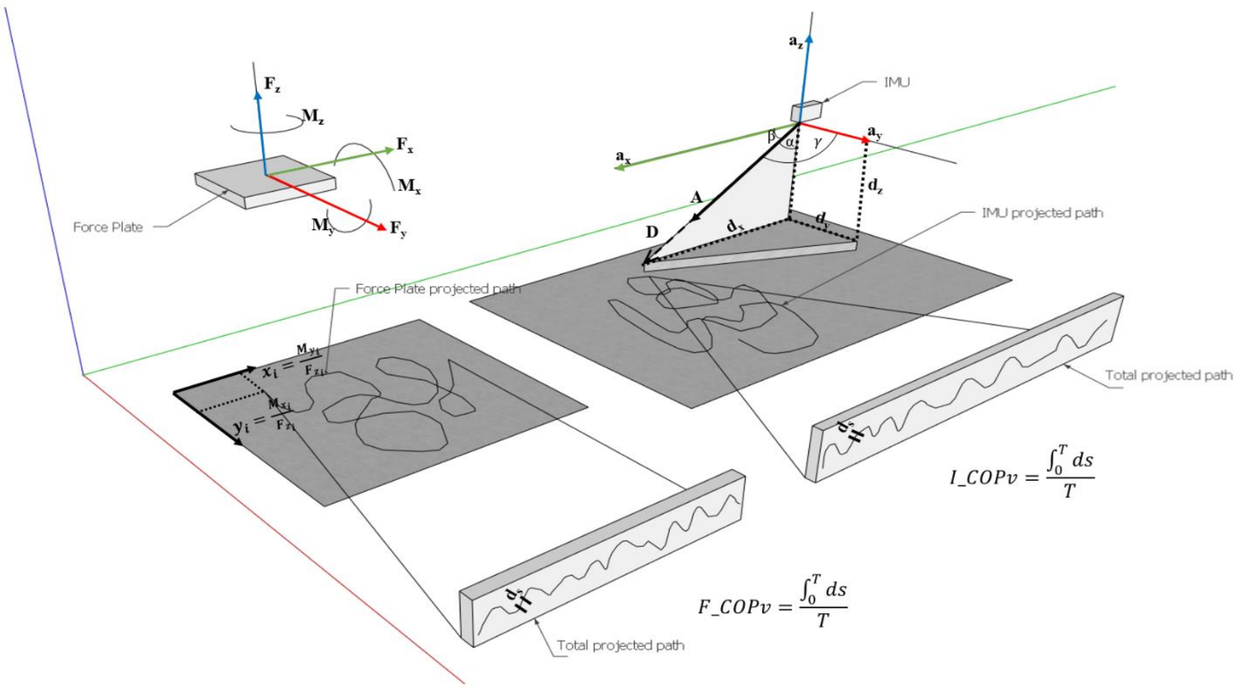

Figure 3-2. Velocity of Center of Pressure Calculation Process from Force Plate and IMU.

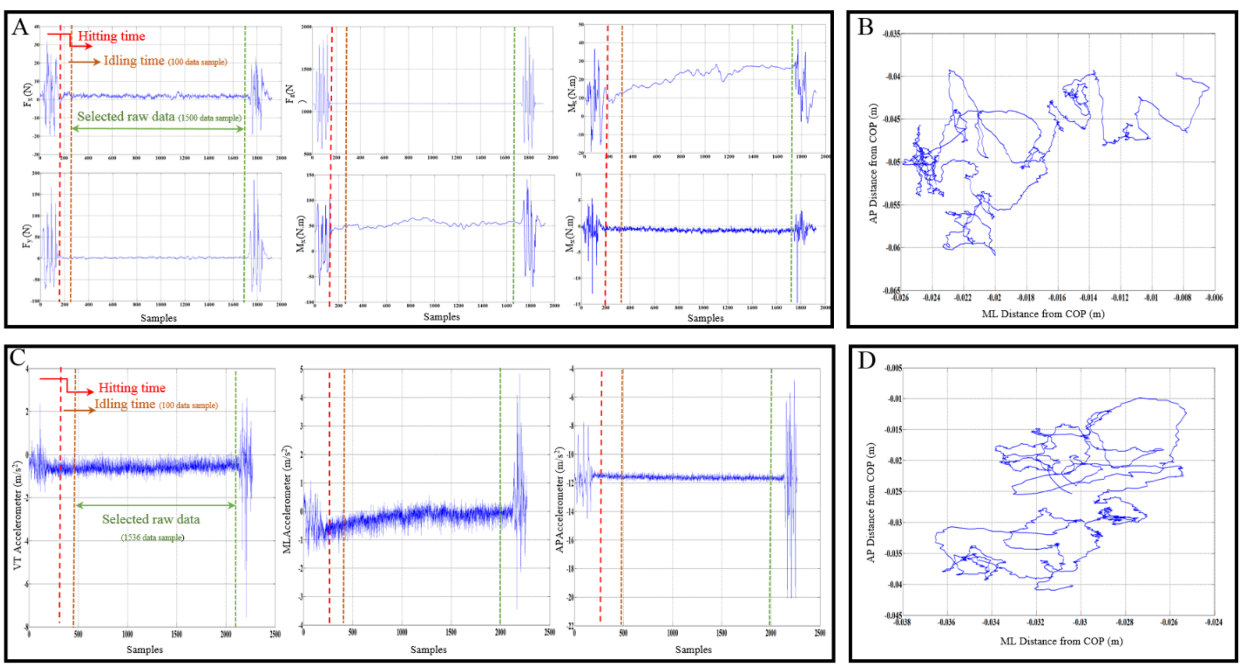

Figure 3-3. Representative Stabilograms Obtained from a Given Subject: (A) Forces and momentums recorded by a force plate in three directions (F_x, F_y, F_z, M_x, M_y, M_z); (B) stabilogram of COP based on force plate; (C) the time series data captured by IMU in three

directions (vertical accelerometer, ML accelerometer, AP accelerometer); (D) stabilogram of COP based on IMUs.

Statistical Analysis

T-test analyzes were conducted for F-COPv, I-COPv and rAcc values, to compare these values in standing and squatting positions for tasks 1, 2,3, and 4. In addition, we performed ANOVA tests for each measure, to compare different tasks based on results from F-COPv, I-COPv and rAcc. Linear or nonlinear relations between different measures were investigated by plotting the data. The alpha level for the t-test and ANOVA test was set at α=0.05. The Spearman's rank correlation (r_s) was used to measure the relationship between calculated COPv from the force plate and IMU. Once again, Spearman's rank correlation coefficient was used to study the relation between rAcc and COPv recorded from IMU sensors. The commercially available SPSS was used for statistical analyzes.

Results

Comparison of Different Postures: Standing-squatting

Figure 3-3 summarizes the mean and standard deviation (SD) for F-COPv, I-COPv and rAcc for different tasks in standing and squatting postures. It was assumed that worker stability is lower in a squatting posture than a standing posture. In all four tasks, the values of F-COPv, I-COPv and rAcc were higher in squatting postures than in standing postures, which is consistent with our assumption. Table 3-2 summarizes the results of the t-tests in comparisons of standing and squatting across different tasks. All three measures confirm a significant difference in standing and squatting postures based on the F-COPv, I-COPv and rAcc p-values in tasks1, 2 and 3. Based on the F-COPV's t-test, there was also a significant difference in task 4 (p=0.003). Although the t-test couldn't show a significant difference between standing and squatting postures in task 4 based on I-COPv and rAcc, the mean values of these measures are still quite different across standing and squatting postures; based on rAcc, for standing, mean=2.96 , SD=1.12 and for squatting, mean=3.86, SD=1.18. Based on ICOPv, for standing, mean=23 mm/sec, SD=10.48 and for squatting, mean= 37.23 mm/sec, SD=22.72.

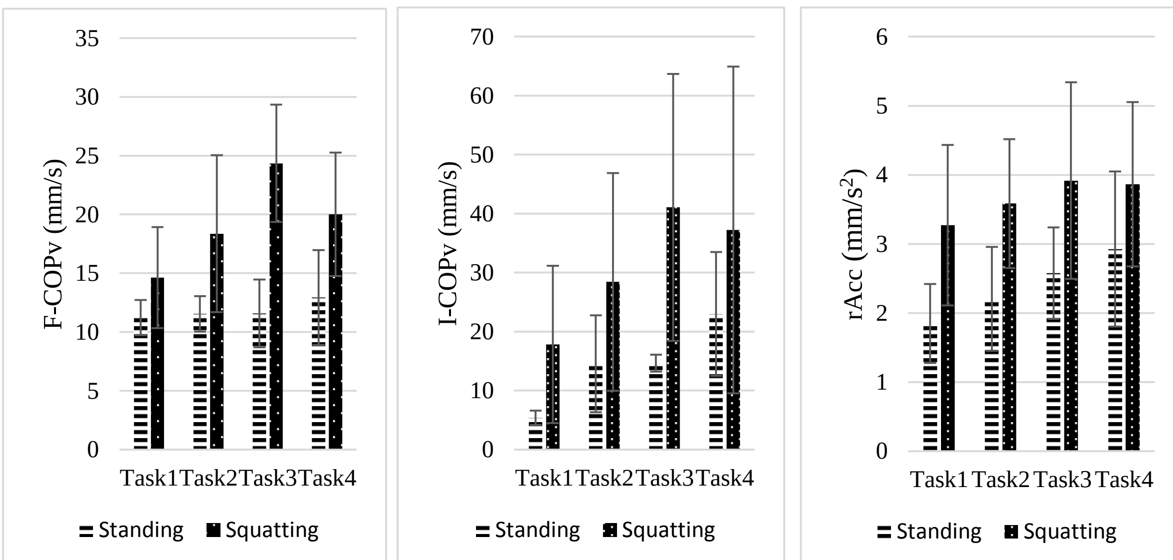

Figure 3-4. Different Task and Posture Means and Standard Deviations for the Value of rAcc, I-COPv and F-COPv.

Table 3-2. T-tests' P-values in the Comparison of Standing and Squatting Postures Across Different Tasks and Measures.

	FCOPv	**ICOPv**	**rAcc**
Task1	**0.037526***	**0.016129***	**0.004026***
Task2	**0.010524***	**0.04959***	**0.0076***
Task3	**0.000682***	**0.005327***	**0.014413***
Task4	**0.003168***	0.144296	0.08136

It was assumed that workers performing tasks 1 and 2 had higher stability than in tasks 3 and 4. Results showed that task 4 had the highest mean value in the standing position, based on F-COPv, I-COPv and rAcc. In the squatting posture, task 3 had the highest value, based on all three measures. Figure 3-5 summarizes the mean and standard deviation for F-COPv, I-COPv and rAcc values of different tasks across standing and squatting postures. Table 3-3 (top) summarizes the results of the ANOVA test between different tasks based on F-COPv. According to these results, a force plate does not show a significant difference between these four tasks, with a p-value of 0.082. Table 3-3 (middle) shows the results of the ANOVA test based on the calculated COPv, which is based on IMU (I-COPv), and there is a significant difference between different tasks, with a p-value of 0.007. Table 3-3 (bottom) also shows a significant difference between different tasks, with a p-value of 0.045.

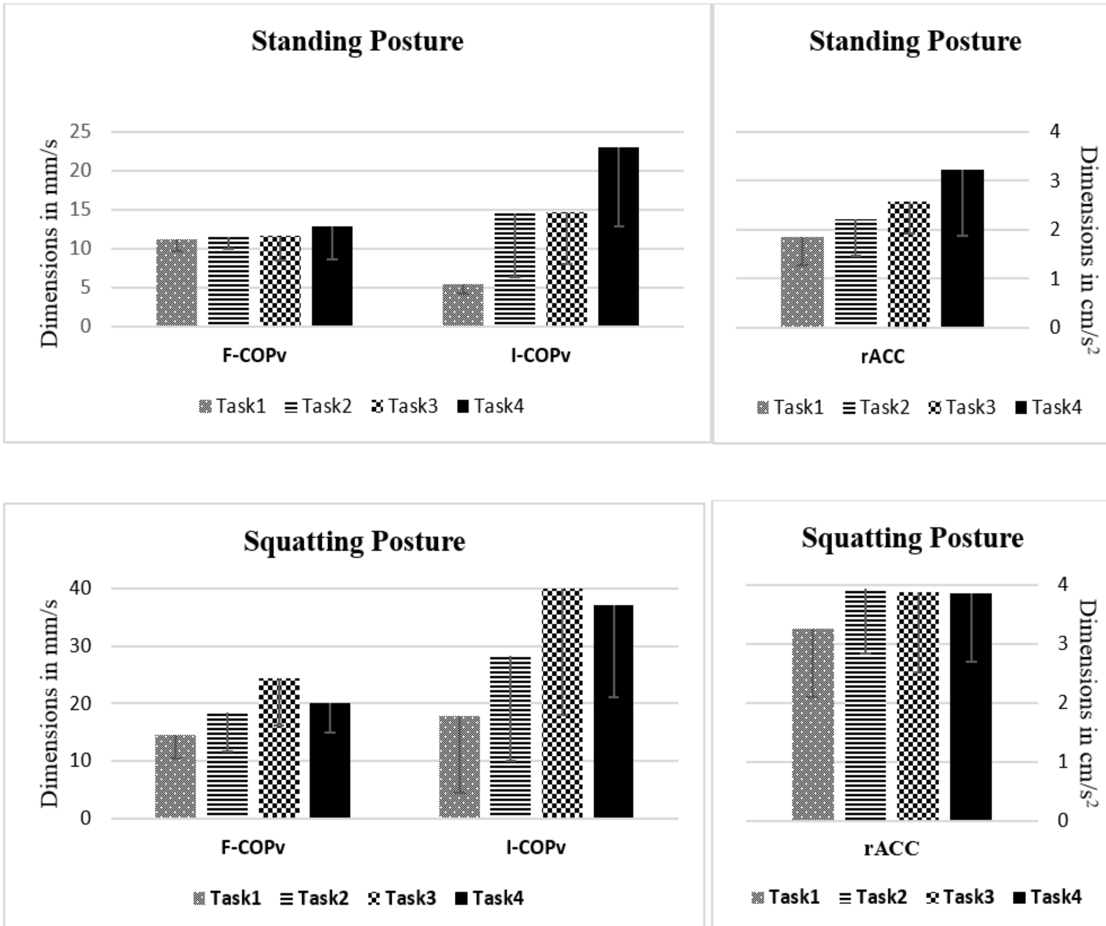

Figure 3-5. Different Task Means and Standard Deviations for the Value of rAcc, I-COPv and F-COPv.

Table 3-3. Summary Results from the AVONA Analysis Across Different Tasks.

ANOVA test based on F-COPv

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	277.6306	3	92.54353125	2.311788	0.082826	2.724944
Within Groups	3042.368	76	40.03115625			
Total	3319.998	79				

ANOVA test based on I-COPv

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4122.225	3	1374.075045	4.337226	**0.007087***	2.724944
Within Groups	24077.53	76	316.8096686			
Total	28199.76	79				

ANOVA test based on rAcc

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	13.99704	3	4.665680283	2.796984	**0.045788***	2.724944
Within Groups	126.7765	76	1.668111377			
Total	140.7735	79				

*P < 0.05 is displayed in bold numbers.

Comparison of the IMU and Force Plate

The correlations between different postural stability measures (F-COPv, I-COPv, r-Acc) in both standing and squatting postures while doing different tasks are listed in Table 3-4. In the standing posture tests, there was almost a strong correlation between all three different measures, which means that both rAcc and I-COPv can be useful for measuring workers' stability in a standing posture. Only rAcc presents a high correlation with F-COPv and I-COPv in the squatting posture. The linear relation between calculated COPv from the force plate and IMUs in the standing posture was investigated by plotting the data (see Figure 3-6).

Table 3-4. Spearman's Rank Correlation Coefficient Between the Force Plate and IMU Measures.

Task1	**Standing**			**Squatting**		
	F-COPv	**I-COPv**	**r-Acc**	**F-COPv**	**I-COPv**	**r-Acc**
F-COPv	1	**0.6***	0.455	1	0.405	0.545
I-COPv	**0.6***	1	**0.751***	0.405	1	**0.703***
rAcc	0.455	**0.751***	1	0.545	**0.703***	1
Task2	**Standing**			**Squatting**		
	F-COPv	**I-COPv**	**r-Acc**	**F-COPv**	**I-COPv**	**r-Acc**
F-COPv	1	**0.88***	**0.712***	1	**0.66***	0.426
I-COPv	**0.88***	1	**0.809***	**0.66***	1	0.37
rAcc	**0.712***	**0.809***	1	0.426	0.37	1
Task3	**Standing**			**Squatting**		
	F-COPv	**I-COPv**	**r-Acc**	**F-COPv**	**I-COPv**	**r-Acc**
F-COPv	1	0.36	0.213	1	0.454	0.332
I-COPv	0.36	1	**0.624***	0.454	1	**0.686***
rAcc	0.213	**0.624***	1	0.332	**0.686***	1
Task4	**Standing**			**Squatting**		
	F-COPv	**I-COPv**	**r-Acc**	**F-COPv**	**I-COPv**	**r-Acc**
F-COPv	1	0.466	**0.875***	1	0.533	**0.705***
I-COPv	0.466	1	**0.717***	0.533	1	**0.732***
rAcc	**0.875***	**0.717***	1	**0.705***	**0.732***	1

*P < 0.05 is displayed in bold numbers.

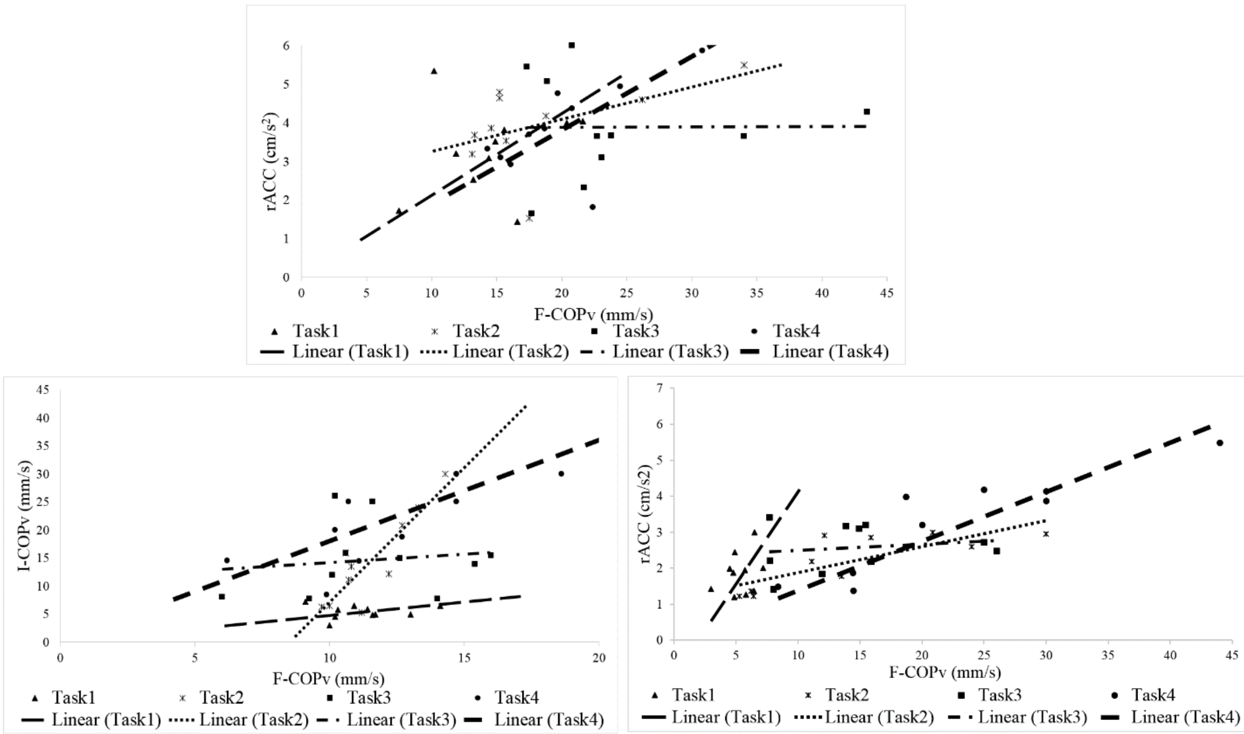

Figure 3-6. The Correlation Between Postural Stability Measures as Computed from Force Plate and IMU.

Discussion

This research aimed to study whether the suggested postural stability metrics have the power to distinguish tasks with a higher risk of falling. Also, this study tested the usefulness of IMUs as devices that can collect kinematic body-motion data for calculation of I-COPv and rAcc. The findings from the force plate were considered ground truth, since the force plate has been used as a reliable device to measure bodily stability for certain subjects and elderly people who have clinical issues with their stability (Shumway-Cook et al. 1988). Based on analyzes done with force-plate data, the four different tasks had a significant difference in their mean value in both standing and squatting. Based on the results, in comparing the tasks in the standing posture, we will consider task 1 as low fall-risk tasks and tasks 2 and 3 as those with a moderate risk of falling; also, task 4 can be considered a high fall-risk task. In the squatting posture, tasks 1 and 2 can be selected as tasks with a lower fall risk compared to tasks 3 and 4. Also, in the comparison of different postures, standing will be considered the low fall-risk posture and squatting will be specified as a high fall-risk task.

The results obtained from I-COPv were consistent with the F-COPv results. Based on the I-COPv results, the highest stability value in the standing posture was that of task 4. In the squatting posture, the maximum postural stability value was related to task 3. There was a significant difference in the mean value of calculated I-COPv in standing and squatting postures. The highest difference between standing and squatting was related to task 3 (with a mean value of 41.053 mm/sec in the squatting posture and 14.64 in standing posture). Tasks 1 and 2 had a lower mean value in both standing and squatting postures than tasks 3 and 4. Also, the rAcc values had the same consistency as the I-COPv results. Based on rAcc, tasks 3 and 4 had higher rAcc values than tasks 1 and 2. Comparing standing and squatting postures, there was a higher rAcc value through all the tasks in the squatting posture than in the standing posture. By changing the task difficulty (different loading configurations and weight or standing posture), rAcc values changed with the same pattern as I-COPv and F-COPv. In the standing posture, most of the postural-stability metrics were correlated based on the Spearman’s rank correlation coefficient test; out of 24 comparisons of different metrics, 16 pairs were correlated (see Table 3-4). A high correlation rate was not seen between different metrics in the squatting posture, which could be related to the low number of subjects. According to Figure 3-6, there was a linear correlation between different metrics with different correlation-slope coefficients. It can be concluded that different metrics have different sensitivities during certain tasks.

The only observed task that wasn't significantly different in standing and squatting was task 4. The low difference between standing and squatting postures in task 4 could be the result of holding loads that have a high impact on both standing and squatting and increase the risk of falling in both postures significantly. On the other hand, for most tasks we could consider the standing position as a more stable posture than the squatting posture. For task 4, both standing and squatting postures could be considered a high fall-risk task. The main reason that workers have higher instability in a squatting position, especially while doing tasks with external forces (attaching a load to the full-body harness or holding a load) can be related to the high pressure on workers' muscles and their body shaking in the squatting position. This vibration will create bodily instability, which causes a fall.

In addition, the difference in I-COPv and rAcc values across different tasks was variable for different subjects. It can be related to the subjects' physical characteristics and body strength. In the other words, the level of difficulty of the various tasks was different for different subjects. For example, for subject 2, the I-COPv value was 5.72 mm/sec while doing task 1 in a standing posture, and the I-COPv value was 26 mm/sec while doing task 3, which is much higher than task 1. One of the test subjects was an ironworker with extensive work experience. Although the F-COPv, I-COPv and rAcc values based on his experiments might show a difference between different tasks, the F-COPv, I-COPv and rAcc values for different tasks were very close together for this subject (I-COPv value,10.1mm/sec for task 1 and 11.7 mm/sec for task 3). This small difference can be related to the body strength of this subject compared to other subjects. In other words, holding a load or attaching a load in the asymmetrical configuration did not cause much difficulty for this worker. These findings confirm that suggested metrics can be used to quantify the fall risk of different workers with different physiological characteristics.

The main contribution of this paper has been to introduce and validate two IMU-based metrics that can allow in-depth analysis of IMU sensor data for the evaluation of construction workers' fall risk in stationary postures. In general, loss of stability will occur when different extrinsic or intrinsic factors affect postural or dynamic stability. The suggested approach can be used for a detailed analysis of the effects of different intrinsic and extrinsic factors bearing on construction workers' postural stability.

Conclusion

This research demonstrated the ability of two IMU-based measures (rAcc and I-COPv), inconsistent with a force plate-based measure (F-COPv), to quantify the fall risk of construction workers in the stationary position. The experimental results from 10 human subjects of various ages and physiological characteristics showed a significant difference in F-COPv values while the subjects were performing different tasks in different postures. The results showed that selected experimental conditions and tasks (tasks 1, 2, 3, and 4 and standing and squatting postures) made a significant difference in postural stability, according to F-COPv, rAcc and I-COPv values. The comparison of the F-COPv, I-COPv and rAcc values indicate that rAcc and I-COPv could provide adequate discriminating power for distinguishing the fall risk of stationary- related tasks.

The results of this research have the potential to identify the most capable workers for some specific tasks and conditions with a higher falling risk. The findings of this research can be a key element in defining a safety threshold for construction sites in those tasks and the workers' level.

Chapter 4. Symmetrical and Asymmetrical Tool Belt Loading Effects on the Postural Stability of Construction Workers

Abstract:

Falls are a leading cause of fatal and nonfatal injuries in construction. One of the most important steps in analytical research to prevent falls is to identify and measure the factors that can affect the construction workers' fall risk. While several intrinsic and extrinsic factors can affect workers' fall risk—such as the effects of aging, jobsite environments, posture and movement characteristics, workers' experience, and workers' equipment type and use— one unanticipated factor that can increase fall risk is the incorrect use of personal protective equipment—including full body safety harnesses and heavy tool belts—when safety harnesses and tool belts are not worn properly or body loading balanced they can cause unstable posture, changes in walking gait, and center of gravity problems. The objective of this study was to analyze the effects of the wearing full body safety harnesses and heavy tool belt loading symmetry on construction worker fall risk. Using the time-series quantitative kinematic measures obtained from Inertial Measurement Units (IMUs) connected to the workers' waistline, the postural stability of a group of subjects was measured by calculating the velocity of Center of Pressure (COPv) and the resultant Accelerometer (rAcc)—lower rAcc and COPv values mean lower fall risk for construction workers. The postural stability for each worker was calculated for two different postures (standing and squatting) and for three different configurations of the tools (without attaching tools to the full-body harness, symmetrical attachment configuration, and asymmetrical attachment configuration). T-test results for mean values of the calculated rAcc and COPv showed significant differences in the postural stability of subjects with

different placement and loading balance configurations of tool belts connected to the fall protection harness. When tools were not placed in the tool belt connected to the fall protection harness, test subjects had the lowest rAcc and COPv values; asymmetrical tool loading configurations rAcc and COPv had higher values than symmetrical loading configurations. The higher risk values associated with asymmetrically connected tools to a full body safety harness suggests the importance of safety harness tool attachment to construction worker fall risk safety.

Introduction

Construction is one of the largest industries by economic impact in the U.S., employing 7% of the total U.S workforce or more than 9 million workers. Construction is in the top 3 most dangerous industries along with mining and agriculture based on annual number of workplace fatalities. Occupational injuries and fatalities in the construction industry lead to high direct and indirect accident costs, such as income loss, reduced workforce productivity, reduced quality of life, increased total project time and cost, cost of medical treatment and follow-up, short term and long term disability, medical services burden, etc. (Horwitz and McCall, 2004; Lipscomb et al., 2003; Meerding et al., 2006). Falling from height is the leading cause of injuries and fatalities in the U.S. and international construction industries (Bentley et al., 2006; Bobick, 2004; Chan et al., 2008; Chi and Wu, 1997; Huang and Hinze, 2003; Meerding et al., 2006; Yung, 2009).

Many construction incidents could be prevented if the causal factors leading to workplace falls were identified and mitigated correctly. There are several identified factors that are associated with falls in construction sites, such as aging workforce effects, jobsite environmental factors, walking and movement characteristics, worker training and experience, and tooling and equipment. One of the overlooked factors that can increase fall risk is the incorrect use of personal protective equipment—including safety harnesses and tool belts—since construction workers and their supervisors often do not pay attention to the loading symmetry of heavily loaded tool belts attached to full body fall protection harnesses (Cory Lyons, personal communications, 2014). One of the reasons this problem exists may be due to the limited explicit knowledge and training related to the effects of improper tool belt loading as part of a full body harness. Proper loading and symmetrical tool placement in a tool belt and full body fall protection harness could help reduce construction worker fall risk. The objective of this study was to assess the effects of tool belt and full body harness loading symmetry on postural stability by measuring and analyzing whole body stability using a wearable inertial measurement unit (IMU) data collection system.

The ability to maintain a position of the body—or more specifically, the body's center of mass—is defined as postural stability (Lord et al., 2007). There are several methods and metrics that have been suggested in clinical and healthcare settings to assess the fall risk of human body subjects by measuring their body postural stability, such as Hurst rescaled range analysis ($H_{R/S}$), average velocity of center of pressure (COPv), and resultant acceleration (rAcc). Hurst rescaled range analysis examines fractal properties after integrating a time series and can be used to characterize a time series of motion data when studying a body's stability (Delignlères et al., 2003). The average velocity of center of pressure (COPv) illustrate the total distance between each consecutive points of the body's center of pressure in the total data collection time (Hufschmidt et al. 1980). COPV is considered to be the most reliable measure used in the biomechanical domain to measure the stability of human bodies in stationary motions (Lafond et al., 2004). Resultant acceleration (rAcc) is another metric used in the clinical domain to measure the human body's stability in a stationary posture (Brumagne et al., 2008; Liu et al., 2012; Soangra and E Lockhart, 2013). rAcc measures the total human body motion in a certain period of time using the accelerometer vector components from inertial measurement units (IMU). In this research, the COPv and rAcc parameters were selected as the metrics for measuring and analyzing construction worker postural stability based on body movement and center of pressure demonstrated by subjects in the standing and squatting postures in the experimental setup.

Experimental Design and Methodology

Measuring Postural Stability

In this paper, resultant accelerometer (rAcc) and the average velocity of the center of pressure (COPv) were selected as two measures to calculate postural stability of construction workers. Resultant acceleration (rAcc) is a metric that was introduced in the clinical domain to measure the human body stability in a stationary posture (Brumagne et al., 2008; Liu et al., 2012; Soangra and E. Lockhart, 2013). The rAcc measures the total human body motion in a certain period of time using the accelerometer vector components from inertial measurement units (IMU). Higher rAcc means higher instability for human subjects.

The average velocity of center of pressure (COPv) was introduced as the most reliable measure for assessing the stability of human bodies in stationary positions within the biomechanical domain (Lafond et al., 2004). COPv is calculated by summing the distance between each consecutive point of the body's center of pressure and dividing this over the total data-collection time (Hufschmidt et al., 1980). In a stable situation, the location of the center of pressure is constant or has a minimum displacement. Increasing the displacement of the center of body location will increase the COPv, and higher COPv means higher instability.

Resultant acceleration (rAcc) was calculated using Equation 1.

[1] $rAcc = \sum(\sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2})$

Where a_x, a_y, a_z are the acceleration measurements from the IMU.

This paper used Mayagoitia's et al. (2002) method to calculate the COPv. The main idea of this method is to measure the sway path of the accelerometer and to assume that this sway path is same as the sway path of the body's center of pressure. The magnitude of the resultant acceleration (A) for each point can be calculated using Equation 2 where a_x, a_y, and a_z are the acceleration measurements from the IMU across each axis (See Figure 4-1-A).

[2] $A_i = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}$

After calculating the A, the angle between the different directions of the accelerometer vectors and the magnitude of the resultant acceleration can be calculated using the group of Equations 3-6.

[3] $\cos\alpha = \frac{a_{xi}}{A}$, $\cos\beta = \frac{a_{yi}}{A}$, $\cos\gamma = \frac{a_{zi}}{A}$

[4] $x_i = D * \cos\alpha$

[5] $y_i = D * \cos\beta$

[6] $z_i = D * \cos\gamma$

Where $\cos\alpha$, $\cos\beta$, $\cos\gamma$ are the directional cosine and α, β, γ are the angles between the components of the acceleration and the resultant acceleration. D is the magnitude of the accelerometer vector.

In the above mentioned equations, D has an unknown value. D can easily be calculated from equation 6 since it can be assumed that z_i has a constant value equal to the height of the IMU. Finding the value of D and replacing D in equations 4 and 5 will lead to one finding the value of x_i and y_i (See Figure 4-1-b). Next, the average velocity of the center of pressure (COPv) was calculated by summing the distance between each consecutive point of the COP and dividing this over the total data collection time (T) using the equation 7 (Hufschmidt et al., 1980).

[7] $COPv = \frac{\sum\sqrt{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}}{\mathrm{T}}$

Where T is the total data collection time and x_i and y_i are the center of body's coordinates. All of the calculations were performed using custom-made software written in MATLAB (ver 8.1.0.604, The Math Works Inc., USA). The commercially available SPSS was used for statistical analyses.

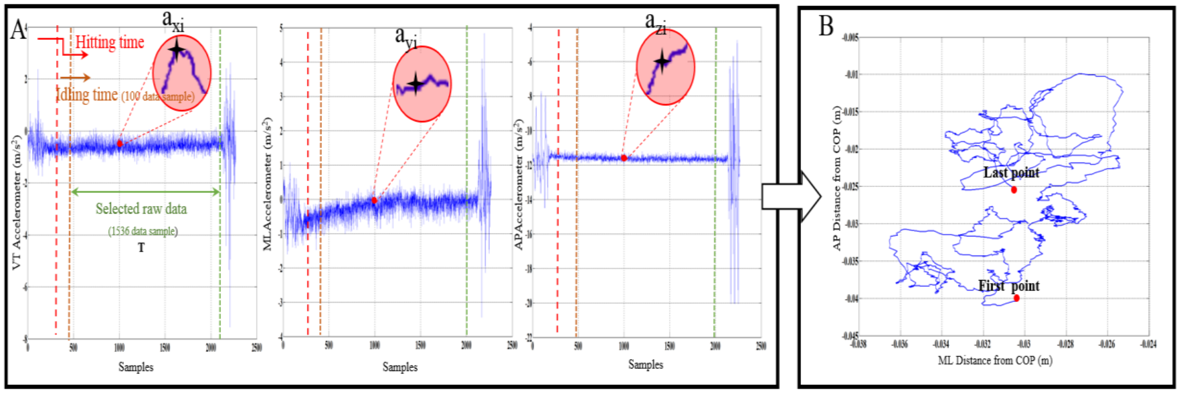

Figure 4-1. Representative Stabilograms Obtained from a Subject. (A) The time-series data captured by IMU in three directions (Vertical accelerometer, ML accelerometer, AP accelerometer). (B) Stabilogram of center of pressure.

Instrumentation, Procedure and Test Subjects

This research project used IMU data to calculate the COPv and rAcc even though most previous research into COPv used a force plate (Brumagne et al., 2008; Chaudhry, Hans et al., 2004; Clair and Riach, 1996; Karlsson and Frykberg, 2000; Önell, 2000; Soangra and E Lockhart, 2013) to measure human subject postural stability. This decision reflects the fact that using a force plate in real world job sites would be cumbersome and difficult since such plates are expensive, heavy, not easily carried, and require a flat stable surface to maintain calibration, accuracy, and repeatability.

To provide a stable surface for the test subjects to use while performing different steps of the test, a flat, stable steel plate was provided. Test subjects were asked to do both standing and squatting postures on the steel plate since the plate could provide the same standing surface condition through all of the stages of the test (See Figure 4-2-g). For all test trials test subjects body motions were recorded using a tri-axial accelerometer (Shimmer 9DOF) (See Figure 4-2-h). Sensors collected 52 data points per second for anterior-poster (AP), medio-lateral (ML), and vertical (VT) directions, each of which were oriented with X, Y, and Z axes, respectively. IMU sensors were attached to the dorsal surface of each test subject's back at a height of 57% of subject's total standing height (stature). According to Mayagoitia et al. (2002), this location is the appropriate human body location that can be selected as the body center of mass point for tracking and analyzing total human body motion.

Ten healthy able bodied human subjects participated in this research. (Mean age: 30.8 years; mean height: 6 ft.; mean weight: 192 lbs.). The subject sample had no reported history of clinical conditions or disabilities that would disqualify them from participation in the research project. All subjects verified that they were not taking any medications, drugs or consuming substances like alcohol that could cause drowsiness or adversely affect their body posture or movement stability. Test subjects with corrected vision wore their eye glasses or contact lenses during the experiments. All test subjects were college graduate student volunteers with no construction work experience.

Test subjects were asked to perform two different postures (standing and squatting) for three different tasks. For Task 1, test subjects stood on the steel plate for 30 second while they wore a full body harness without any connected tools; the subjects then repeated the test for another 30 seconds in a squatting position (See Figure 4-2-a&d). For Task 2, subjects repeated the standing and squatting motions—same as Task 1—while their full body harness was loaded with tools in a symmetrical configurations (See Figure 4-2-b&e). Task 3 repeated the same test as the first two tasks but with tools attached to the full body harness in an asymmetrical configuration (See Figure 4-2-c&f). The tools used in these tasks were selected from common sets of ironworkers tools for tool belts (See Figure 4-2-

I). The total weight of the tools, tool belt, and full body fall protection harness was 30.0 lbs. The total weight of just the tools was 9 lbs. For the symmetrical tool belt configuration, tools were loaded with an equal weight on the right and left side of the tool belt. For the asymmetrical configuration, all the tools were loaded into the left side of the tool belt and fall protection harness.

Visual inputs—such as high and low-contrast visual acuity, contrast sensitivity, depth perception, stereopsis, and lower visual field size— are considered one of the extrinsic factors that could affect human body stability as a destructive factor (Jeka et al. 2004; Lord and Menz 2000); Visual inputs can disturb the human subjects and affect their stability by moving their bodies upright posture. To provide the same conditions for the different subjects while they performed different tasks, a white screen was installed in front of the subjects that covered the subjects' vision completely. Subjects were asked to look forward and not to move their heads. The testing location was in a human factors and safety test lab in almost an imperturbable place protected from noise, disturbance, or distraction sources. The test lab environment helped to eliminate test procedure interference and avoid test subjects distractions.

Factors that could have increased data collection error were: (1) assigned test task ordering effects and (2) confounding effects due to test subject physical fatigue. In order to prevent or reduce the task orders effects physical fatigue confounding, 5 minutes rest was provided between different test tasks for each subject, and test tasks were randomly assigned for each subject. Before starting the experiment subjects were informed about the experimental procedure and any questions about the procedure were addressed. Figure 4-1 summarizes the different experimental tests (Tasks 1, 2, and 3) in this study.

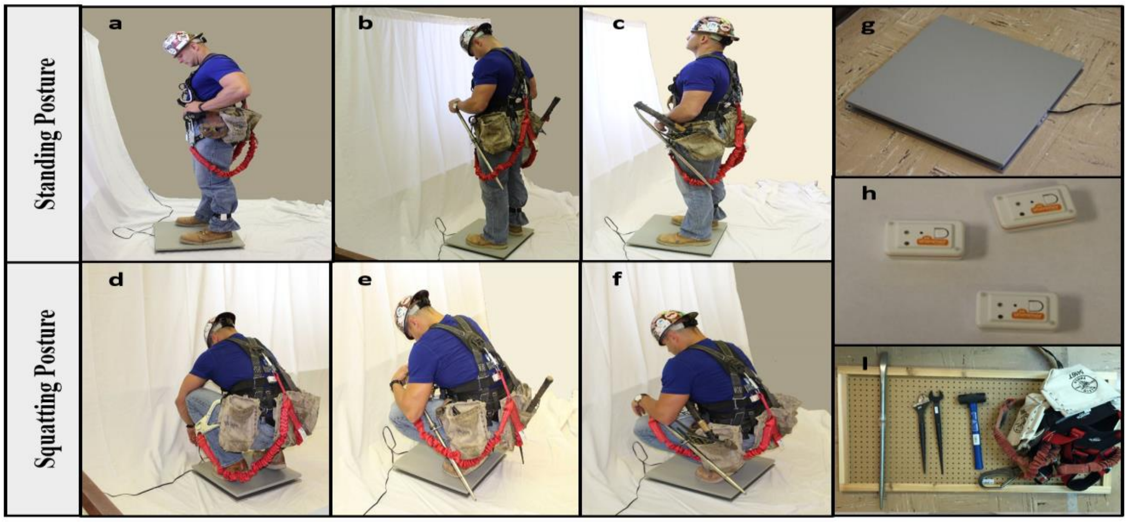

Figure 4-2. Illustration of the Experiment: (a) Standing while wearing full body harness without any connected tools; (b) Standing while wearing full body harness laden with some tools in the symmetrical configuration; (c) Standing while wearing full body harness laden with tools in asymmetrical configuration (d) Squatting while wearing full body harness without any connected tools; (e) Squatting while wearing full body harness laden with some tools in the symmetrical configuration; (f) Squatting while wearing full body harness laden with tools in asymmetrical configuration; (g) Steel plate with a flat surface; (h) Inertial Measurement Units; (I) Selected connected tools (right to left: full body fall protection harness and tool belt bag, 5 lb. sledge hammer , finish construction wrench, erection wrenches, pry bar, and pinch bars)

Statistical analysis

T-test Analysis

T-test analyses for small equal sample sizes were conducted for rAcc and COPv values between Task 1 (standing and squatting while wearing full body harness without a load) and Task 2 (standing and squatting while wearing full body harness laden with tools in a symmetrical configuration), and between Task 2 and Task 3 (standing and squatting while wearing full body harness loaded with some tools in an asymmetrical configuration). The alpha level for the t-test was set at $\alpha=0.05$.

Two-way ANOVA

Two two-way analysis of variance (ANOVA) were performed for rAcc and COPv values to compare the effects of the loaded -tools' configuration on rAcc and COPv values. The alpha level for ANOVA test was set at $\alpha=0.05$.

Results

The mean and standard deviation (SD) values of rAcc and COPv values are shown in the Figure 4-3. For both standing and squatting postures, rAcc and COPv had their highest value in Task 3. The highest overall COPv was found in the squatting posture of Task 3 as 41.05, while the minimum value was found in the standing posture of Task 1 as 5.379. Higher rAcc and COPv values specify the low postural stability of the subject, which can be interpreted as having a higher fall risk. Similar to the COPv results, the highest rAcc value was found in the squatting posture of Task 3 as 41.05, and the lowest rAcc was found in the standing posture of Task 1 as 1.848.

Table 4-1 summarizes the results of the t-test between different loaded tools configurations in the standing and squatting postures. The results show a significant difference in the comparison between Task 1 and Task 3 in both the standing and squatting postures, Task 2 and Task 3 in both postures, and Task 1 and Task 2 in the standing posture. The t-test only failed to confirm a significant difference in the comparison between Task 1 and Task 2 in the squatting posture. While the t-test did not show significant difference in comparing the Task 1 and Task 2 in the squatting posture, however, there was a significant difference in the mean value of both rAcc and Copv in these two cases. The lowest t-test p-value appeared in comparing Task 1 and Task 2 which implies that there is a significant effect of improperly loaded-tools' configuration on construction worker stability.

Table 4-2 summarizes the results of the ANOVA test in the comparison between the different tasks in their respective standing and squatting postures. The ANOVA test results also indicate a significant difference in both rAcc and COPv among the three tasks in both the standing and squatting postures. The p-value of COPv in both standing and squatting postures was lower than the p value of rAcc, which again shows that COPv demonstrates more significant differences in the comparisons between the different tasks.

Although both rAcc and COPv metrics have the same trend in comparing different loaded -tools' configuration in standing and squatting postures, there was a higher sensitivity in COPv values rather than rAcc values when changing the tasks, according to Figure 4-3 Another result of this paper is the higher value for rAcc and COPv for the different tasks in the squatting posture rather than the standing posture, which shows that construction workers have a higher instability in the squatting posture than the standing posture. Also, the difference of in the calculated COPv between different tasks is higher in the squatting posture rather than the standing posture. This implies that the load configuration may have a higher adverse effect in more instable postures—such as squatting—than in stable postures—such as standing.

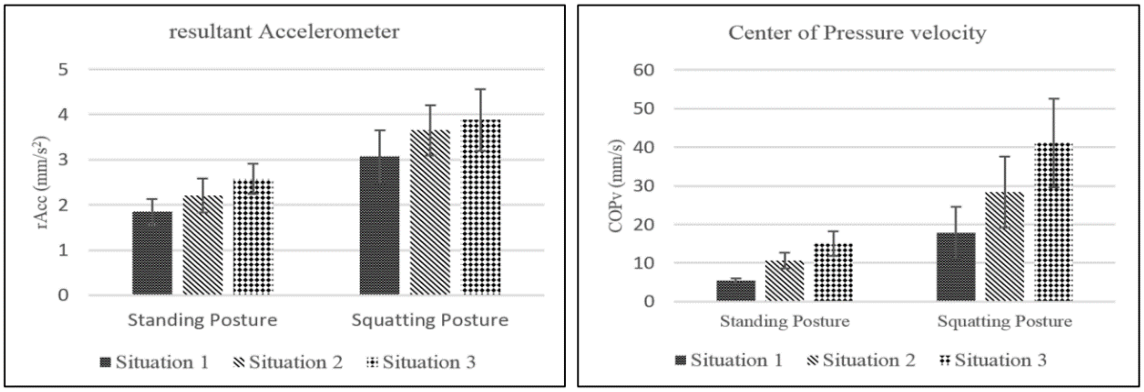

Figure 4-3. rAcc and COPv Values for Different Full Body Harness Tool Configurations in Standing and Squatting Postures.

Table 4-1. T-tests P Values between Different Loaded-tools' Configuration and Measures in Standing and Squatting Postures (T1=Task 1, T2=Task 2, T3=Task 3).

	Standing Posture			Squatting Posture		
COPv	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
T1	-	0.0024*	0.00039*	-	0.1274	0.0101*
T2	0.0024*	-	0.0495*	0.1274	-	0.0152*
T3	0.0003*	0.0495*	-	0.0101*	0.0152*	-

Table 4-2. ANOVA Ttest P Values between Different Loaded-tools' Configuration and Measures.

	Standing Posture	**Squatting Posture**
COPv	0.005*	0.0008*
rAcc	0.018*	0.031*

Conclusion and Discussion

The goal of this research was to demonstrate the effects of tool belt loading symmetry on posture stability of construction workers wearing a tool belt connected to a full body fall protection harness. Sometimes, young construction workers do not fully understand the importance of symmetrical tool belt loading and its relationship to working postural stability and lower fall risk. This research reinforces the importance of proper tool belt loading for young or less experienced construction workers.

The results of this research revealed that asymmetrical tool belt loading was associated with lower posture stability in the standing squatting postures when compared with symmetrical tool belt loading. In addition, it was found that even a symmetrical tool belt loading condition will result in some instability for construction workers when compared to a situation in which there are no tools loaded in the tool belt fall protection harness system. Another key finding was the confirmation of the usefulness of the suggested postural stability metrics in distinguishing the fall risk of construction workers while performing tasks with different fall risk profiles. These results also highlight the value of using IMU wearable sensors as a possible monitoring device to assess construction workers' fall risk. IMU sensors can attach to construction workers to measure the stability of construction workers' while they perform different tasks in different postures on a construction site and can foreseeably be used as a method to prevent fall accidents.

Chapter 5. Conclusions and Recommendations for Future Research

Conclusions

Each chapter's conclusions are discussed at the end of that chapter. The main research conclusions of this thesis are be summarized as follows:

- This thesis investigates the ability of Max LE to measure the gait stability of construction workers. The results indicate that Max LE could provide adequate discriminating power for distinguishing high fall-risk tasks. This outcome highlights numerous opportunities to utilize Max LE for various applications in construction-safety management and is expected to help open new areas of research by introducing a reliable measure for quantifying the fall risk of construction workers across different tasks in different locations.
- Also, this thesis investigate the ability of two postural stability metrics _rAcc and I-COPv_ to measure construction workers' postural stability using kinematic time-series data from IMU sensors. The results, show the ability of rAcc and I-COPv to assess workers' fall risk while doing different tasks in stationary postures. rAcc and I-COPv are expected to help improving the safety in the construction sites by opening new areas of research in quantifying the fall risk of construction workers' in the stationary postures.
- The suggested postural stability and gait stability metrics were used to measure the effect one of the extrinsic factors _ personal protective equipment _ on workers' stability. The results showed that asymmetrical tool-belt loading was associated with lower posture stability in the standing and squatting postures compared to symmetrical tool belt loading. In addition, it was found that even symmetrical tool

belt loading will result in some instability for workers compared no tools being loaded in the tool-belt fall-protection harness.

Recommendations for Future Studies

This research contributed to developing an overall fall assessment framework by introducing and validating metrics that can measure workers' gait and postural stability. Then, an application of suggested metrics has been illustrated in chapter 4. Some of the possible future research related to each section of the thesis is presented below.

Measuring Construction Workers' Gait And Postural

Future research could be conducted to further ascertain the validity of Max LE, rAcc, and I-COPv in the different experimental settings that reflect the working environments of different trades. In addition, future research should investigate how to increase the discriminating power of suggested metrics in this thesis by changing the data-collection schemes of IMU sensors (e.g., sampling frequency and body location where IMU sensors will be attached). In addition, future research should investigate how and to what extent diverse factors (e.g., training, physiological characteristics) affect the intra-subject variability and inter-subject variability of Max LE, rAcc, and I-COPv values. Also, future research should look into the usefulness of postural stability metrics in construction environments, which can provide insights into fall-risk assessment in common tasks in construction.

Future research can use the method suggested here for developing a real-time fall-risk monitoring tool. Also, the fall-risk quantification measures introduced can be an effective way to study the effectiveness of current training programs. Workers' gait and postural stability can be calculated before and after safety-training programs. The comparison of the values of gait and postural stability metrics before and after safety-training programs can be a measure for assessing the usefulness of such programs.

Several limitations remain in this research. First, the small number of test subjects can affect the validity of the comparisons of different tasks and postures. Also, the data was collected in a laboratory experiment setup. The data collected in the laboratory can vary from that of real job sites. Future research can increase the number of subjects while doing different tasks in a real job site environment.

Application of Suggested Postural and Gait Stability Metrics

Future research should examine the effects of other intrinsic and extrinsic factors—such as walking speed, construction-site walking-surface friction characteristics, worker age and worker training and experience—on workers' postural and work-movement stability, since these factors may adversely affect worker safety. Other future studies could examine the sensitivity of different stability metrics to find the most sensitive metrics to compare the effects of different intrinsic and extrinsic factors on work posture and movement stability.

References

Abarbanel, H. (1996). *Analysis of observed chaotic data*. Springer Verlag. New York.

Abarbanel, H. D. I., and Kennel, M. B. (1993). "Local false nearest neighbors and dynamical dimensions from observed chaotic data." *Physical Review E*, 47(5), 3057–3068.

Abderrahim, M., Diez, R., Boudjabeur, S., Navarro-Suñer, J., and Balaguer, M. (2005). "An IT Infrastructure and safe collaboration in modern construction site." 11–14.

Beavers, J., Moore, J., and Schriver, W. (2009). "Steel Erection Fatalities in the Construction Industry." *Journal of Construction Engineering and Management*, 135(3), 227–234.

Bentley, T. A., Hide, S., Tappin, D., Moore, D., Legg, S., Ashby, L., and Parker, R. (2006). "Investigating risk factors for slips, trips and falls in New Zealand residential construction using incident-centred and incident-independent methods." *Ergonomics*, 49(1), 62–77.

Bobick, T. (2004). "Falls through Roof and Floor Openings and Surfaces, Including Skylights: 1992–2000." *Journal of Construction Engineering and Management*, 130(6), 895–907.

Boman, K., and Jalavisto, E. (1953). "Standing steadiness in old and young persons." *Annales Medicinae Eperimentalis et Biologiae Fenniae*, 31(4), 447–55.

Brilakis, I., Park, M.-W., and Jog, G. (2011). "Automated vision tracking of project related entities." *Advanced Engineering Informatics*, 25(4), 713–724.

Broomhead, D., and King, G. P. (1986). "Extracting qualitative dynamics from experimental data." *Physica D: Nonlinear Phenomena*, 20(2), 217–236.

Bruijn, S. M., Bregmanc, D. J. J., Meijer, O. G., Beek, P. J., and Dieen, J. H. van. (2011). "The validity of stability measures: A modelling approach." *Journal of Biomechanics*, 44(0), 2401–2408.

Bruijn, S., Kate, W. T., Faber, G., Meijer, O., Beek, P., and Dieën, J. (2010). "Estimating Dynamic Gait Stability Using Data from Non-aligned Inertial Sensors." *Annals of Biomedical Engineering*, 38(8), 2588–2593.

Bruijn, S. M., Dieën, J. H. van, Meijer, O. G., and Beek, P. J. (2009). "Statistical precision and sensitivity of measures of dynamic gait stability." *Journal of Neuroscience Methods*, 178(2), 327 – 333.

Bruijn, S. M., Meijer, O. G., Beek, P. J., and Dieën, J. H. van. (2013). "Assessing the stability of human locomotion: a review of current measures." *Journal of the Royal Society*, 10(83).

Brumagne, S., Janssens, L., Janssens, E., and Goddyn, L. (2008). "Altered postural control in anticipation of postural instability in persons with recurrent low back pain." *Gait & Posture*, 28(4), 657 – 662.

Bureau of Labor Statistics (BLS). (2013). "Fatal work injuries, by industry and contractor-adjusted industry, by selected industry, 2012." *Injuries, Illnesses, and Fatalities*, U.S. Dept. of Labor, Washington, DC, < http://www.bls.gov/iif/oshwc/cfoi/cfch0012.pdf >

Bureau of Labor Statistics (BLS). (2011). "Fatal falls to lower level by height of fall, 2011" *Injuries, Illnesses, and Fatalities,* U.S. Dept. of Labor, Washington, DC, < http://www.bls.gov/iif/oshwc/cfoi/cfch0010.pdf>

Buzzi, U., and Ulrich, N. (2004). “Dynamic stability of gait cycles as a function of speed and system constraints.” *Motor Control*, 8(3), 241–54.

Cao, L. (1997). “Practical method for determining the minimum embedding dimension of a scalar time series.” *Physica D: Nonlinear Phenomena*, 110(1–2), 43 – 50.

Carpenter, G., and Toole, T. M. (2011). “Prevention through Design: An Important Aspect of Social Sustainability.” *ICSDC 2011*, 187–195.

Chan, A., Wong, F., Chan, D., Yam, M., Kwok, A., Lam, E., and Cheung, E. (2008). “Work at Height Fatalities in the Repair, Maintenance, Alteration, and Addition Works.” *Journal of Construction Engineering and Management*, 134(7), 527–535.

Chang, M. D., Sejdić, E., Wright, V., and Chau, T. (2010). “Measures of dynamic stability: Detecting differences between walking overground and on a compliant surface.” *Human Movement Science*, 29(6), 977 – 986.

Chaudhry, Hans, Quigley, Karen S, Findley, Thomas, and Bukiet, Bruce. (2004). “Measures of postural stability.” *Journal of Rehabilitation Research & Development*, 41(5), 713–720.

Cheng, T., Migliaccio, G., Teizer, J., and Gatti, U. (2013). “Data Fusion of Real-Time Location Sensing and Physiological Status Monitoring for Ergonomics Analysis of Construction Workers.” *Journal of Computing in Civil Engineering*, 27(3), 320–335.

Chi, S., and Caldas, C. H. (2011). “Automated Object Identification Using Optical Video Cameras on Construction Sites.” *Computer-Aided Civil and Infrastructure Engineering*, 26(5), 368–380.

Chi, C.-F., and Wu, M.-L. (1997). “Fatal occupational injuries in Taiwan — Relationship between fatality rate and age.” *Safety Science*, 27(1), 1 – 17.

Clair, K. L., and Riach, C. (1996). “Postural stability measures: what to measure and for how long.” *Clinical Biomechanics*, 11(3), 176 – 178.

The Center for Construction Research and Training (CPWR) (2013). "Chart 33a. Working at heights on the job, selected occupations" *O*NET Database and Occupational Exposures in Construction,* The center for Construction Research and Training, Silver Spring, MD, < http://www.cpwr.com/sites/default/files/publications/CB%20page%2033.pdf>

Delignlères, D., Deschamps, T., Legros, A., and Caillou, N. (2003). “A Methodological Note on Nonlinear Time Series Analysis: Is the Open-and Closed-Loop Model of Collins and De Luca (1993) a Statistical Artifact?” *Journal of Motor Behavior*, 35(1), 86–96.

Dickstein, R., Shupert, C. L., and Horak, F. B. (2003). “Corrigendum to Abstract ‘Fingertip touch improves postural stability in patients with peripheral neuropathy’: [Gait and Posture 14 (2001) 238–247].” *Gait & Posture*, 17(2), 189 – 192.

DiDomenico, A., McGorry, R. W., Huang, Y.-H., and Blair, M. F. (2010). “Perceptions of postural stability after transitioning to standing among construction workers.” *Safety science*, 48(2), 166–172.

Dieën, J. H. van, Koppes, L. L. J., and Twisk, J. W. R. (2010). “Postural sway parameters in seated balancing; their reliability and relationship with balancing performance.” *Gait & Posture*, 31(1), 42 – 46.

Dingwell, J. B., and Cusumano, J. P. (2000). “Nonlinear time series analysis of normal and pathological human walking.” *Chaos: An Interdisciplinary Journal of Nonlinear Science,* 10(4), 848–863.

Dingwell, J. B., and Martin, L. C. (2006). “Kinematic variability and local dynamic stability of upper body motions when walking at different speeds.” *Journal of Biomechanics,* 39(3), 444 – 452.

Dingwell, J. ., Cusumano, J. ., Cavanagh, P. ., and Sternad, D. (2001). “Local dynamic stability versus kinematic variability of continuous overground and treadmill walking.” *Journal of Biomechanical Engineering*, 27–32.

Dingwell, J. ., and Kang, H. . (2007). “Differences between local and orbital dynamic stability during human walking.” *Journal of Biomechanical Engineering*, 129, 586–593.

Duff, A., Robertson, I., Phillips, R., and Cooper, M. (1994). “Improving safety by the modification of behaviour.” *Construction Management and Economics*, 12(1), 67–78.

Dzeng, R.-J., Fang, Y.-C., and Chen, I.-C. (2014). “A feasibility study of using smartphone built-in accelerometers to detect fall portents.” *Automation in Construction,* 38(0), 74 – 86.

Eckmann, J. ., and Ruelle, D. (1985). “Ergodic theory of chaos and strange attractors.” *Rev. Modern Phys*, 57(3), 617–656.

England, S. A., and Granata, K. P. (2007). “The influence of gait speed on local dynamic stability of walking.” *Gait & Posture,* 25(2), 172 – 178.

Escorcia, V., Dávila, M., Golparvar-Fard, M., and Niebles, J. (2012). "Automated Vision-Based Recognition of Construction Worker Actions for Building Interior Construction Operations Using RGBD Cameras." *Construction Research Congress 2012*, American Society of Civil Engineers, 879–888.

Fredericks, T., Abudayyeh, O., Choi, S., Wiersma, M., and Charles, M. (2005). "Occupational Injuries and Fatalities in the Roofing Contracting Industry." *Journal of Construction Engineering and Management*, 131(11), 1233–1240.

Gambatese, J., Behm, M., and Hinze, J. (2005). "Viability of Designing for Construction Worker Safety." *Journal of Construction Engineering and Management*, 131(9), 1029–1036.

Gates, D. H., and Dingwell, J. B. (2009). "Comparison of different state space definitions for local dynamic stability analyses." *Journal of biomechanics*, 42(9), 1345–1349.

Grabowski, M., Ayyalasomayajula, P., Merrick, J., and Mccafferty, D. (2007). "Accident precursors and safety nets: leading indicators of tanker operations safety." *Maritime Policy & Management*, 34(5), 405–425.

Grassberger, P. (2007). "Grassberger-Procaccia algorithm." *Scholarpedia*, 2(5), 3043.

Griffin, M. A., and Neal, A. (2000). "Perceptions of safety at work: A framework for linking safety climate to safety performance, knowledge, and motivation." *Journal of Occupational Health Psychology*, 5(3), 347–358.

Hallowell, M., and Gambatese, J. (2009). "Activity-Based Safety Risk Quantification for Concrete Formwork Construction." *Journal of Construction Engineering and Management*, 135(10), 990–998.

Hamacher, D., Singh, N. B., Van Dieën, J. H., Heller, M. O., and Taylor, W. R. (2011). "Kinematic measures for assessing gait stability in elderly individuals: a systematic review." *Journal of The Royal Society Interface*, 8(65), 1682–1698.

Han, S., and Lee, S. (2013). "A vision-based motion capture and recognition framework for behavior-based safety management." *Automation in Construction*, 35, 131–141.

Han, S., Lee, S., and Peña-Mora, F. (2013). "Comparative Study of Motion Features for Similarity-Based Modeling and Classification of Unsafe Actions in Construction." *Journal of Computing in Civil Engineering*, 0(ja), null.

Hausdorff, J. (2005). "Gait variability: methods, modeling and meaning." *Journal of NeuroEngineering and Rehabilitation*, 2(1), 19.

Helander, M. G. (1991). "Safety hazards and motivation for safe work in the construction industry." *Int. J. Ind. Ergon.*, 8(0), 205–223.

Hellebrandt, F. A., and Braun, G. L. (1939). "The influence of sex and age on the postural sway of man." *American Journal of Physical Anthropology*, 24(3), 347–360.

Herman, T., Giladi, N., Gurevich, T., and Hausdorff, J. M. (2005). "Gait instability and fractal dynamics of older adults with a 'cautious' gait: why do certain older adults walk fearfully?" *Gait & Posture*, 21(2), 178 – 185.

Horak, F. B. (1987). "Clinical Measurement of Postural Control in Adults." *Physical Therapy*, 67(12), 1881–1885.

Horwitz, I. B., and McCall, B. P. (2004). "Disabling and Fatal Occupational Claim Rates, Risks, and Costs in the Oregon Construction Industry 1990–1997." *Journal of Occupational and Environmental Hygiene*, 1(10), 688–698.

Hsiao, H., and Simeonov, P. (2001). "Preventing falls from roofs: a critical review." *Ergonomics*, 44(5), 537–561.

Huang, X., and Hinze, J. (2003). "Analysis of Construction Worker Fall Accidents." *Journal of Construction Engineering and Management*, 129(3), 262–271.

Hufschmidt, A., Dichgans, J., Mauritz, K.-H., and Hufschmidt, M. (1980). "Some methods and parameters of body sway quantification and their neurological applications." *Archiv für Psychiatrie und Nervenkrankheiten*, 228(2), 135–150.

Hurmuzlu, Y., Basdogan, C., and Stoianovici, D. (1996). "Kinematics and Dynamic Stability of the Locomotion of Post-Polio Patients." *Journal of Biomechanical Engineering*, 118(3), 405–411.

Im, H.-J., Kwon, Y.-J., Kim, S.-G., Kim, Y.-K., Ju, Y.-S., and Lee, H.-P. (2009). "The characteristics of fatal occupational injuries in Korea's construction industry, 1997–2004." *Safety Science*, 47(8), 1159 – 1162.

Iosa, M., Morone, G., Fusco, A., Pratesi, L., Bragoni, M., Coiro, P., Multari, M., Venturiero, V., De Angelis, D., and Paolucci, S. (2012). "Effects of Walking Endurance Reduction on Gait Stability in Patients with Stroke." *Stroke Research and Treatment*, 2012.

Jebelli, H., Ahn, R. A., and Stentz, L. S. (2014). "The Validation of Gait-Stability Metrics to Assess Construction Workers' Fall Risk." *International Conference on Computing in Civil and Building Engineering*.

Jeka, J., Kiemel, T., Creath, R., and Peterka, R. (2004). "Controlling human upright posture: velocity information is more accurate than position or acceleration." *Journal of Neurophysiology*, 92(4), 2368–79.

Johnson, H., Singh, A., and Young, R. (1998). "Fall Protection Analysis for Workers on Residential Roofs." *Journal of Construction Engineering and Management*, 124(5), 418–428.

Jordan, K., Challis, J. H., and Newell, K. M. (2007). "Walking speed influences on gait cycle variability." *Gait & Posture*, 26(1), 128 – 134.

Joshua, L., and Varghese, K. (2011). "Accelerometer-Based Activity Recognition in Construction." *Journal of Computing in Civil Engineering*, 25(5), 370–379.

Kang, H. G., and Dingwell, J. B. (2008). "Effects of walking speed, strength and range of motion on gait stability in healthy older adults." *Journal of Biomechanics*, 41(14), 2899 – 2905.

Karlsson, A., and Frykberg, G. (2000). "Correlations between force plate measures for assessment of balance." *Clinical Biomechanics*, 15(5), 365 – 369.

Karlsson, A., and Lanshammar, H. (1997). "Analysis of postural sway strategies using an inverted pendulum model and force plate data." *Gait & Posture*, 5(3), 198 – 203.

Kavanagh, J. J., and Menz, H. B. (2008). "Accelerometry: A technique for quantifying movement patterns during walking." *Gait & Posture*, 28(1), 1–15.

Kennel, M. B., Brown, R., and Abarbanel, H. D. I. (1992). "Determining embedding dimension for phase-space reconstruction using a geometrical construction." *Physical Review A*, 45(6), 3403–3411.

Lafond, D., Corriveau, H., Hébert, R., and Prince, F. (2004). "Intrasession reliability of center of pressure measures of postural steadiness in healthy elderly people." *Archives of Physical Medicine and Rehabilitation*, 85(6), 896 – 901.

Leipholz, K. (1987). *Stability theory: An introduction to the stability of dynamic systems and rigid bodies*. Stuttgart/Chichester, England and New York, B. G. Teubner/John Wiley.

Lingard, H. (2002). "The effect of first aid training on Australian construction workers' occupational health and safety motivation and risk control behavior." *Journal of Safety Research*, 33(2), 209 – 230.

Lingard, H., and Rowlinson, S. (1997). "Behavior-based safety management in Hong Kong's construction industry." *Journal of Safety Research*, 28(4), 243 – 256.

Lipscomb, H. J., Dement, J. M., and Behlman, R. (2003). "Direct Costs and Patterns of Injuries Among Residential Carpenters, 1995–2000." *Journal of Occupational and Environmental Medicine*, 45(8).

Liu, J., and Lockhart, T. E. (2013). "Local Dynamic Stability Associated with Load Carrying." *Safety and Health at Work*, 4(1), 46 – 51.

Liu, J., Zhang, X., Lockhart, T. E., and Sternad, D. (2012). "Fall Risk Assessments Based on Postural and Dynamic Stability Using Inertial Measurement Unit." *Safety and Health at Work (SH@W)*, 3, 192–198.

Lord, S. R., and Menz, H. B. (2000). "Visual Contributions to Postural Stability in Older Adults." *Gerontology*, 46(6), 306–310.

Lord, S. R., Sherrington, C., Menz, H. B., and Close, J. C. (2007). *Falls in older people: risk factors and strategies for prevention*. Cambridge University Press.

MacCollum, D. V. (1995). *Construction Safety Planning*. John Wiley and Sons.

Manor, B., and Li, L. (2009). “Characteristics of functional gait among people with and without peripheral neuropathy.” *Gait Posture*, 30(2), 263–6.

Mayagoitia, R. E., Lötters, J. C., Veltink, P. H., and Hermens, H. (2002). “Standing balance evaluation using a triaxial accelerometer.” *Gait & Posture*, 16(1), 55 – 59.

McGraw, B., McClenaghan, B. A., Williams, H. G., Dickerson, J., and Ward, D. S. (2000). “Gait and postural stability in obese and nonobese prepubertal boys.” *Archives of Physical Medicine and Rehabilitation*, 81(4), 484 – 489.

Meerding, W. J., Mulder, S., and van Beeck, E. F. (2006). “Incidence and costs of injuries in The Netherlands.” *The European Journal of Public Health*, 16(3), 271–277.

Moraiti, C., Stergiou, N., Ristanis, S., and Georgoulis, A. (2007). “ACL deficiency affects stride-to-stride variability as measured using nonlinear methodology.” *Knee Surgery, Sports Traumatology, Arthroscopy*, 15(12), 1406–1413.

National Safety Council (NSC). (2013). “Injury Facts®, 2013 Edition”. Itasca, IL: Author. Library of Congress Catalog Card Number: 99-74142

Norris, J. A., Marsh, A. P., Smith, I. J., Kohut, R. I., and Miller, M. E. (2005). “Ability of static and statistical mechanics posturographic measures to distinguish between age and fall risk.” *Journal of Biomechanics*, 38(6), 1263 – 1272.

Occupational Safety & Health Administration (OSHA). (1999). “Safety and Health Regulations for Construction.” Code of Federal Regulations 29, section 500, 501, 502, and 503 of part 1926 (29 CFR1926.500, Office of the Federal Register, Washington, DC.<

https://www.osha.gov/pls/oshaweb/owasrch.search_form?p_doc_type=STANDARDS&p_toc_level=1&p_keyvalue=1926>

Önell, A. (2000). "The vertical ground reaction force for analysis of balance?" *Gait & Posture*, 12(1), 7 – 13.

Packard, N., Crutchfield, J., and Shaw, R. (1980). "Geometry from a Time-Series." *Phys Rev Lett*, 45, 712–6.

Parker, T. S., and Chua, L. O. (1990). *Practical numerical algorithms for chaotic systems*. Springer-Verlag, New York.

Park, M.-W., and Brilakis, I. (2012). "Construction worker detection in video frames for initializing vision trackers." *Automation in Construction*, 28, 15–25.

Peng, C.-K., Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., and Goldberger, A. L. (1993). "Long-range anticorrelations and non-Gaussian behavior of the heartbeat." *Phys. Rev. Lett.*, 70(9), 1343–1346.

Perell, K. L., Nelson, A., Goldman, R. L., Luther, S. L., Prieto-Lewis, N., and Rubenstein, L. Z. (2001). "Fall Risk Assessment Measures: An Analytic Review." *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(12), M761–M766.

Prieto, T. ., Myklebust, J. ., Hoffmann, R. ., Lovett, E. ., and Myklebust, B. . (1996). "Measures of postural steadiness: differences between healthy young and elderly adults." *Biomedical Engineering, IEEE Transactions on*, 43(9), 956–966.

Qi, J., Issa, R., Olbina, S., and Hinze, J. (2013). "Use of BIM in Design to Prevent Construction Worker Falls." *Journal of Computing in Civil Engineering*, 0(ja), null.

Qu, X. (2013). “Effects of cognitive and physical loads on local dynamic stability during gait.” *Applied Ergonomics*, 44(3), 455 – 458.

Ray, S. J., and Teizer, J. (2012). “Real-time construction worker posture analysis for ergonomics training.” *Advanced Engineering Informatics*, 26(2), 439–455.

Reeves, N. P., Narendra, K. S., and Cholewicki, J. (2007). “Spine stability: The six blind men and the elephant.” *Clinical Biomechanics*, 22(3), 266 – 274.

Rivara, F. P., and Thompson, D. C. (2000). “Prevention of falls in the construction industry: Evidence for program effectiveness.” *American Journal of Preventive Medicine*, 18(4, Supplement 1), 23 – 26.

Rosenstein, M. T., Collins, J. J., and Luca, C. J. D. (1993). “A practical method for calculating largest Lyapunov exponents from small data sets.” *Physica D: Nonlinear Phenomena*, 65(1–2), 117 – 134.

Roux, J.-C., Simoyi, R. H., and Swinney, H. L. (1983). “Observation of a strange attractor.” *Physica D: Nonlinear Phenomena*, 8(1), 257–266.

Seimetz, C., Tan, D., Katayama, R., and Lockhart, T. (2012). “A comparison between methods of measuring postrual stability: force plates versus accelerometers.” *Biomed Sci Instrum*, 48, 386–392.

Schiffbauer, W. H., and Mowrey, G. L. (2008). *An environmentally robust proximity warning system for surface and underground mining applications*. National Institute of Safety and Health, Pittsburg, PA.

Schooten, K. S. van, Rispens, S. M., Pijnappels, M., Daffertshofer, A., and Dieen, J. H. van. (2013). “Assessing gait stability: The influence of state space reconstruction on inter- and intra-day reliability of local dynamic stability during over-ground walking." *Journal of Biomechanics*, 46(1), 137 – 141.

Segal, A. D., Orendurff, M. S., Czerniecki, J. M., Shofer, J. B., and Klute, G. K. (2008). "Local dynamic stability in turning and straight-line gait." *Journal of Biomechanics*, 41(7), 1486 – 1493.

Shumway-Cook, A., Anson, D., and Haller, S. (1988). "Postural sway biofeedback: its effect on reestablishing stance stability in hemiplegic patients." *Archives of physical medicine and rehabilitation*, 69(6), 395—400.

Simeonov, P., Hsiao, H., Powers, J., Ammons, D., Kau, T., and Amendola, A. (2011). "Postural stability effects of random vibration at the feet of construction workers in simulated elevation." *Applied ergonomics*, 42(5), 672–681.

Soangra, R., and E Lockhart, T. (2013). "Comparison of intra-individual physiological sway complexity from force plate and inertial measurement unit." *Biomed Sci Instrum*, 49, 180–186.

Sokas, R., Emile, J., Nickels, L., Gao, W., and Gittleman, J. (2009). "An intervention effectiveness study of hazard awareness training in the construction building trades." *Public Health Reports*, 124, 161–168.

Sousa, V., Almeida, N. M., and Dias, L. A. (2014). "Risk-based management of occupational safety and health in the construction industry – Part 1: Background knowledge." *Safety Science,* 66(0), 75 – 86.

Strogatz SH. (1998). *Nonlinear dynamics and chaos.* Addison-Wesley Publishing Company, New York

Takens, F. (1981). “Detecting strange attractors in turbulence.” *Dynamical Systems and Turbulence, Warwick 1980*, Lecture Notes in Mathematics, D. Rand and L.-S. Young, eds., Springer Berlin Heidelberg, 366–381.

Tanaka, H., Nakashizuka, M., Uetake, T., and Itoh, T. (2000). “The effects of visual input on postural control mechanisms: an analysis of center-of-pressure trajectories using the auto-regressive model.” *Journal of human ergology*, 29, 15–25.

Teizer, J., Allread, B. S., Fullerton, C. E., and Hinze, J. (2010). “Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system.” *Automation in Construction*, 19(5), 630–640.

Teizer, J., Cheng, T., and Fang, Y. (2013). “Location tracking and data visualization technology to advance construction ironworkers’ education and training in safety and productivity.” *Automation in Construction*, 35, 53–68.

Teizer, J., and Vela, P. A. (2009). “Personnel tracking on construction sites using video cameras.” *Advanced Engineering Informatics*, 23(4), 452–462.

Toole, T. (2005). “Increasing Engineers’ Role in Construction Safety: Opportunities and Barriers.” *Journal of Professional Issues in Engineering Education and Practice*, 131(3), 199–207.

Tversky, A., and Kahneman, D. (1974). “Judgment under Uncertainty: Heuristics and Biases.” *Science*, 185(4157), 1124–1131.

Warren, W., Kay, B., Zosh, W., Duchon, A., and Sahuc, S. (2001). “Optic flow is used to control human walking.” *nature neuroscience*, 4(2), 213–6.

Weerasinghe, I., and Ruwanpura, J. (2010). “Automated Multiple Objects Tracking System (AMOTS).” *Construction Research Congress 2010*, American Society of Civil Engineers, 11–20.

West, B., and Scafetta, N. (2005). “A Multifractal Dynamical Model of Human Gait.” *Fractals in Biology and Medicine*, Mathematics and Biosciences in Interaction, G. Losa, D. Merlini, T. Nonnenmacher, and E. Weibel, eds., Birkhäuser Basel, 131–140.

Wilkins, J. R. (2011). “Construction workers’ perceptions of health and safety training programmes.” *Construction Management and Economics*, 29(10), 1017–1026.

Winter, D., Patla, A., and Frank, J. (1990). “Assessment of balance control in humans.” *Medical Progress through Technology*, 16, 31–51.

Wu, W., Yang, H., Chew, D. A. S., Yang, S., Gibb, A. G. F., and Li, Q. (2010). “Towards an autonomous real-time tracking system of near-miss accidents on construction sites.” *Automation in Construction*, 19(2), 134–141.

Yakhdani, H. R. F., Bafghi, H. A., Meijer, O. G., Bruijn, S. M., Dikkenberg, N. van den, Stibbe, A. B., Royen, B. J. van, and Dieën, J. H. van. (2010). “Stability and variability of knee kinematics during gait in knee osteoarthritis before and after replacement surgery.” *Clinical Biomechanics*, 25(3), 230 – 236.

Yung, P. (2009). “Institutional arrangements and construction safety in China: an empirical examination.” *Construction Management and Economics*, 27(5), 439–450.

Zhang, S., Teizer, J., Lee, J.-K., Eastman, C. M., and Venugopal, M. (2013). “Building Information Modeling (BIM) and Safety: Automatic Safety Checking of

Construction Models and Schedules." *Automation in Construction*, 29(0), 183 – 195.

Zhou, W., Whyte, J., and Sacks, R. (2012). "Construction safety and digital design: A review." *Automation in Construction*, 22(0), 102 – 111.