THESIS

A COMPARISON OF WEARABLE MEASUREMENT SYSTEMS FOR ESTIMATING TRUNK POSTURES IN MANUAL MATERIAL HANDLING

Submitted by

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ABSTRACT

A COMPARISON OF WEARABLE MEASUREMENT SYSTEMS FOR ESTIMATING TRUNK POSTURES IN MANUAL MATERIAL HANDLING

Epidemiologic studies have established that awkward trunk postures during manual materials handling are associated with an increased risk of developing occupational low back disorders. With recent advances in motion capture technology, emerging wearable measurement systems have been designed to quantify trunk postures for exposure assessments. Wearable measurement systems integrate portable microelectromechanical sensors, real-time processing algorithms, and large memory capacity to effectively quantify trunk postures. Wearable measurement systems have been available primarily as research tools, but are now quickly becoming accessible to health and safety professionals for industrial application. Although some of these systems can be highly complex and deter health and safety professionals from using them, other systems can serve as a simpler, more user-friendly alternative. These simple wearable measurement systems are designed to be less intricate, allowing health and safety professionals to be more willing to utilize them in occupational posture assessments. Unfortunately, concerns regarding the comparability and agreement between simple and complex wearable measurement systems for estimating trunk postures are yet to be fully addressed. Furthermore, application of wearable measurement systems has been affected by the lack of adaptability of sensor placement to work around obstructive equipment and bulky gear workers often wear on the job.

The aims of the present study were to 1) compare the Bioharness™ 3, a simple wearable measurement system, to Xsens™, a complex wearable measurement system, for estimating trunk postures during simulated manual material handling tasks and 2) to explore the

effects of Xsens sensor placement on assessing trunk postures. Thirty participants wore the two systems simultaneously during simulated tasks in the laboratory that involved reaching, lifting, lowering, and pushing a load for ten minutes.

Results indicated that the Bioharness 3 and Xsens systems are comparable for strictly estimating trunk postures that involved flexion and extension of 30° or less. Although limited to a short range of trunk postures, the Bioharness also exhibited moderate to strong agreement and correlations with the Xsens system for measuring key metrics commonly used in exposure assessments, including amplitude probability distribution functions and percent time spent in specific trunk posture categories or bins. The Bioharness appeared to be an a more intuitive alternative to the Xsens system for posture analysis, but industrial use of the device should be warranted in the context of the exposure assessment goals.

In addition, a single motion sensor from the Xsens system placed on the sternum yielded comparable and consistent estimates to a sensor secured on the sternum relative to a motion sensor on the sacrum. Estimates included descriptive measures of trunk flexion and extension and percent time spent in specific trunk posture categories. Using one motion sensor instead of two may serve as an alternative for sensor placement configuration in situations where worker portable equipment or personal preference prevents preferred sensor placement.

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INTRODUCTION

Background

For decades, low back disorders (LBDs) have been recognized as a major cause of injury and disability among many occupational populations (NRC, 2001; Marras et al., 2009). A low back disorder refers to an inflammatory and/or degenerative form of cumulative trauma that affects musculature, bones, tendons, ligaments, and other supporting structures of the back (OSHA, 2016a, NRC, 2001). According to the Bureau of Labor Statistics (LBS), the United States had an incidence rate of 17.3 per 10,000 full-time workers who experienced occupational back injuries in 2015 (BLS, 2016a). The trunk and back were the third most affected areas by injuries that caused workers to lose days away from work in 2015 (BLS, 2016b). Globally, it has been estimated that LBDs are responsible for causing over 800,000 disability-adjusted lost years annually (Punnett et al., 2005). Some of the most common LBDs include, but are not limited to, muscular strains and tears, herniated discs, and radiculopathy or sciatica (Andersson, 1997). Common signs include chronic pain, discomfort during activity or static postures, and loss of mobility (Cooper, 2015; OSHA, 2016b). Signs of LBDs may emerge periodically as result of cumulative trauma in the workplace and consequently lead to possible muscular failure and physical disability (Konz and Johnson, 2007). More than 22 million cases of low back pain lasting at least one week or more happen each year and result in about 150 million days away from work (Guo, Tanaka, Halperin, et al., 1999). On average, people with low back pain acquire health care expenditures about 60% higher than those without low back pain (Luo et al., 2004). Direct costs, including lost wages and medical treatment, from low back pain have been estimated to range between $12 billion and $90 billion each year in the United States (Dagenais, Caro, and Haldeman, 2008). The symptoms and prevalence of LBDs are consistently underreported in compensation data suggesting that cost could be higher than previously recorded (Wuellner, Adams, and Bonauto, 2016; Evanoff, Abedin, Grayson, et al., 2002). Low back disorders place a substantial physical and financial burden on workers, their families, and the rest of society.

A combination of physical risk factors has been identified to increase the probability of developing LBDs in occupational settings (da Costa and Vieira, 2010; Putz-Anderson and Bernard, 1997; Trask, et al., 2016; Wai et al., 2010; Bao et al., 2016; Waters et al., 2007). Physical factors such as forceful lifting, heavy physical work, whole body vibration, and static and dynamic awkward postures have been associated with increasing the risk of LBDs (Putz-Anderson and Bernard, 1997). A number of systematic reviews have suggested a causal relationship between LBDs and awkward postures, specifically postures of the trunk (Andersen, Haahr and Frost, 2007; Punnett and Wegman, 2004; Putz-Anderson and Bernard, 1997; Marras et al., 1995; da Costa and Vieira, 2010: Jonsson, 1988; Punnett et al., 1991). To meet job demands, workers often experience these types of trunk postures from lifting materials while stooped, twisting to reach tools, and holding static trunk positions (Dempsey, 1998; Ayoub and Mital, 1989). Certain tasks such as manual material handling (MMH) routinely demand workers to engage in movements that induce awkward trunk postures (Coenen et al., 2013; Putz-Anderson and Bernard, 1997; Marras; 2010). Manual material handling involves subtasks such as lifting, lowering, carrying, pushing, and pulling materials, products, and/or people (Dempsey, 1998). In 2007, the National Institute for Occupational Safety and Health (NIOSH) published the *Ergonomics Guidelines of Manual Material Handling* acknowledging that awkward trunk postures may lead to injury, wasted energy, and wasted time at work. In an attempt to improve work conditions, NIOSH has called for improved exposure assessment methods, emphasizing on the importance of effectively quantifying exposure to awkward postures in MMH tasks (CDIR, 2007).

Direct exposure methods have become common tools used in the quantitative analysis of trunk postures. Direct exposure methods focus on estimating the magnitude, duration, and frequency of trunk postures by focusing on the motions of the trunk (e.g. trunk flexion, rotation, lateral bending). Direct exposure methods have been popular because of their precision and accuracy but have been limited by being intrusive for workers, constrained to laboratory use, and costly for industrial application (Li and Buckle, 1999). In recent years, interest in wearable measurement systems for measuring human motion as an alternative to traditional direct exposure methods has increased significantly (Chaffin et al., 2017; Chan et al., 2012). Wearable measurement systems rely on miniature motion sensors to quantify body and segment acceleration, velocity, and orientation. As a result of recent technological advancements, wearable measurement systems have become more portable for field application, conformable to wear, and cheaper to manufacture than traditional methods (Chaffin et al., 2017).

Figure 1: Individual fitted with Xsens system.

Wearable measurement systems can be categorized into two groups: complex and simple wearable measurement systems. A *complex wearable measurement system* can be defined as a system that requires extensive preparation, intricate calibration and data processing procedures, and a certain degree of proficiency to operate and troubleshoot. One example is Xsens™ (Awinda, Xsens Technologies, NL), an inertial measurement system that uses inertial measurement unit (IMUs) sensors to estimate human motion, including motion of the trunk (Roetenberg, 2009). The Xsens system requires background knowledge of biomechanics, placement of multiple sensors on different anatomical landmarks, and knowledge of data management and data extraction (Figure 1). The Xsens system has been used primarily as a research tool in human motion studies, with a limited number of studies focusing on its effectiveness in industrial application (Cuesta-Vargas et al., 2010; Nahavandi et al., 2016; Vignais et al., 2013; Wang, Dai, and Ning, 2015; Colombo et al, 2012; Schmuntzsch, Yilmaz and Rotting, 2015; Ciuti et al., 2015). Complex systems such as Xsens are crucial in research application, but a high degree of sophistication may prevent occupational professionals from adapting them in field application.

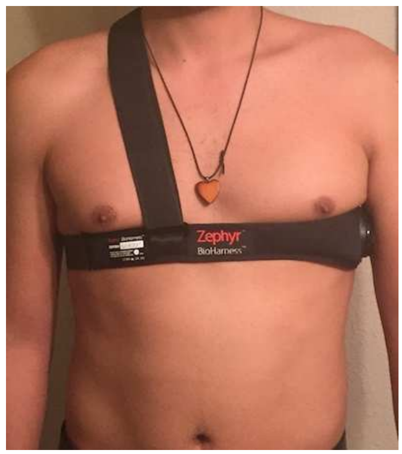

Figure 2: Individual wearing Bioharness 3.

In contrast to complex wearable measurement systems, simple wearable measurement systems allow users to measure trunk motion with more ease. A *simple wearable measurement system* can be defined as a system that requires minimal time to secure on users and short calibration and data processing procedures. One example is the Zephyr™ Bioharness 3 (Zephyr Technology Corporation, USA), a physiological monitoring system capable of quantifying trunk posture as well as heart rate and breathing rate (Zephyr Technology, 2012). The Bioharness 3 only relies on one sensor and data can be accessed without the need of intricate data extraction techniques (Figures 2). Although the Bioharness 3 has been used in field studies focusing on industries such as construction and firefighting, it is yet to be used consistently in evaluating trunk postures in industrial settings (Cheng et al., 2013; Migliaccio et al., 2012; Gatti et al., 2014;

Hernandez, Cowings, and Toscano, 2012; Różanowski et al., 2015; Miszuk, Hurt, and Rannam, 2015; Wang et al., 2015; Wang and Fu, 2016).

Another limitation of current wearable measurement systems is the lack of knowledge on of the effects of different sensor placement on estimating trunk postures. Studies have analyzed trunk postures using sensors located on the chest or sternum, the lumbar and thoracic regions of the back, shoulders, head, and side of the trunk (Fethke et al., 2011; Wong et al., 2009; Faber et al., 2009; Lee et al., 2017; Driel et al. 2012; Graham et al., 2009; Schall et al., 2015a; Yan et al., 2017). No consensus on ideal placement of sensors on different parts of the trunk has been established. With limited research focused on different methods for assessing trunk postures, further investigation continues to be in demand.

Scope of Study

The lack of understanding between simple and complex wearable measurement systems for trunk posture estimation is a primary concern in occupational health and safety (David, 2005; Chiasson, Imbeau, Aubry, and Delisle, 2012). The purpose of this study was to evaluate the comparability and agreement between the Bioharness 3, a simple wearable measurement system, and Xsens, a complex wearable measurement system, for estimating trunk postures during simulated MMH tasks. Specifically, the study focused on metrics of trunk posture that are commonly used in exposure assessments. The proposed research was necessary because comparative studies between commercially-available wearable measurement systems continue to be scarce. Information on occupational trunk postures derived from wearable measurement systems can be beneficial for characterizing work based on physical demands, assessing risk of low back injury, managing high-risk jobs, implementing protective interventions, and improving return-to-work strategies. By establishing a degree of comparability and agreement between the Bioharness and Xsens system, the Bioharness 3 can be considered an alternative to complex systems for posture analyses.

Furthermore, the study explored the effect of sensor placement for evaluating trunk postures using Xsens sensors. Determining potential similarities among motion sensors placed on different regions of the trunk can improve the adaptability of wearable measurement systems in the field. Having the ability to secure sensors on different parts of the trunk without significant effects on trunk posture estimates can help overcome challenges health and safety professionals often face. Challenges include obtrusive protective equipment preventing sensor placement, sensors being disturbed by thermal, electromagnetic, and mechanical forces, and worker anthropometrics preventing the identification of necessary body landmarks.

Aims of Study

1. Compare trunk posture estimates from the Bioharness 3, simple wearable measurement system, to estimates from Xsens, a complex wearable measurement system. The variables that were compared included: trunk flexion and extension in the sagittal plane, time spent in posture categories of trunk flexion and extension (<0°, 0°-30°, 30°-60°, and >60°), and number of times flexion thresholds were exceeded (above 30°and 60°).

    Objective 1.1: Evaluate any similarities between summary measures of trunk flexion and extension estimates from the Bioharness 3 and Xsens systems

    Objective 1.2: Evaluate agreement of trunk flexion and extension estimates from the Bioharness 3 and Xsens systems

    Objective 1.3: Evaluate potential agreement and correlations between the Bioharness 3 and Xsens for measuring key metrics used in exposure assessments

2. Evaluate the effect of different sensor placement on trunk posture estimates for wearable measurement systems. Variables compared included were the same as those presented in Aim 1.

Objective 2.1: Evaluate any similarities between summary measures of trunk flexion and extension estimates from Xsens sensors placed on the shoulder, sternum, and sacrum

Objective 2.2: Evaluate agreement of trunk flexion and extension estimates from Xsens sensors placed on the shoulder, sternum, and sacrum

Objective 2.3: Evaluate potential agreement and correlations among Xsens sensors placed on the shoulder, sternum, and sacrum for measuring key metrics used in exposure assessments

REVIEW OF LITERATURE

Awkward Trunk Postures

Trunk postures regarded as awkward or non-neutral have been defined as mild to extreme deviations from resting positions (Putz-Anderson and Bernard, 1997). Awkward trunk postures include motions such flexion and hyperextension or bending in the sagittal plane, twisting in the transverse plane, and lateral bending in the frontal plane. No consensus on the definition of awkward postures exists in the literature as it tends to be dependent on the context of the job tasks, the type of posture analysis, among other factors. Occupational awkward postures have been suggested to have potential effects on the musculoskeletal integrity of the back and trunk. When working in awkward trunk postures, spinal loading and intervertebral disc pressure increase, potentially resulting in impairment or injury due to overexertion (Jäger et al., 2000; Kumar, 2001; McGill, 1997). The effect of awkward trunk posture has been suggested to increase as the deviation of the trunk increases (Putz-Anderson and Bernard, 1997). In periods of prolonged awkward trunk postures, stress on the spine progressively increases joint hypermobility and reduces the safety margin of tissue strain (Adams et al., 1980). Sustained awkward trunk postures can also result in a reduction of blood supply to stabilizing musculature due to compressed capillaries and veins (Vieira and Kumar, 2004; Astrand et al., 2003). The supply of oxygen and other nutrients to back muscles becomes limited, allows waste products to build up, and leads to fatigue and discomfort (Garg, 1979). Highly repetitive postural changes have also been suggested to increase tissue fatigue and induce micro-strain on the low back (Dolan and Adams, 1998). When lifting or lowering loads, increasing the rate has been suggested to cause the activating muscle tissue to reach failure at the earlier periods of the task (Carter and Hayes, 1977). Experiencing increased spinal loading while in awkward postures is normal and part of daily living, but if necessary recovery is not met, the probability of experiencing muscular strain and injury increases (Brinckmann, Biggemann, and Hilweg, 1988).

Since LBDs can also be a result of social or personal factors, no consensus on the causal relationship between LBDs and awkward trunk postures exists, so further investigation on this matter still requires attention (Marras, 2000).

Specific thresholds or limits at which trunk postures become an occupational hazard continue to be undefined (Hoy et al., 2010). For instance, thresholds that separate mild, moderate, and extreme trunk postures have been inconsistent in the literature and more concrete standardization continues to be in need. Studies that use different thresholds to classify trunk postures make it difficult for cross-evaluations of their findings. In a systematic review, Wai et al. (2010) evaluated 35 studies where a variety of defined trunk posture categories were used to evaluate awkward trunk postures. Wai et al. (2010) concluded that most epidemiologic studies have used thresholds at 45° of trunk flexion or greater to define extreme trunk postures (Jansen et al.,2004; Hoogendoorn et al., 2002; Yip, 2004; Josephson et al., 1998; Tubach et al., 2002). Another review by Juul-Kristensesn et al. (2001) evaluated a series of posture assessment methods and also indicated that a threshold of 45° of trunk flexion has been one of the most repetitively used in observation-based methods. The National Institute of Occupational Safety and Health suggested that researchers should consider classifying trunk postures into four major categories based on increments of 30° (i.e. 0°-30°, 30°-60°, 60°-90°, and >90°) (NIOSH, 2014). Although this classification was largely designed to facilitate how assessors differentiate ranges of trunk flexion using observational methods, it can serve as the basis for standardizing how trunk postures are categorized for assessing risk. Studies such as Villumsen et al. (2015), Lee et al., (2017), and Coenen et al. (2014) have utilized this posture categorization system to determine the severity of awkward trunk postures. The classification of trunk postures is critical in exposure assessment studies and in the continuing effort to improve how awkward trunk postures are evaluated in the job.

Manual Material Handling

The presence of awkward trunk postures is common in jobs that require worker engagement in manual material handling (MMH), one of the most practiced intensive manual tasks across industries (Putz-Anderson and Bernard, 1997; Hoogendorn et al., 1999; Putz-Anderson and Bernard, 1997). In a longitudinal study at a large automotive company, Keyserling et al. (1992) assessed the exposure of assembly line workers to awkward trunk posture. Keyserling et al. (1992) indicated that mild trunk postures (>20° of flexion) were present in 89% of the jobs and severe trunk postures (>45° of flexion) accounted for 59% of the jobs. The mild and severe trunk postures were observed to be a result from workers reaching for parts inside bins or lifting and carrying objects from the ground to a higher level. Punnett et al. (1991) investigated the exposure to awkward postures of assembly line workers who were mostly responsible for MMH tasks. Of the 259 workers involved in MMH tasks, 84% were exposed to mild trunk postures (> 20° of flexion) and 51% were exposed to severe trunk postures (>45° of flexion). Workers in the sample reported to be mostly responsible for transporting and handling tools and small parts.

Workers who engage in MMH tasks have been suggested to be at a greater risk of injury than workers who do not handle materials as part of their job (Matsui et al., 1997; Putz-Anderson and Bernard, 1997; Snook, 1978; Bigos et al., 1986). There has been a series of epidemiologic studies that suggest a level of association between LBDs and MMH tasks (Teschke, 2009). In a cross-sectional study, Burdorf et al. (1991) investigated the effect of MMH tasks on the development of low back pain for concrete workers. After a 12-month follow up, Burdorf et al. (1991) determined that low back pain of concrete workers who were repetitively engaged in lifting with awkward postures was significantly more prevalent than low back pain of workers who did little lifting (OR 2.8, 95% CI 1.3–6.0). In a prospective cohort study, Anderson et al. (2007) looked at almost 4,000 service and industrial workers to explore possible associations between increased exposure to MMH tasks and severe pain. The MMH tasks studied included symmetrical and asymmetrical lifting (i.e. lifting in multiple planes of motion), pulling and pushing loads, squatting, standing, and repetitive movements. The results of this study indicated that highly repetitive MMH was significantly associated with low back pain (Hazard Ratios [HR],1.7, 95% CI 1.2–2.6). Lifting more than 100 kilograms (kg) per hour was also associated with increased low back pain (HR 1.5, 95% CI 1.0–2.3). Squatting was shown to be marginally associated with regional pain, not just pain of the low back (HR 1.5, 95% CI 1.0–2.1). In a prospective study by Tubach et al. (2002), researchers recruited about 2,000 workers in electrical and gas industry to investigate the prevalence of severe cases of low back pain and physical work load in MMH tasks. Severe cases of low back pain were defined as cases that required sick leave. Work load was defined as bending, twisting, and carrying loads. The results indicated that carrying loads over 10 kg (Relative risk [RR] 4.1, 95% CI 2.2–7.5) and bending repetitively (RR 8.2, 95% CI 3.7–17.9) everyday were strongly associated with sick days due to low back pain. Other studies have also shown associations between low back disorders (LBD) and trunk postures exceeding 20° and 45° of flexion in MMH (Josephson et al., 1998; Tubach et al., 2002; Jansen et al., 2004; Hoogendorn et al., 2002; Yip 2004). It is still difficult to establish a concrete dose-response relationship between LBD and MMH, however. This is mostly in part due to the multifactorial nature of LBDs (Marras, 2000; Christie et al.,1995). Awkward trunk postures adapted in MMH jobs have been a target of health and safety professionals who aim to recognize, quantify, and control their prevalence in occupational settings (Mital, 1997). To achieve that, professionals have relied on a number of exposure assessment methods over the years.

Types of Exposure Assessment Tools

The National Institute of Occupational Safety and Health (NIOSH) has acknowledged the importance of having highly tested exposure assessment methods and has consistently encouraged the improvement of existing and new methods (NIOSH, 2016). Exposure assessments allow researchers and other professionals to improve injury prevention strategies, physical demand programs, job classification systems, and control implementation systems (Burdorf et al., 1992; Li and Buckle, 1999; Tescke et al., 2009). Exposure assessment methods are separated into three major categories: self-report, observational, and direct. Due to the multifactorial nature of MSDs and LBDs, each type of method addresses a variety of factors and their use depends on the goals of the assessment, the access to resources, and limitations of the procedure (Li and Buckle, 1999; David, 2005). An appropriate exposure assessment method should be comprised of task distribution, occurrence of different tasks in the job, and affected body parts involved (Winkel and Mathiassen, 1994). A number of methods have been developed to assess the exposure to awkward postures, each possessing their respective advantages and disadvantages.

Self-reports

Self-reports, such as surveys and questionnaires, are designed to collect data on physical, psychosocial, and perceptual factors in the working environment. This is one of the oldest methods and heavily relies on written reports based on perceived sensation from participants and reported prevalence of certain activities (David, 2005; Spielholz et al., 2001). Posture-based reports typically identify discomfort and pain of a body part for a specific amount of time. These methods are adequate for large sample sizes, but they are expensive to administer and analyze and are significantly affected by participant recall and reporting bias (Burdoff, 1992; Viikari-Juntura, et al., 1996). Self-reports have limited reliability and precision for estimating exposure to awkward postures (Van der Beek and Frings-Dresen, 1998; Burdorf, 1995). They are also limited to qualitative classification of physical exposure (e.g., light, moderate, heavy loads). In addition, poor design of the surveys or questionnaire may yield difficulty for participants to read and interpret what is asked of them (Spielholz et al., 2001).

Observational Methods

Observational methods require raters to collect data by watching participants perform tasks. Data collection can be gathered through on-site assessments or using advanced tools (e.g. video, biomechanical models) aided by computer software (Chaffin, Anderson, and Martin, 1999; Li and Buckle, 1999; David, 2005). Although field methods are limited by observation time, video-based methods provide a more detailed and quantifiable source of exposure data for long durations of data collection (Spielholz et al., 2001). Some examples of observational methods include the NIOSH Lifting Equation, Oak Working Posture Analysis System, the Rapid Upper Limb Assessment, PLIBEL, and Rapid Entire Body Assessment, among others (Li and Buckle, 1995). Simple observational methods are less expensive and can be applied to a number of workspaces, but more advanced methods require highly skilled raters and expensive equipment (David, 2005). Observation methods that rely on video recording also are prone to not adequately representing the tasks at hand (Spielholz et al., 2001). This is due to limited recording of partial task cycles and behavioral effects yielding systematic bias. Other problems with these methods include high time consumption and insufficient reliability (Burdorf et al., 1992).

Direct Methods

Direct methods quantitatively measure a combination of kinematics or kinetics exerted on the human body and are often complemented with physiological estimates. In a systematic review of posture-based assessments, Li and Buckle (1999) described direct methods as sensing devices attached to the full body or specific limbs to quantify biomechanical response to physical work. Direct methods are effective in measuring all the elements that characterize work postures (i.e. intensity, frequency, duration) simultaneously in dynamic environments (Burdorf and Van der Beek, 1999, Burdorf, 1995; Winkel and Mathiassen, 1992). Motion-based direct methods are praised for their high degree of data resolution, precision, and accuracy. The first types of direct methods could only be used to evaluate static postures, making it difficult to analyze dynamic activities, such as lifting (Li and Buckle, 1999). In the past two decades, however, advancements in technology used in direct assessments has made it possible to evaluate job tasks in the field with little disruption and user-friendly systems (Burdorf and Van der Beek, 1999; David, 2005; Marras et al., 2010).

Some of the types of direct methods popular for exposure assessments include optoelectronic, goniometric/electrogoniometric, and electromagnetic systems, along with more modern accelerometry-based and inertial measurement systems (Li and Buckle, 1995; Garg and Kapellusch, 2009; Marras et al., 2010). Other tools include electromyography, physiological monitoring systems, and force plates/gauges (Konz and Johnson, 2007). Optoelectronic systems, such as Vicon (Vicon, Oxford, UK), use reflective markers appended to limb landmarks and high frame cameras to calculate and log continuous streams of kinematic data. Optoelectronic systems, however, are often limited by being restricted to laboratory conditions (Marras et al., 2010; Li and Buckle; 1999). Goniometric systems rely on goniometers to estimate the joint angle between two adjacent limbs or segments but, despite having well-established precision and accuracy, are sensitive to unstable environments and inconsistent in highly complex movements (e.g. shoulder) (Clarkson, 2000; Marras et al., 2010). Electromagnetic systems use magnetic fields to sense the positions and orientation of different receivers allowing estimated motion at six degrees of motion, unlike other simpler direct tools (Meskers et al., 1999; LaScalza, Arico, and Hughes, 2003). Electromagnetic systems allow for exposure estimates of complex tasks but often lack versatility when operating under highly magnetic environments (Li and Buckle, 1999). These systems have the ability to calculate exposure but are limited in field application due to restraining movement and workflow (Kim et al., 2012; Faber et al., 2008; Morlock et al., 2000). For the purpose of this thesis, accelerometry-based and inertial measurement systems methods will be explored at a greater depth.

Accelerometry Based Systems

Introduction

Quantification of occupational physical exposures typically focuses on the kinematics (e.g. acceleration, angular displacement) or the kinetics (e.g. ground forces, moments) placed on the body through interactions with the work environment. While kinetic measures are often acquired using biomechanical modeling or instruments such as force plates, kinematic measures can be obtained through the use of accelerometer-based systems. Accelerometer-based systems, often referred to as accelerometers, have been used to recognize and evaluate human activity/tasks, vibration, energy expenditure, and body and segment position and orientation (Zimmerman and Cook, 1997; Berquer, Smith and Davis, 2002; Bouten et al., 1997; Joshua and Varghese, 2010; Tulen et al., 1997; Walker et al., 1997; Ray and Teizer, 2012). Accelerometers are motion sensors that can measure the acceleration of moving objects, which can be used to estimate orientation with respect to a reference axis (e.g. horizontal, gravity). Acceleration is proportional to the force acting on the sensor and can be used to determine the magnitude and repetition of a movement (Yang and Hsu 2010). To measure acceleration changes, accelerometers rely on the shifts in movement of a seismic crystal or mass attached to a mechanical suspension system inside the sensor (Godfrey et al., 2008). The physical changes of the seismic mass are then transduced into electrical signals that can be interpreted as acceleration data (Yang and Hsu 2010). Through integration of acceleration, accelerometers can yield linear and angular velocity and position of a segment over time. Two of the most used types of accelerometers are piezoresistive and piezoelectric accelerometers (Fahrenberg et al., 1997; Godfrey et al., 2008). Piezoresistive accelerometers have a cantilever beam with a proof mass that, when moved, produces an electrical signal corresponding to the resulting changes in acceleration. In a piezoelectric accelerometer, the sensing component bends resulting in an electrical output that can be transduced into digital data (Fahrenberg et al., 1997). Recommendations on the most ideal locations of accelerometers include body segments that are least prone to artifact movement: the collarbone, the sides of ribcage, waist, thighs, shin, and top of the foot (Fahrenberg et al., 1997). However, placement depends on the part of the body that is being measured, with the trunk being the most commonly used for measuring full body movements and postures. No specific consensus on the optimal placement of sensors has been reached in the current literature.

Validity and reliability of postural measures

Segment orientation or inclination is a basic accelerometer metric based on the acceleration from body segments (e.g. head, arms, legs) and acceleration from gravity (Karantonis et al., 2006; Yang and Hsu, 2009). Although segment orientation can be estimated using a uniaxial accelerometer, this does not take into account acceleration on other planes of motion, failing to limit noise and represent orientation adequately (Fahrenberg et al., 1997; Juul-Kristensen et al., 2001). To close this gap, triaxial accelerometers have been developed to measure orientation around orthogonal axes (3 degrees of freedom) (Juul-Kristensen et al., 2001). To compliment this relatively new technology, a number of mathematical algorithms have been developed for estimation of static and dynamic trunk postures in clinical and ergonomic studies (Fisher, 2010; Jovanov et al., 2013; Wong and Wong, 2008; Wong and Wong, 2009; Amasay et al., 2009; Juul-Kristensen et al., 2001). Triaxial accelerometers have been validated as posture assessment tools in laboratory and field studies.

Amasay et al. (2009) used a triaxial accelerometer (Virtual Corset, Microstrain Inc., USA) to measure the orientation of objects during static conditions and orientation error during dynamic conditions. Static conditions were created by attaching the accelerometer to a vase and rotating it accordingly to desired rotation angles (10° to 360°, 10° increments). Dynamic conditions were created by attaching the accelerometer and potentiometer (reference sensor) to a pendulum that was released at different heights (0–10 cm, 2 cm increments; 10–25 cm in 5 cm increments) to simulate the movement of a body segment (e.g. shoulder) around a joint. Amasay et al. (2009) determined that the sensor accurately estimated orientation under static conditions (RMS angle error = <1°). Under dynamic conditions, the orientation error from the sensor was relatively low (RMSD = 3°).

Hansson et al. (2001) used triaxial accelerometers fixed to a head model (“jig”) as part of a posture analysis of static and non-static postures. Orientation was calculated from acceleration data using spherical coordinate transformations. Under static conditions at 0°, 30°, 60°, 90°, 120°, 150°, and 180° of sagittal tilting, results indicated that the sensors accurately calculated the orientation of the head model (angular error = 1.3°, angular noise = 0.04°). For non-static conditions, Hansson et al. (2001) concluded that although acceleration data was accurate, orientation data could not be interpreted from the acceleration data due to high angular error from inconstant speeds. Hansson et al. (2001) explained that higher angular errors occurred because of the sensitivity of accelerometers to radial and tangential accelerations. Since accelerometers use the line of gravity as the reference vector to estimate orientation, the presence of dynamic accelerations can cause the reference vector to deviate from the line of gravity (Hansson et al., 2001). The effect of inconstant speeds on orientation estimates from accelerometers has been explored in other studies.

In Korshøj et al. (2014), a triaxial accelerometer (ActiGraph GT3X+, ActiGraph, LLC, USA) was validated against a magnetic tracking device for estimating arm postures in simulated working tasks. Simulated working tasks included a 30-minute protocol of dynamic arm elevations at a fast (0.50 Hz), intermediate (0.25 Hz) and slow (0.125 Hz) pace. Low root-mean-square errors indicated accurate measures in slow and medium tasks (RMSE=2.2°-3.6°), but failed in fast paced tasks (RMSE=~10°).

In a comparative study, Lee et al. (2017) focused on using two commercially distributed accelerometers, the Bioharness 3 (Zephyr Technology Corporation, USA) and the ActiGraph GT9X Link (ActiGraph, LLC, USA), to analyze the effect of speed and sensor placement on trunk posture estimates. The sensors were placed on chest and under the armpit for the

Bioharness 3 and the head, shoulder, chest, side of waist, and lower back for the ActiGraph as the reference system. The systems measured trunk flexion at a “fast” (1.00 Hz); “medium” (0.67 Hz), and “low” (0.50 Hz) speeds during lifting tasks. The results indicated that the Bioharness 3 placed on the chest and under the armpit had an acceptable level of agreement for measuring trunk postures at slow speeds (0.5 Hz) for tasks that induced trunk flexion at 45° or less. Agreement was reported to be unacceptable between the systems for tasks that involved faster speeds and trunk flexion of 90°. Lee et. (2017) also presented metrics of time spent in certain posture categories but no further statistical analysis was performed with those metrics.

Although investigators have presented evidence to support the accuracy of accelerometers and comparability among different accelerometer types, research focusing on the reliability or agreement of accelerometers is still in need. There are also insufficient studies supporting the use of accelerometers to assess more dynamic, complex postures. No consensus on the specifications of accelerometer for postural analysis has been established so selection of sensor should continue to be a major of emphasis of studies testing the practicality and versatility of accelerometers (Trost et al., 2005).

Application

Accelerometers have been primary tools in measuring body motion as a way to evaluate exposure to occupational awkward postures in various industries. In Ribeiro et al. (2011), an accelerometer (Spineangel, Movement Metrics, NZ) was used to measure the exposure of health workers to trunk posture changes. Ribeiro et al. (2011) relied on an approach to examine a combination of three domains of cumulative exposure: magnitude, frequency and duration. The results indicated that the workers spent about 5.0% of their time in trunk flexion greater than 30°and 0.2% of the total time in trunk postures with greater than 60° of flexion. In addition, the number of times workers transitioned above specific thresholds (30°, 45°, and 60°) were the following: 30° of flexion was exceeded 1069 times per hour; 45°of flexion was exceeded 121 times per hour, and 60° of flexion was exceeded 8 times per hour. Ribeiro et al. (2011)

concluded that the Spineangle had an excellent within-day reliability for measuring postural changes for numerous workers (ICC=0.84), but made no final remarks on the potential effects the measured exposure had on the workers. Ettinger et al. (2013) assessed the exposure of dental hygienists to awkward upper extremity postures using accelerometers (Virtual Corset, Microstrain Inc., Williston, USA). Exposure to awkward postures during full workdays of workers was analyzed and was compared to office workers in the same company. The results suggested that the dental hygienists spent an average of 7% of their workday with arms above 60◦ of humeral elevation and 71% of their work time was spent in pseudo-static working postures. Ettinger et al. (2013) indicated that this type of research helps professionals take a step closer to better understanding association between working postures and upper extremity disorders. Hess et al. (2010) investigated exposure of masons to repetitive heavy lifting and buttering through the use of accelerometers attached to the upper arms (Virtual Corset, Microstrain Inc., Williston, USA). Physical exposure of 41 workers who handled two different types of concrete blocks was quantified to determine which concrete blocks imposed the greatest percent time spent in certain shoulder postures (above 30°, 60°, and 90° of elevation). Hess et al. (2010) successfully characterized the shoulder posture of workers in the specific job and concluded that there were no significant differences between the two types of blocks ($p>0.05$). Accelerometers have been popular to in posture-based exposure assessments for different body segments and have shown to be versatile in a number of industries.

Advantages and Disadvantages

Accelerometer-based systems exhibit their own advantages and disadvantages. Their application heavily depends on the purpose of the assessment, the work environment, the number of people being studied, and the duration of data collection (Li and Buckle, 1999). Body-mounted accelerometers exhibit versatility in field and lab application. They possess the ability to simultaneously measure full work days of multiple workers, have large memory logging capacity, and impose minimal interruption in workers' daily activities and duties (Li and Buckle, 1999). Accelerometers are capable of obtaining on-body recordings, measure motion with three degrees of freedom, and estimate body postures or orientation more accurately than traditional uniaxial sensing systems (Yang and Hsu, 2010). There has been a consistent flow of literature using accelerometers to investigate physical exposures in a number of industries, with the accelerometer being the primary sensor or a component of a larger system (Berquer, Smith, and Davis, 2002; Jorgensen and Viswanathan, 2005; Bernmark and Wiktorin, 2002; Grant, Johnson, and Galinsky, 1995). However, issues such as the failure to capture rapid and noncyclic movements limit the application of accelerometers in occupations that are fast paced and require complex movements (Hansson et al. 2001).

Inertial Measurement Systems

Introduction

Inertial measurement systems use a combination of sensors and complementary algorithms to record human motion. Although there a number of different models of commercially-available inertial measurement systems on the market, these systems are based on the same technology and principals for quantifying human motion, including segment orientation. The major physical component of inertial measurement systems is the inertial measurement unit. Inertial measurement units (IMU) are miniature and lightweight electronic devices that can estimate orientation or postures of body segments by combining the output from multiple microelectromechanical sensors. Microelectromechanical sensors (MEMS) for measuring human motion typically include accelerometers, gyroscopes, and magnetometers. Accelerometers measure proper and gravitational acceleration ($g=9.81\ m/s^2$) of body segments which can provide orientation data relative to a global reference system (Roetenberg et al., 2009). Accelerometers are not sensitive to changes in vertical rotation and are limited in measuring orientation during rapid movements (Giansanti, Maccioni, and Macellari, 2005). Gyroscopes measure angular velocity which can be integrated to estimate changes in orientation with respect to an initial orientation in the global reference system (Roetenberg et al., 2009). Gyroscopes can be subject to error from integration over time, making orientation estimates accurate for a limited time (Giansanti, Maccioni, and Macellari, 2005). Magnetometers can detect the direction of Earth's magnetic field (as a compass), estimate axial rotation, and give orientation information that can be used to reduce integration drift error (Roetenberg, Luinge, and Veltink, 2003). However, ferromagnetic materials, such as metal equipment, and other sources that emit magnetic fields can disrupt magnetometers, increasing the error in estimating orientations. To yield accurate estimates of orientation, IMUs combine the output from MEMS and utilize complimentary filtering methods to reduce the effect MEMS have separately (Roetenberg et al., 2009). Kalman filtering, for example, is a signal processing method that uses combined estimates from MEMS to keep orientation drift errors bounded (Kalman, 1960; Sabatini, 2006). Kalman filtering combines gyroscope, accelerometer, and magnetometer data with potential noise and weights the sources over time. Weighting the orientation data from the three sources with information based on their signal characteristics allows the IMU to determine the best use of the data from the MEMS under different conditions (Roetenberg, 2005). Kalman filtering provides a combined orientation estimate with a reduced integration drift error and robust to magnetic interferences, making inertial measurement systems a more preferred alternative to other motion based systems.

Validity and reliability of postural measures

The validity and reliability of inertial measurement systems needs to be investigated extensively to support its use in trunk posture analyses. Jasiewicz et al. (2007) investigated the accuracy and repeatability of an inertial measurement system (Inertial Cube 3, Intersense Inc., USA) for measuring neck flexion in the sagittal plane with an IMU placed over the location of seventh cervical vertebra (C7). By comparing the inertial measurement system to an electromagnetic motion system (3Space Fastrak, Polhemus, Colchester, USA) that has been considered to be a 'gold standard' for motion analysis, the study reported high cross-correlations (>0.97) and low root mean errors (RMSE) (rotation = 2.3 ± 0.9° flexion/extension =

2.1 ± 1.1°, lateral bending = 2.5 ± 0.9°). Results indicated that the inertial measurement exhibited a proper level of concurrent validity and high level of reliability and could be considered a proper motion assessment tool for this task.

Schepers et al. (2009) compared an inertial measurement system (Xsens Mtx with Xbus, Xsens Technologies, NL) to a validated optoelectronic system (Vicon, Oxford Metrics, UK) for measuring orientation of the trunk. Trunk orientation was derived from an IMU placed on the upper back at the level of the first thoracic vertebra. The RMSE reported for the rotation and flexion of the trunk were 4.3 ± 0.3° and 4.5 ± 0.7°, respectively. The study determined that inertial measurement system allowed accurate tracking of relative orientation of the human trunk.

Goodvin et al. (2006) verified the accuracy of an inertial measurement system (Xsens Awinda, Xsens Technologies, NL) by comparing it to an optical motion capturing system (Vicon 460, Vicon Motion Systems Inc., USA) for simple human motions (e.g. lifting, sitting, standing up). The orientations of the neck region between C1 and C7T1, the torso region between C7T1 and L4, and the lower back region between L4L5 and the sacrum were measured by both systems to model the motion of the spine. The results indicated low average deviations between the systems for all three regions: the neck region (roll = 0.1°, pitch = 0.42°, yaw = 0.2°), the torso region (roll = 0.03°, pitch = 0.06°, yaw= 0.23°) and the lower back region (roll = 3.1°, pitch = 0.33°, yaw = 1.35). Goodvin and Park (2006) conclude that the inertial measurement system could accurately measure spinal orientations in daily living consistently.

In Schall et al. (2016), the accuracy and repeatability of an inertial measurement system (I2 M Motion Tracking, Series SXT, NexGen Ergonomics, Inc., CAN) was tested against an optoelectronic system (Vicon T10S, Vicon Systems, USA) in laboratory and field–based settings over 8-hour periods. The study focused on tasks specific to dairy parlor work and evaluated the trunk and upper arm postures by looking at trunk angular displacement (i.e. flexion/extension, lateral bending) and upper arm elevation, respectively. Methods to estimate trunk angular displacement and upper arm elevation included the use of multiple IMUs placed on different landmarks (e.g. sternum, pelvis, upper arm) and multiple estimate configurations (accelerometer-only vs all IMU components) and complementary weighting algorithms. Results of the study indicated small sample-to-sample root mean square differences (RMSD) for the trunk (RMSD = 4.1°- 6.6°) and upper arm (RMSD = 7.2°-12.1°) between two systems in both the lab and field-based parts of the study. The mean angular displacement and angular displacement variation (10^{th}-90^{th} percentile difference) for the trunk and upper arm did not change for more than 4.5° in the laboratory portion and no more than 1.5° in the field portion. Schall et al. (2016) suggested that the inertial measurement system could serve as an accurate and stable tool for measuring trunk and upper arm postures for 8-hour data collection sessions.

In a related study, Schall et al. (2015a) investigated different methods for estimating trunk angular displacement using an inertial measurement system (I2M Motion Tracking System, SXT IMUs, Nexgen Ergonomics, Inc., CA) against the Lumbar Motion Monitor (Biomec Inc., OH), a previously validated field-based electrogoniometer for measuring spinal motion. The placement of IMUs and configurations for trunk angular displacement estimates followed similar methods and variables used in Schall et al., (2016), with the addition of axial rotation of the trunk. Participants in the study wore the systems simultaneously and engaged in controlled repetitive MMH tasks. Schall et al. (2015a) concluded that the trunk angular displacement estimates from an IMU on the sternum relative to the IMU on the pelvis had the smallest root-mean square differences estimates (6°-10°). The study also suggested that future investigators should consider the use of a two IMU (on sternum and sacrum), complementary weighting algorithm-based method to estimate trunk postures than just relying on individual inertial sensors.

In a study by Kim et al. (2012), an inertial measurement system (Xsens Awinda, Xsens Technologies, NL) and its built-in biomechanical model were evaluated for quantifying human movement during MMH tasks over prolonged duration. Participants in the study carried out simulated MMH tasks that included symmetrical lifting, lowering, pushing and carrying and asymmetrical lifting in a lab setting. Joint angles and velocities of the shoulder, hip, knee and the lumbosacral joint (L5S1) were measured by the inertial measurement system and compared to the measurements of a validated optoelectronic system (Vicon MX, Vicon Motion Systems Inc., USA). For joint angles, the study concluded that the measurements between the two systems were significantly different in performance. However, these differences did not increase over time suggesting that the inertial measurement system could yield stable estimates over long periods of time (mean error difference <3.7°). Additionally, the study suggested that the particular inertial measuring system estimated joint angles more accurately in dynamic tasks where movements were predominantly taking place in one plane of motion (e.g. symmetrical lifting) (mean difference error < 4.56°). The use of inertial measurement systems to accurately measure trunk postures in a laboratory setting has been supported, but more research is needed to test how these tools can be used in industrial settings.

Application

Inertial measurement systems have been used in a limited number of field-based studies. In Schall et al. (2015b), IMUs were used to assess physical activity, fatigue, and postures of the trunk and upper extremities of nurses. Trunk flexion and extension, trunk lateral bending, and arm elevation were measured using three IMUs. Exposure was described using selected percentiles from amplitude probability distribution functions and percent time in >45° of trunk flexion and >60° of elevated arms. The results revealed that nurses spent ~90% of their time in postures less than 45° of trunk flexion and left and right arms were elevated under 60° for ~95% of the work shifts. Although no high exposure to awkward postures was determined, the study successfully used IMUs to assess the physical exposure of the nurses. Inertial measurement systems are relatively new and their use as exposure assessment tools is minimal in the literature as of this point.

Advantages and Disadvantages

Inertial measurement systems have become more popular since these systems can overcome the challenges individual MEMS historically have had for quantifying complex movement for long durations (Roetenberg et al., 2009). Aside from their small size, wireless capabilities, and data logging capacity, inertial measurement systems can measure inclination and position of body segments relative to each other and to a global coordinate system, which can provide vital information when looking at worker-environment interaction. Inertial measurement systems have certain application limitations. With inertial measurement systems relying on magnetometers to produce measures, data is subject to be corrupted by prolonged interaction with environments that produce high levels of magnetic interference. The instability in highly magnetic environments limits the types of industries and durations inertial measurement system can operate in before ferromagnetic materials affect inertial data. Further field-based application of inertial measurement system continues to be necessary to better understand the conditions in which these systems can operate accurately and reliably. Due to the complex nature of certain inertial measurement systems, they are more commonly used in medical, exercise, and ergonomic research by trained professionals, making industrial application rare.

METHODS

Participants

A convenience sample of 30 healthy participants was recruited from Colorado State University. Participants were excluded if they were under 18 years of old age or reported experiencing musculoskeletal pain or injury during the time of data collection. No previous experience in MMH was required from participants. Participants filled out and signed forms of consent and photograph release prior to starting the study after having requirements expanded to them. All procedures in the study were reviewed and approved by the Colorado State University Institutional Review Board.

Simulated MMH tasks

Participants completed a MMH task in a laboratory setting. The MMH task required participants to continuously handle a 1.0 lb. (0.45 kg) cardboard box (length x width x depth = 15 in x 11 in x 2 in) on a table. A lightweight cardboard box was chosen to reduce the impact fatigue or physical strain could have on the well-being of participants. Data collection began with participants standing upright in a neutral position with arms to the side and feet parallel to one another. The cardboard box was placed within arm's each. The MMH task was designed to include the most common types of MMH motions (Ciriello et al. 1999). Participants were required to 1) reach with both hands and bring the box close to the body (A in Figure 3), 2) lower the box to ground level at participants' discretion without releasing the box (B in Figure 3), 3) lift the box back to the table (C in Figure 3), and 4) push the box across table with both hands (D in Figure 3) all in one continuous motion. Participants then returned to neutral position, indicating the completion of one MMH task cycle. Participants were given five to six seconds of active recovery in the form of walking between MMH task cycles. Participants were required to complete MMH task cycles for a total of ten minutes. The frequency of the task was self-paced with participants completing five to eight MMH task cycles per minute.

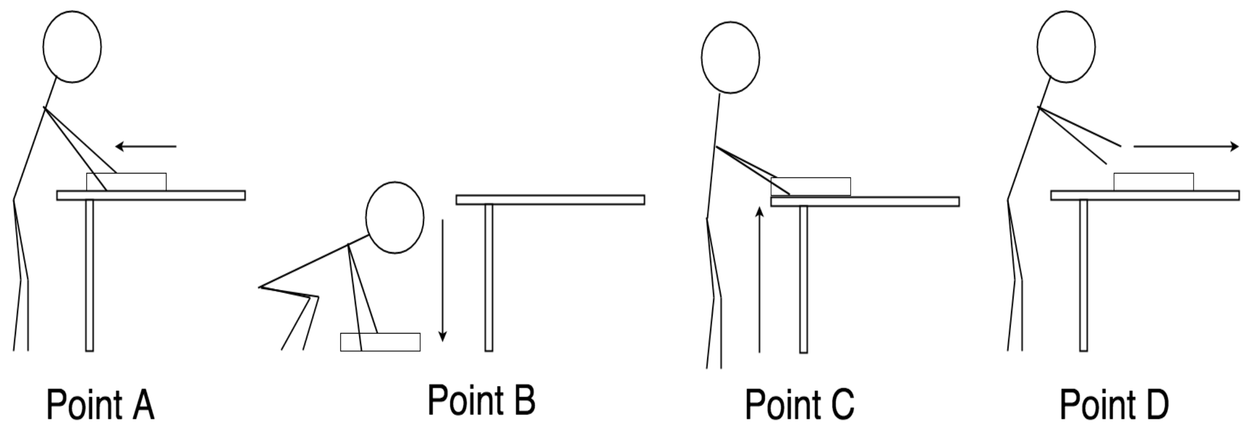

Figure 3: Sequence of motions in simulated MMH task.

Instrumentation

Bioharness 3

Each participant was fitted with a Zephyr™ Bioharness 3 (Zephyr Technology Corporation, USA), a physiological monitoring system designed to measure heart rate, breathing rate, activity, core temperature, and trunk postures (Zephyr Technology, 2012). The Bioharness 3 consists of a Velcro strap (18 g) and a detachable module (diameter x width = 1.1 in x 0,28 in, 71 g) shown in Figure 4 (Zephyr Technology, 2012). The module has an internal battery life for up to 26 hours for data logging per charge and a memory capacity of approximately 55 hours (Zephyr Technology, 2012). Two sizes of Velcro straps (small = 27-33 in, large = 33-41 in) were used to accommodate different participant trunk dimensions. An additional diagonal strap provided by the manufacturer was used to secure the Bioharness 3 in place to prevent movement due to rapid motions or sweat. The Bioharness 3 module was secured on each participant below the pectoral midline and aligned along the axillary midline and the xiphoid process of the sternum (1 in Figure 5). Placement of the Bioharness 3 was in accordance with manufacturer's recommendations and previous studies (Lee et al., 2017; Stenerson et al., 2014; Muaremi, et al., 2013; Jovanov et al., 2013; Milosevic et al., 2012).

Figure 4: Bioharness 3 module.

The Bioharness 3 has a piezoelectric accelerometer (triaxial, g's= ±16) that was used to estimate trunk posture in terms of trunk flexion and extension in the sagittal plane (Zephyr Technology, 2012). Raw acceleration output for the Bioharness 3 was reported in units of bits (1 g=83 bits). Acceleration data was recorded and downloaded through the manufacturer-supplied software (Omnisense™ Analysis, Zephyr Technology, USA). Acceleration was measured at a sampling rate of 100 Hz, low-pass filtered (zero-phase, 2^{nd} Order Butterworth, 3 Hz cut-off frequency) and resampled to 10 Hz using Matlab (R2016b, The MathWorks Inc., Natick, MA). Degrees of trunk flexion and extension in the sagittal plane were calculated as arctan(AccZ/AccX) X 180/π where AccZ was the acceleration in the sagittal plane and AccX was the acceleration in the vertical plane corresponding to the gravitational acceleration (Fisher, 2010). The Bioharness 3 does not have an initial calibration procedure so the present study developed a method to normalize the trunk flexion and extension estimates. Participants were asked to stand against a vertical surface in neutral position prior to calibration. Neutral position required participants to firmly press heels and trunk against a vertical surface. After turning on the Bioharness 3, participants were asked to stand still for 30 seconds. Average trunk flexion/extension was calculated from those initial 30 seconds and used to normalize participants' starting neutral position to zero degrees. The present study evaluated trunk flexion/extension estimates from the Bioharness 3 using two configurations: 1) non-normalized estimates (BH1) and 2) normalized estimates (BH2). Estimates from BH1 were included as it is how the manufacturer provides raw and summary data of trunk flexion/extension and they are likely the estimates professionals would commonly use. Despite showing high levels of reliability and accuracy in the lab and field settings, the lack of consistent research prevented Bioharness 3 from being considered a ‘gold-standard’ for trunk flexion/extension estimation (Gatti, Miglaccio, and Schneider, 2011; Johnstone et al., 2012a; Johnstone et al., 2012b; Johnstone et al., 2012c).

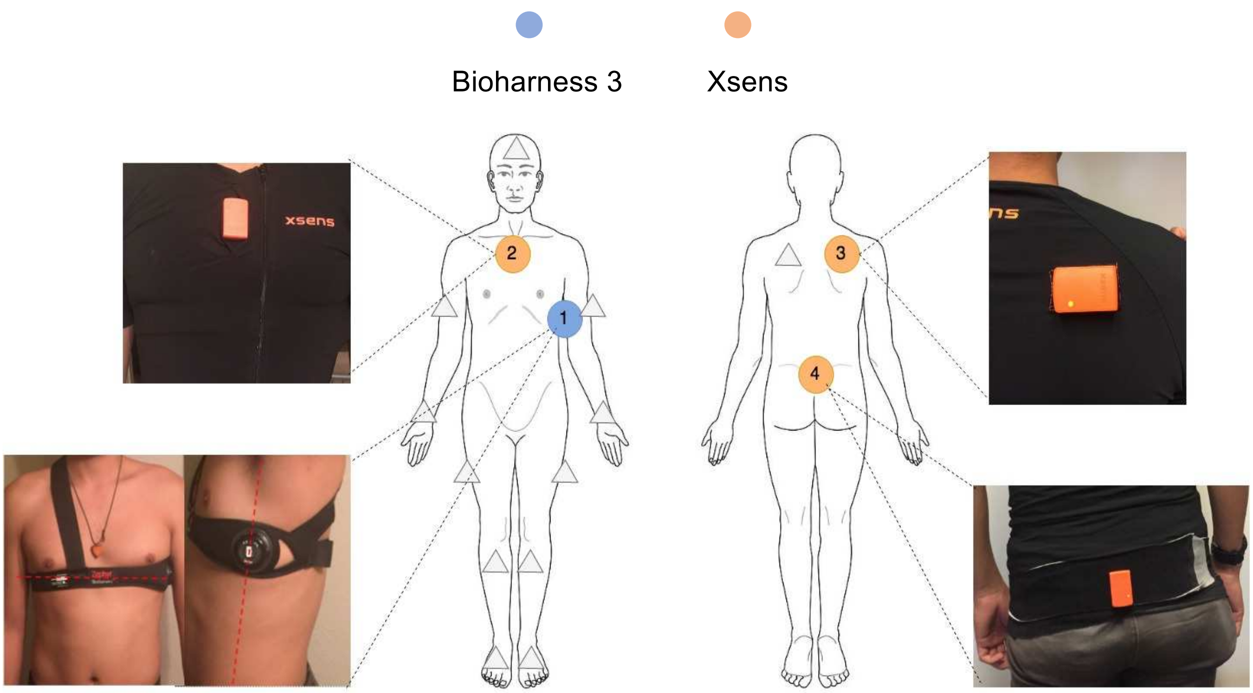

Figure 5: Sensor/module placement for 1) Bioharness 3 under left armpit, 2) Xsens sensor on sternum, 3) Xsens sensor on right shoulder, and 4) Xsens sensor on sacrum. Grey triangles mark Xsens sensors necessary for system operation but not used to calculate trunk posture estimates.

Xsens

Each participant was also fitted with Xsens™ (Xsens Technologies, NL), an inertial measurement system designed for full body and segment motion estimation. The system model used was the Xsens MVN BIOMECH Awinda which consisted of 17 inertial measurement units (IMUs) attached to body segments simultaneously using Velcro straps, a unisex spandex shirt, a headband, and two pairs of gloves (Xsens Technologies B.V., 2015). Each IMU (height x length x width= 55 mm x 40 mm x 10 mm, 16 g) contained a piezoelectric accelerometer (triaxial, ± 16 g), gyroscope (triaxial, ± 2000 deg/sec), magnetometer, and barometer and it is shown in Figure 6 (Xsens Technologies B.V., 2015). The Xsens system estimates velocity, acceleration, and position at a sampling rate of 60 Hz.

Each of the 17 IMUs were secured on the body following anatomical landmarks suggested by the manufacturer: the midfoot of left and right foot (feet), the medial surface of the right and left tibia (lower legs), lateral side above the right and left femur (upper legs), flat on the sacrum, flat on the sternum, left and right scapula (shoulders), lateral side of right and left humerus (upper arms), lateral side of right and left forearm (forearms), backside of the right and left hand (hands), and any side on the head (head) (Figure 5). The Velcro straps were used to secure the IMUs on the feet, lower legs, upper legs, sacrum, upper arms, and forearms. The spandex shirt was used to secure the IMUs on the shoulders and sternum. The headband was used to secure the sensor on the head. The gloves were used to secure the IMUs on the hands. The present study only focused on IMUs on the sternum (2 in Figure 5), right shoulder (3 in Figure 5), and sacrum (4 in Figure 5) but use of additional IMUs was mandatory to execute calibration, data collection, and data processing.

Figure 6: Inertial measurement unit (IMU).

The Xsens system provided trunk flexion and extension estimates in the sagittal plane based on IMU motion data, Kalman filtering (Xsens Kalman Filter for Human Movement, Xsens Technologies, NL), body dimensions for each participant, and a built-in biomechanical model.

Required body dimensions included body height (top of head to ground), wing span (right to left fingertip), foot length (heel to longest toe), ankle height (lateral malleolus to ground), shoulder width (right to left acromion process), hip height (grater trochanter to ground), knee height (lateral epicondyle to ground), and shoe sole height. Body dimensions were recorded and inputted into supplier-provided software (Xsens MVN Studio 4.0, Xsens Technologies, NL). The biomechanical model was based upon the segment axes definitions and origins recommended by the International Society of Biomechanics (Wu et al., 2005; Wu et al., 2002). The biomechanical model was built on a total of 23 body segments including the sacrum (pelvis), the fifth lumbar vertebra (L5), the third lumbar vertebra (L3), the twelfth thoracic vertebra (T12), eight thoracic vertebra (T8), and the right and left shoulders, upper arms, forearms, hands, upper legs, lower legs, feet and toes (Roetenberg, 2009). Although the T8 segment was labeled as such, its trunk motion estimates were derived from the IMU located on the *sternum* and not directly from the eighth thoracic vertebra (Xsens Technologies B.V., 2015). The T8 segment was referred to as sternum in the present study for simplification purposes. Trunk motion data was recorded in relation to a global reference system which the manufacturer defined as a right handed Cartesian co-ordinate system (Xsens Technologies B.V., 2015). Estimates of absolute trunk flexion and extension for the sternum, sacrum, and right shoulder segments were recorded in Euler angle form and were downloaded in quaternion form using Xsens MVN Studio 4.0 (Xsens Technologies, NL). Quaternion values were then resampled at 10 Hz and converted to rotation angles using Matlab (r2016b, The MathWorks Inc., Natick, MA).

Three configurations of trunk flexion and extension in the sagittal plane were used: 1) the sternum segment values relative to sacrum segment values (X-SST), 2) sternum segment values only (X-ST), and 3) right shoulder segment values only (X-SH). Using trunk flexion and extension estimates derived from IMUs on the right shoulder and sternum was in accordance with manufacture's requirements of sensor placement and with previous studies in the literature (Plamondon et al., 2007; Foerster, Smeja, and Fahrenberg, 1999; Manson et al., 2000; Lee et al., 2017; Fethke et al., 2011; Driel et al. 2012; Graham et al., 2009; Schall et al., 2015a; Yan et al., 2017). Using estimates from the sternum IMU relative to the sacrum IMU was used as the reference method in the present study because 1) it was a method recommended by the manufacturer and 2) it was similar to comparative studies that have shown this method to be comparable to gold-standard motion systems (i.e. optoelectronicsystems) for full body and trunk motions (Roetenberg, 2009; Salas, et al., 2016; Schepers et al., 2009; Schall et al., 2015a; Schall et al., 2015b; Schall et al., 2016; Plamondon et al., 2007; Robert-Lachaine et al., 2016; Wong and Wong, 2008; Van Driel et al., 2009; Bauer et a., 2015; Kim and Nussbaum, 2013; Godwin, Agnew, and Stevenson, 2009).

Calibration of the Xsens system involved participants assuming an “N-pose” where they stood in an upright position, feet parallel and 30.5 cm apart, arms extended alongside body (vertically), thumbs facing forward, and eyes facing forward. Calibration process was initiated using Xsens MVN Studio (Xsens Technologies, NL) and lasted approximately ten seconds. The software reported the quality of calibration as “good”, “acceptable”, “fair” and “poor”. Calibration quality of “acceptable” or “good” were considered adequate before proceeding with data collection as recommended by the manufacturer.

Statistical analysis

The first step was to create ensemble averages of trunk flexion/extension estimates for each participant using a custom signal processing tool developed in Matlab (r2016b, The MathWorks Inc., Natick, MA). The maximum peaks of trunk flexion in each MMH task cycle and the average time between peaks were detected. To capture all the motions in each MMH task cycle (i.e. reach, lower, lift, push), half of average time between peaks was used to extract the trunk motion estimates before and after the maximum peaks for each MMH cycle. All extracted MMH task cycles were aligned using the maximum peaks as the reference point to form ensemble averages for each measurement method (BH1, BH2, X-SST, X-ST, and X-SH) per participant. Trunk flexion was presented as positive values, and trunk extension as negative values. The arithmetic mean, peak flexion, peak extension were calculated for the ensemble averages of each measurement method. Additionally, the 10th percentile, 50th percentile, 90th percentile, 99th percentile, and variation of trunk flexion and extension (difference between 90th and 10th percentiles) of the amplitude probability distribution function were calculated (Jonsson, 1982). The 10th, 50th, and 90th percentiles, and variation of trunk flexion/extension are common metrics in exposure assessment studies (Schall et al., 2016; Schall et al.,2015a; Hansson et al., 2010; Lee et al., 2017; Kazmierczak et al. 2005; Hansson et al. 2010; Schall et al., 2015b; Salas, et al., 2016; Howarth et al., 2016). The 10th, 50th and 90th percentiles have been used to represent "static", "dynamic" (median), and "peak" trunk flexion and extension, respectively (Salas et al., 2016).

Sample-to-sample root mean square difference (RMDS) were also calculated for the ensemble average of each participant. The RMDS was calculated by using Equation (1) where θ'_i was the estimate from X-SST, θ_i was the estimate from an alternative method, n was the number of samples in the ensemble average, and *i* was the sample of interest.

$$RMSD = \sqrt{\sum_{i=1}^{n}(\theta_i - \theta'_i)^2 /n} \tag{1}$$

To evaluate agreement among measuremet methods, a Bland Altman analysis was used to calculate the mean difference (mean bias), upper limit of agreement (LOA_{upper}), and lower limit of agreement (LOA_{lower}) for the trunk flexion/extension of ensemble averages. The X-SST method was used as the reference method as previously discussed (Bland and Altman, 1986). Limits of agreement (LOA) were calculated using Equation (2), where $\bar{\mathrm{d}}$ was the mean difference and SD was the standard deviation of the trunk flexion/extension differences:

$$\mathrm{LOA} = \bar{\mathrm{d}} \pm 1.96(SD) \tag{2}$$

The range of acceptable limits of agreement continues to depend on interpretation by safety and health researchers and not on statistical evaluation (Bland and Altman, 1986). For the present study, the bigger absolute limit of agreement (upper or lower) was interpreted as followed: LOA<5° as optimal, LOA<10° as acceptable, and LOA>10° as not acceptable agreement (El-Zayat et al., 2013; Schiefer et al., 2014). Normality of the difference between methods was evaluated with a Shapiro–Wilk test and graphical evaluation (observed vs. predicted values).

Pearson correlation coefficients for the mean, 10^{th}, 50^{th}, and 90^{th} percentiles, and variation of trunk flexion/extension were calculated. Criteria used to evaluate the strength of linear relationship between metrics was the following: no linear relationship = 0, weak = 0.10 to 0.30, moderate = 0.30 to 0.50, and strong = 0.50 and higher (Taylor, 1990). Significance level was set at 0.05. Potential agreement for the mean, 10^{th}, 50^{th}, and 90^{th} percentiles, and variation of trunk flexion/extension estimates was evaluated using intraclass correlation coefficients (ICC). Estimates of ICC and their 95% confident intervals were based on a mean-rating (k = 5), absolute-agreement, two-way mixed-effects model. Agreement level was concluded using criteria by Lee et al. (1989) for the $95^{\%}$ confidence intervals of the ICC: ICC<0.50 as poor agreement, 0.50<ICC<0.75 as moderate agreement, and ICC>0.75 as strong agreement.

The second step was to measure participant's time spent in specific trunk posture categories. Percent time was calculated for the whole ten minutes of the simulated MMH task for each participant. The trunk categories were divided into four specific ranges based suggestions and use in previous research (Marklin and Cherney, 2005; Hoogendorn et al, 2000; Korshøj, et al., 2014; NIOSH, 2015; Villumsen et al., 2015; Coenen et al., 2014). The four categories were defined as trunk flexion and extension in the sagittal plane at <0° (Category 1), 0°-30° (Category 2), 31°-60° (Category 3), and >61° (Category 4) (Figure 7). Posture transition count were also calculated and were defined as the times of total instances participants exceeded thresholds of 30° (Transitions 1) and 60° (Transition 2) of trunk flexion in the sagittal plane (Figure 7). The use of transition count as a common metric in posture assessments is limited in the literature, but it can be beneficial when understanding the frequency of exposure to occupational awkward trunk postures (Ribeiro et al. 2011). Pearson correlation coefficients and intraclass correlation coefficients for the percent time in Category 1 to 4 and transition count for Transition 1 and 2 per measurement method were executed using the same specifications previously discussed. Data analysis procedures were conducted using SPSS (Version 21.0, IBM Corp., USA) and graphic procedures were conducted in Excel 2017 (Version 15.36, Microsoft, USA).

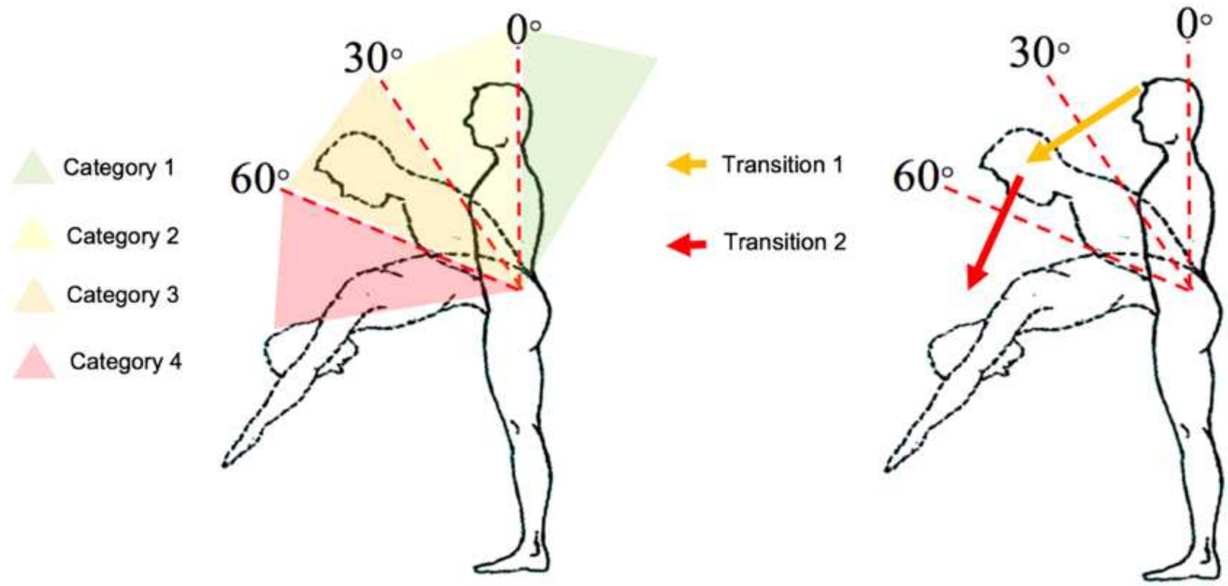

Figure 7: Posture categories and transitions of trunk flexion and extension in sagittal plane.

RESULTS

All participants were recruited from the Colorado State University in Fort Collins, Colorado, USA. Thirty-two healthy people initiated the simulated tasks but only thirty participated to completion due to lack of interest in the study. The participants (n=30) were 53% male and 47% female (mean age = 25 years, SD = 4.0; mean height = 452 cm, SD = 27.4 cm).

Estimates of trunk flexion and extension from the reference method, X-SST, and alternative measurement methods, BH1, BH2, X-ST, and X-SH were used to produce ensemble averages of trunk flexion and extension (Figure 8). The majority of ensemble averages of the participants had three primary peaks characterized by the reaching, pushing, and lowering/lifting motions, respectively, of the simulated MMH task. Ensemble averages typically ranged from approximately three to ten seconds in duration. The largest peak of trunk flexion consistently occurred though the lowering/lifting steps of the MMH task. Figures of ensemble averages for each participant are provided in the *Index*.

Trunk flexion and extension

Mean and standard deviation for the summary measures of the ensemble averages are provided on Table 1. Mean summary measures from BH1 and BH2 estimates had the largest differences when compared to reference method, X-SST. On average, BH1 summary measures were lower than summary measures from X-SST, with the exception of the 90th percentile which was comparable. Mean trunk flexion and extension, 10th percentile, 50th percentile, and peak extension estimates from BH2 were comparable to the estimates from X-SST, but peak flexion and the 90th percentile were notably higher for BH2.

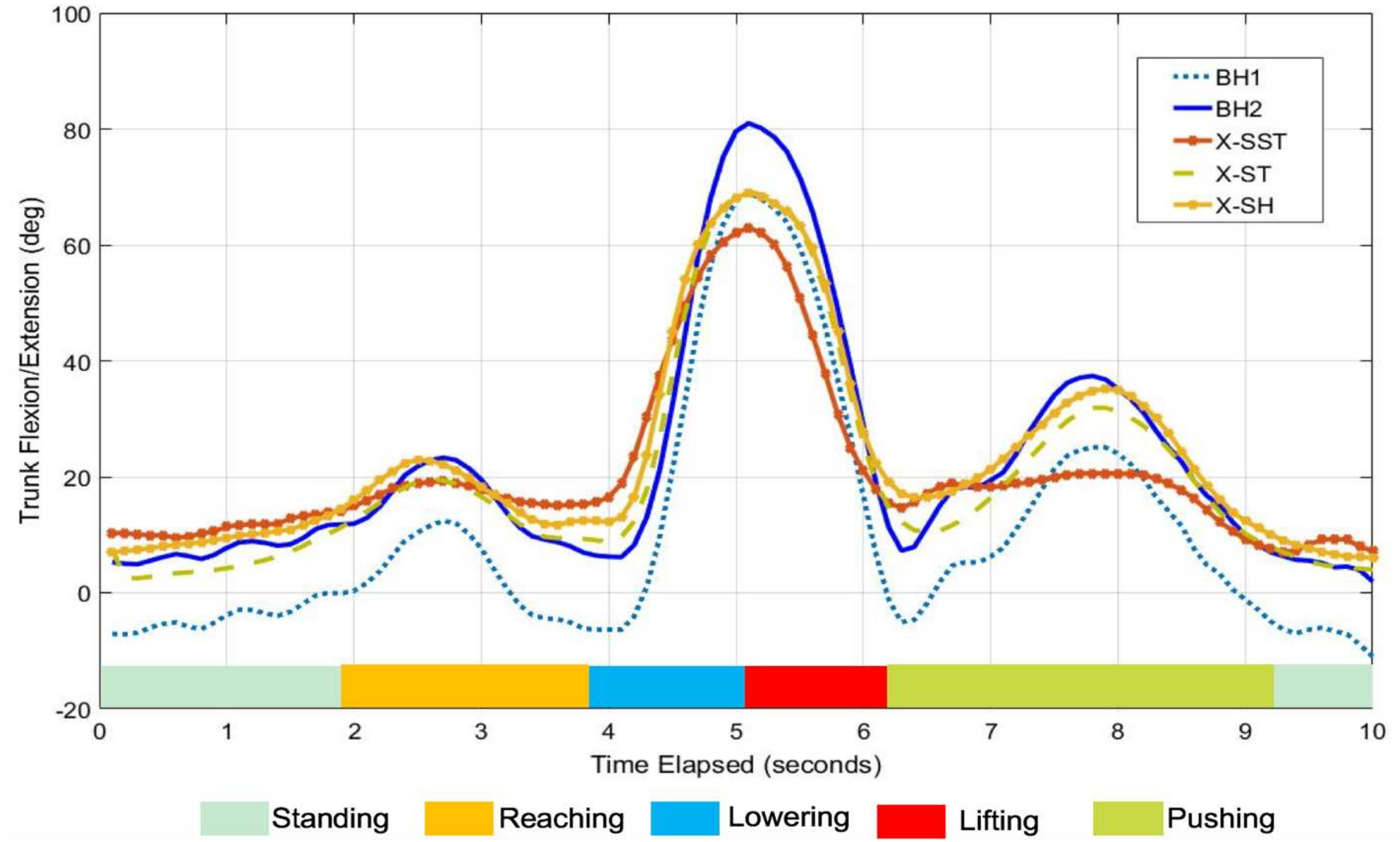

Figure 8: Example of ensemble average of trunk flexion and extension waveform in sagittal plane by measurement method for one participant.

Summary measures including the mean, peak flexion and extension, 10th percentile, 50th percentile, 90th percentile, and variation (90th-10th percentile) of trunk flexion estimates from X-SH were similar to summary measured from the reference system. Similarly, summary measures of X-ST were mostly comparable, but values for peak flexion and extension, and 90th percentile were higher than estimates from X-SST.

Pearson correlation coefficients, sample-to-sample root-mean square differences (RMSD), and Bland Altman analysis per measurement method are provided on Table 2. High correlation coefficients between the four alternative methods and the reference method (X-STT) were observed ($r>0.90$, $p<0.05$). Average RMSD estimates were observed to be the relatively large for the four measurement methods. Average RMSD estimates were largest for the BH1 and the lowest for X-ST. For measurements of ensemble average flexion and extension, Bland Altman analysis indicated a mean difference of 9.3° between BH1 and the reference method which was the highest among the measurement methods. The mean difference between BH2 and the reference method was 1.5° of flexion and extension. The 95% limits of agreement between BH1/BH2 and the reference methods ranged from 12° to 30° of flexion and extension. Bland Altman analysis also indicated small mean differences of about 1° and 95% limits of agreement ranging from approximately 13° to 15° of flexion and extension between X-ST/X-SH and the reference system.

Table 1: Mean (SD) of summary measures for trunk flexion/extension ensemble averages by measurement method*

Summary Measure	BH1	BH2	X-SST	X-ST	X-SH
Mean (°)	22.6 (12.5)	33.5 (11.9)	32.0 (9.3)	33.1 (9.9)	30.9 (9.6)
Peak flexion (°)	70.1 (13.6)	81.0 (14.6)	60.3 (7.8)	69.3 (7.7)	64.2 (9.3)
Peak extension (°)	-4.1 (9.5)	6.7 (8.5)	15.5 (9.0)	11.0 (9.0)	9.8 (9.1)
10th percentile (°)	-0.3 (10.0)	16.7 (8.9)	18.8 (8.6)	14.3 (9.0)	14.3 (9.3)
50th percentile (°)	15.7 (14.5)	26.4 (13.6)	27.7 (10.3)	27.6 (12.1)	26.0 (11.5)
90th percentile (°)	61.2 (16.2)	72.3 (16.6)	54.4 (9.8)	62.8 (9.2)	57.7 (9.6)
99th percentile (°)	69.9 (14.1)	80.8 (14.7)	60.2 (7.8)	69.2 (7.7)	64.1 (9.3)
Variation (90th-10th %)	61.6 (15.8)	61.7 (15.5)	35.6 (8.3)	48.6 (10.6)	43.4 (11.6)

*BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Table 2: Mean (SD) of Pearson correlation coefficient (r), sample-to-sample RMSD, and Bland Altman mean difference and 95% limits of agreement for trunk flexion/extension ensemble averages by measurement method***

Summary Measure	BH1	BH2	X-SST	X-ST	X-SH
Sample-to-sample RMSD** (°)	15.5 (4.6)	12.5 (4.9)	REF	8.6 (3.4)	9.9 (4.2)
Pearson correlation coefficient (r)*	0.94 (0.08)	0.95 (0.05)	REF	0.94 (0.06)	0.91 (0.08)
Mean Difference (°)	-9.3 (6.3)	1.5 (6.6)	REF	1.1 (5.1)	-1 .0 (7.6)
Upper Limit of Agreement (°)	12.0 (12.1)	22. 6 (13.1)	REF	15.2 (8.7)	13.0 (8.3)
Lower Limit of Agreement (°)	-30.7 (9.7)	-19.6 (9.0)	REF	-12.9 (7.0)	-15.1 (10.5)
Upper-Lower (°)	42.6 (18.0)	42.3 (18.2)	REF	28.0 (12.1)	28.1 (11.1)

REF= reference method
*Pearson correlation coefficients were statistically significant ($p<0.05$) unless noted otherwise
**RMSD=root-mean square difference
***BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Table 3: Pearson correlation coefficients (r)* for the mean, 10th percentile, 50th percentile, 90th percentile, and variation of trunk flexion/extension by measurement method**

Summary Measure	BH1	BH2	X-SST	X-ST	X-SH
Mean (r)	0.87	0.83	REF	0.86	0.68
10th percentile (r)	0.78	0.80	REF	0.86	0.57
50th percentile (r)	0.88	0.84	REF	0.88	0.65
90th percentile (r)	0.67	0.63	REF	0.54	0.55
Variation (90th-10th %) (r)	0.48	0.49	REF	0.56	0.50

REF= reference method
*Pearson correlation coefficients were statistically significant (p<0.05) unless noted otherwise (two-tailed)
**BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Pearson correlation coefficients for summary measures including the mean, 10th percentile, 50th percentile, 90th percentile, and variation of trunk flexion and extension per measurement method are provided on Table 3. Summary measures from BH1 and BH2 were observed to have moderate to strong correlation coefficients, ranging from 0.48 to 0.88. Similarly, X-ST and X-SH summary measures were observed to have strong correlation coefficients, ranging from 0.50 to 0.88.

The results of the intraclass correlation coefficients for X-SST and the alternate measurement methods are provided in Table 4. Intraclass correlation coefficients and 95% confidence intervals suggested that there was moderate to strong agreement between BH1 and BH2 against the reference method for estimating the 10th percentile, 50th percentile, 90th percentile, and variation of trunk flexion and extension. For X-SH and X-SH, moderate to strong agreement was only observed for the 10th and 50th percentile estimates.

Table 4: Intraclass correlation coefficients (ICC) and 95% confidence intervals for 10th, 50th, and 90th percentiles and variation of trunk flexion/extension estimates between reference* and alternative methods**

		95% Confidence Interval	
	Intraclass Correlation Coefficient (ICC)[b]	Lower Bound	Upper Bound
10th percentile			
BH1	0.87	0.72	0.93
BH2	0.88	0.76	0.94
X-ST	0.92	0.84	0.96
X-SH	0.93	0.85	0.96
50th percentile			
BH1	0.90	0.80	0.95
BH2	0.89	0.77	0.94
X-ST	0.92	0.84	0.96
X-SH	0.78	0.55	0.89
90th percentile			
BH1	0.74	0.53	0.87
BH2	0.71	0.51	0.86
X-ST	0.70	0.37	0.85
X-SH	0.71	0.39	0.86
Variation (90th-10th %)			
BH1	0.57	0.49	0.79
BH2	0.57	0.41	0.77
X-ST	0.70	0.37	0.85
X-SH	0.63	0.24	0.82

*Reference method =X-SST, alternative methods = BH1, BH2, X-ST, X-SH
b=ICC for average measures using a consistency definition, two way mixed models effect
**BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Percent time

Mean percent time spent in four trunk posture categories per measurement method for the total duration of the ten minute MMH task is presented in Figure 9. The participants on average spent approximately 60% of the time in Category 2 (0°-30°), about ~20% in Category 3 (30°-60°), and the rest of their time dispersed among Category 1 (<0°) and Category 4 (>60°). Summary measures and Pearson correlation coefficients of percent time in each category by measurement method are presented in Table 5. Mean percent time in for BH1 and BH2 was noticeably higher for Category 1 and Category 4 than the reference method, respectively. While BH1 percent time estimates in Category 2 were lower than the reference method, BH2 percent time estimates in that posture category were more comparable to the reference method. Percent time estimates for X-ST and X-SH were the most similar to estimates from the reference system. Moderate to strong correlation coefficients were observed between BH2 and the reference system for percent time in Category 2, Category 3 and Category 4. Strong correlation coefficients were also observed between X-ST and the reference method across all four posture categories.

Intraclass correlation coefficients and 95% confidence intervals of the percent time spent in each posture category are provided on Table 6. Percent time estimates in Category 1 to 3 from BH2 were observed to be moderately consistent with estimates from the reference method. Estimates from BH2 were also reported to be higher than estimates from BH1. High intraclass correlation coefficients of X-ST also indicated moderate agreement with the reference method through all four posture categories. Percent time estimates from X-SH were a relatively more inconsistent with only moderate agreement shown in Category 2 and 4.

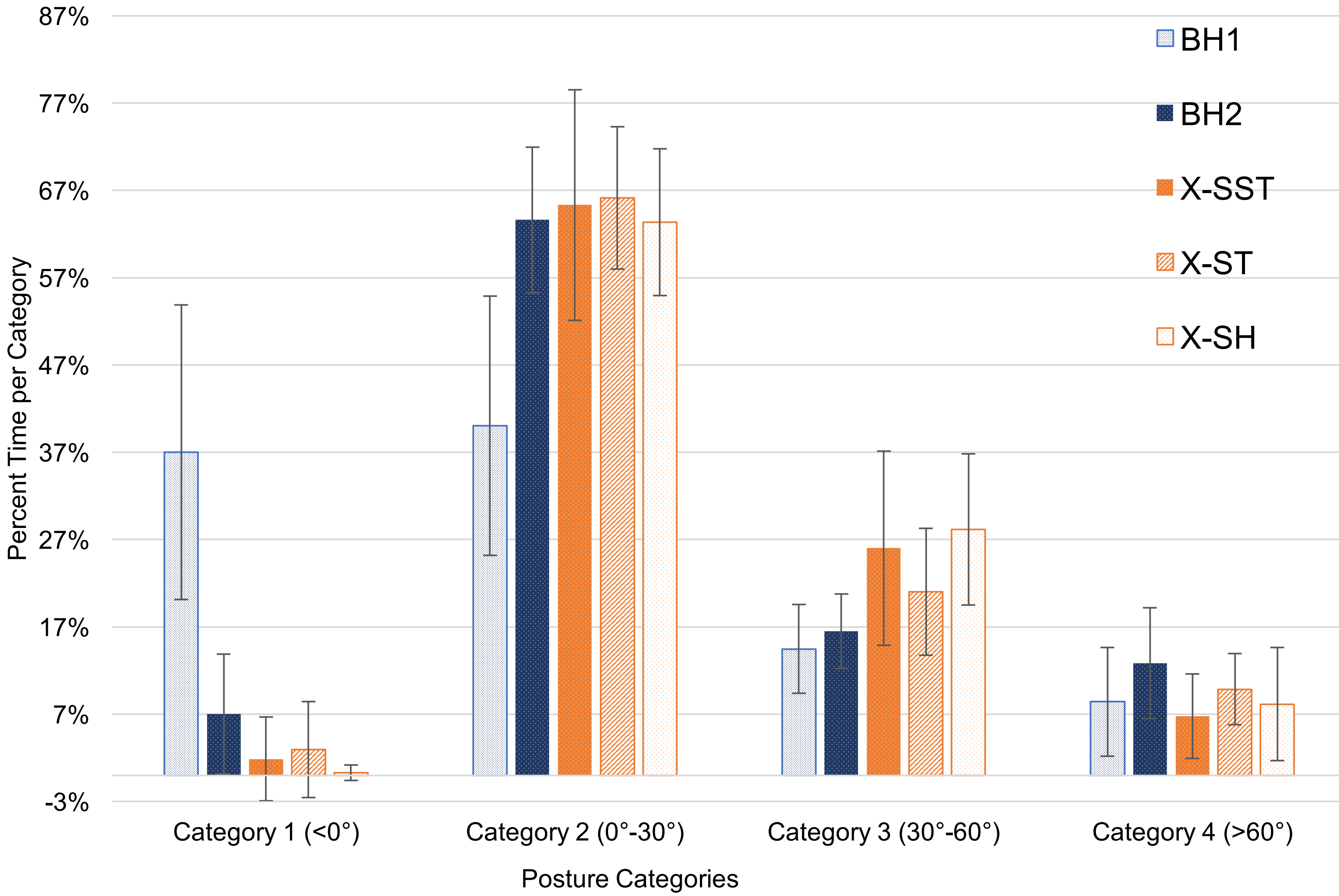

Figure 9: Mean percent time (±SD) in Category 1 to 4 for each measurement method

Table 5: Summary measures of percent time in Category 1 to 4* per measurement method***

Summary measure	BH1	BH2	X-SST	X-ST	X-SH
Category 1					
Minimum (%)	4.0	0.1	0.0	0.0	0.0
Maximum (%)	66.0	32.1	19.6	21.1	4.6
Mean (%)	37.0	7.0	1.9	3.0	0.3
Standard Deviation (%)	16.9	6.9	4.8	5.5	0.9
Pearson correlation coefficient (r)**	0.21	0.14	REF	0.57	-0.11
Category 2					
Minimum (%)	16.0	45.3	30.7	44.4	43.8
Maximum (%)	74.0	77.0	83.8	79.1	78.6
Mean (%)	40.1	63.6	65.3	66.1	63.4
Standard Deviation (%)	14.9	8.3	13.2	8.1	8.4
Pearson correlation coefficient (r)**	0.00	0.37	REF	0.60	0.60
Category 3					
Minimum (%)	6.0	8.5	11.4	7.0	9.2
Maximum (%)	22.0	24.1	56.0	42.0	43.9
Mean (%)	14.5	16.5	26.0	21.0	28.2
Standard Deviation (%)	5.1	4.3	11.1	7.3	8.6
Pearson correlation coefficient (r)**	0.57	0.50	REF	0.58	0.47
Category 4					
Minimum (%)	0.0	1.2	0.0	0.2	0.0
Maximum (%)	31.0	35.2	16.8	18.4	21.8
Mean (%)	8.4	12.9	6.8	9.9	8.2
Standard Deviation (%)	6.2	6.4	4.9	4.0	6.5
Pearson correlation coefficient (r)**	0.46	0.60	REF	0.50	0.51

* Percent time in Category 1 (>0°), Category 2 (0°-30°), Category 3 (30°-60°), and Category 4 (≥60°) trunk flexion/extension in sagittal plane

**Pearson correlation coefficients were statistically significant ($p<0.05$) unless noted otherwise

***BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Table 6: Intraclass correlation coefficients (ICC) and 95% confidence intervals for percent time estimates in Category 1 to 4 between reference* and alternative methods**

		95% Confidence Interval	
	Intraclass Correlation Coefficient (ICC)[b]	Lower Bound	Upper Bound
Category 1			
BH1	0.20	-0.69	0.62
BH2	0.23	-0.62	0.63
X-ST	0.72	0.51	0.87
X-SH	0.38	-1.27	0.49
Category 2			
BH1	0.00	-1.10	0.52
BH2	0.59	0.52	0.68
X-ST	0.70	0.52	0.86
X-SH	0.71	0.59	0.86
Category 3			
BH1	0.60	0.47	0.81
BH2	0.61	0.48	0.76
X-ST	0.69	0.46	0.86
X-SH	0.63	0.52	0.82
Category 4			
BH1	0.72	0.59	0.82
BH2	0.73	0.62	0.87
X-ST	0.66	0.58	0.74
X-SH	0.65	0.57	0.74

b=ICC for average measures using a consistency definition, two way mixed models effect
*Reference method =X-SST, alternative methods = BH1, BH2, X-ST, X-SH
**BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Transitions

The mean number or count of posture transitions estimated per measurement method for Transition 1 (exceed 30° of flexion) and Transition 2 (exceeded 60° of flexion) are shown in Figure 10. On average, subjects exceeded 30° of flexion at least 100 times, and in some cases some measurement methods estimated up to 200 times. Although measurement methods reported highly variable values, participants were observed to exceed 60° of flexion approximately 50 times. Summary measures and Pearson correlation coefficients for the posture transition times for Transition 1 and Transition 2 per measurement method are provided in Table 6. On average, BH1, BH2, X-ST, and X-SH estimated less posture transitions than the reference method for Transition 1 but more posture transitions for Transition 2. The BH2 method estimated posture transitions almost twice as much as the reference method for Transition 2. The BH2 and X-ST methods showed to have moderate to strong linear relationships when compared to the reference method for both Transition 1 and 2 (Table 7). There were moderate correlations coefficients between the reference method and BH1 and X-SH for Transition 1 only.

Intraclass correlation coefficients for the transition count estimates in Transition 1 and Transition 2 per measurement method are provided on Table 8. Low intraclass correlation coefficients for Transition 1 and 2 suggested poor agreement among all four measurement methods. Estimates from X-ST showed the highest intraclass correlation coefficients and narrowest confidence intervals.

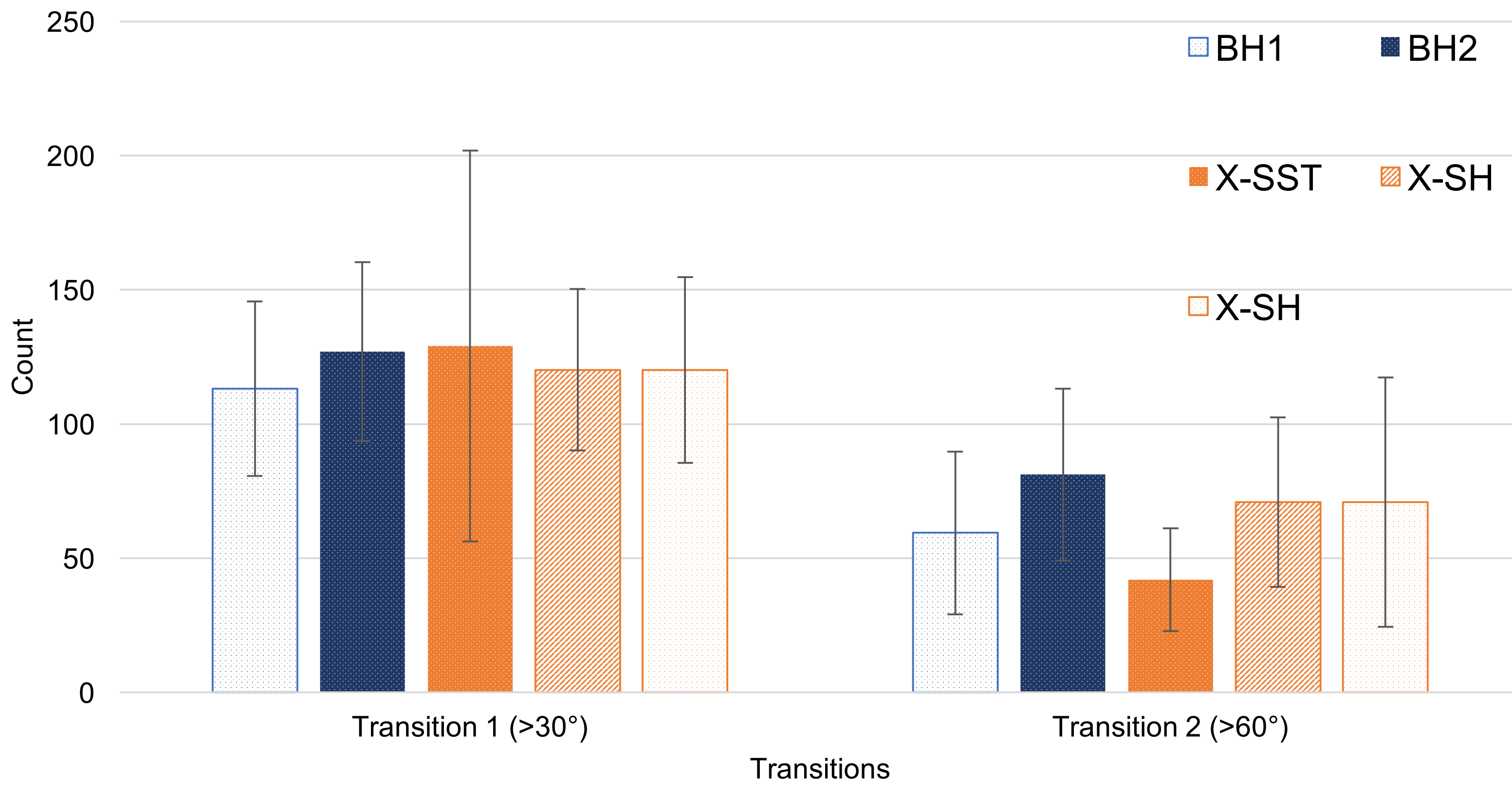

Figure 10: Average transition times (±SD) by measurement method.

Table 7: Summary measures of Transition 1 and 2* by measurement method***

Summary measure	BH1	BH2	X-SST	X-ST	X-SH
Transition 1					
Minimum	58	63	52	59	55
Maximum	185	185	364	163	209
Mean	113.1	126.9	129.0	108.0	120.2
Std. Deviation	32.0	32.8	72.7	29.6	34.4
Pearson correlation coefficient (r)**	0.40	0.51	REF	0.37	0.39
Transition 2					
Minimum	5	21	0	6	3
Maximum	143	152	73	151	166
Mean	59.4	81.2	42.0	68.1	70.9
Std. Deviation	29.7	31.8	20.3	31.1	47.2
Pearson correlation coefficient (r)**	0.01	0.42	REF	0.54	0.19

*Transition 1 = exceeds 30°, Transition 2 = exceeds 60°

**Pearson correlation coefficients were statistically significant ($p<0.05$) unless noted otherwise

***BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

Table 8: Intraclass correlation coefficients (ICC) and 95% confidence intervals for transition count estimates in Transition 1 and 2 between reference* and alternative methods**

		95% Confidence Interval	
	Intraclass Correlation Coefficient (ICC)[b]	Lower Bound	Upper Bound
Transition 1			
BH1	0.46	-0.14	0.74
BH2	0.45	-0.15	0.74
X-ST	0.52	0.00	0.77
X-SH	0.44	-0.17	0.74
Transition 2			
BH1	0.02	-1.07	0.53
BH2	0.30	-0.47	0.67
X-ST	0.56	0.07	0.79
X-SH	0.56	0.08	0.79

b=ICC for average measures using a consistency definition, two way mixed models effect
Reference method =X-SST, alternative methods = BH1, BH2, X-ST, X-SH
**BH1= non-normalized estimates from Bioharness 3, BH2= normalized estimates from Bioharness3, X-SST= IMU on sternum relative to IMU on sacrum, X-ST=estimates from Xsens IMU on sternum, X-SH=estimates from Xsens IMU on right shoulder.

DISCUSSION

Simple vs Complex Measurement Systems

The present study compared the trunk posture estimates of the Bioharness 3 as represented by non-normalized (BH1) and normalized (BH2) values with the Xsens system as represented by values from an IMU on sternum relative to IMU on the sacrum (X-SST). The study specifically focused on trunk flexion/extension in the sagittal plane, percent time in four trunk posture categories, and number of times specific flexion thresholds were exceeded. The study aimed to determine of the Bioharness 3 could serve as an alternative to the Xsens system for estimating exposure to awkward trunk postures.

Trunk flexion and extension

Summary measures of trunk flexion and extension between normalized Bioharness 3 data and the Xsens data derived from sacrum and sternum sensors were comparable primarily when participants remained in postures of approximately 30° of flexion or less. The estimates of mean trunk flexion and extension, 10th percentile, and 50th percentile were relatively similar for these two systems, with differences of less than ~2° (Table 1). During greater trunk flexion as indicated by the 90th percentile, the Bioharness overestimated trunk flexion as much as 5° to 18° compared to the Xsens system. Due to the novelty of the present study to compare commercially-available wearable measurement systems, there is a lack of research work that can be directly compared to the results presented in the study. Although not directly comparable, the results from the present study are similar to the findings from previous work comparing IMUs to an electrogoinometry system by Schall et al. (2015a). Schall et al. (2015a) compared IMUs with different placement configurations to a validated field-based electrogoinometry system, the Lumbar Motion Monitor, for measuring trunk flexion and extension in simulated MMH tasks. Two of these configurations included accelerometry-based estimates from an IMU on the chest, and complementary weighting algorithm-based estimates from an IMU (accelerometer + gyroscope) on the chest relative to an IMU (accelerometer + gyroscope) on the sacrum, which were similar to the methods used in the present study. Schall et al. (2015a) reported comparable mean trunk flexion and extension and 10th percentile estimates between the two IMU configurations. In a similar study, Schall et al., (2016) used the same IMU configurations from Schall et al., (2015a) to compare the IMUs with a highly validated optoelectronic system for field and laboratory-based tasks. Schall et al. (2016) indicated that summary measures, including the mean, 10th percentile, and 50th percentile of trunk angular displacement, were comparable between the two IMU configurations. Reported differences between summary measures from the two IMU configurations were less than ~3° in both Schall et al. (2016) and Schall et al. (2015a). Both Schall et al. (2015a) and Schall et al. (2016) also reported discrepancies between the 90th percentiles from the accelerometry-based IMU on the chest and the complementary weighting algorithm-based IMU on the chest relative to the IMU on the sacrum. These differences ranged between 7° and 14° of trunk flexion.

The differences between the Bioharness 3 and Xsens for quantifying higher ranges of trunk flexion (>30° of flexion) are consistent with results from Lee et al. (2017) who compared the Bioharness 3 to other motion sensors. Lee et al. (2017) compared trunk flexion and extension estimates between Bioharness 3 and a chest-mounted accelerometer lifting tasks at selected speeds. The results from Lee et al., (2017) indicated that, when participants were asked to bend to a fixed flexion point of 90°, the differences between the two systems for the 90th percentile estimates were ~10° of trunk flexion for slow speeds (30 bends per minute) and ~13° for faster speeds (60 bends per minute). The results from Lee et al. (2017) should be interpreted in the context of certain differences to the present study. In addition to having a small sample size (n=1), the motion sensors used were not IMUs and they have not been previously validated in posture analysis studies.

Practical measures in exposure assessments

The Bioharness 3 showed to estimate key summary measures commonly used in physical measurement assessments consistently to the Xsens system. Moderate to strong correlation coefficients between the Bioharness and Xsens systems for estimating the 10th, 50th, 90th percentile, and variation of trunk flexion and extension (90th-10th percentiles) were observed (Table 3). Additionally, acceptable agreement based on the intraclass correlation coefficients and 95% confidence internals was established between the Xsens and Bioharness 3 systems for quantifying the 10th, 50th, and 90th percentile of trunk flexion and extension (Table 4). First introduced in Jonsson (1978) for exposure assessments using electromyography, percentiles of exposure from amplitude probability distribution functions have been used extensively as descriptive metrics in occupational studies of biomechanical exposures. Previous literature has shown the use of these descriptive metrics for characterizing jobs and tasks, evaluating effectiveness of interventions, assessing associations between body movements and injury/pain, and comparing exposure assessment tools (Wahlström et al., 2010: Hansson et al., 2010; Kazmierczak et al. 2005; Schall et al., 2015b; Salas, et al., 2016; Howarth et al., 2016; Vasseljen and Westgaard, 1997; Bao, Mathiassen, and Winkel, 1996; Balogh et al., 2006; Unge et al., 2007; Forsman et al., 2002; Jonker, Rolander, and Balogh, 2009; Åkesson et al., 1997).

Another key metric commonly used in exposure assessments is time in specific posture categories. In the present study, estimates of percent time showed acceptable agreement between the Bioharness and Xsens. Moderate to strong correlations between the two methods for estimating percent time in Category 2 (0°-30°), Category 3 (30°-60°), and Category 4 (>60°) were observed (Table 5). Moderate to strong agreement for Category 2, 3, and 4 was also reported based upon the intraclass correlation coefficients (Table 6). Assessing time in posture categories has been shown to be practical in a number of industries including manufacturing, nursing, retail, forestry work, military, construction, among others (Wai et al., 2010). In Lee et al. (2017), percent time in posture categories of 30°-60°, 60°-90°, and >90° of trunk flexion was measured by the Bioharness 3 and a chest-mounted accelerometer. Both methods estimated comparable time spent in each category, but not statistical method was used to assess if there were significantly different or correlated between the measurements. Percent time estimates from both systems were compared to video recording, however, which indicated that the estimates from the Bioharness and reference accelerometer were comparable to what assessors observed in video.

RMSD and Bland Altman

Unexpected results were observed in the present study. Large differences between Xsens and Bioharness 3 for the ensemble averages of trunk flexion and extension values were observed. On average, relatively high sample-to-sample RMSD (root-mean square differences) between the Bioharness 3 and Xsens for estimating trunk postures ranged between ~12° and 15° of flexion. There are no specific guidelines on the ideal RMSD estimates between systems for trunk posture analysis, but previous studies have considered RMSD estimates greater than 10° of flexion to be insufficient to establish comparability (Schall et al., 2016, Schall et al., 2015b; Lee et al., 2017). Schall et al. (2016) and Schall et al (2015b) reported RMSD values from an accelerometry-based IMU on the chest and a complementary weighting algorithm-based sternum IMU relative to a sacrum IMU. The two IMU methods were compared to previously validated reference motion capture systems, but inferences can be made upon the differences between the RMDS values reported for the two IMU methods. Both Schall et al. (2016) and Schall et al (2015b) reported RMSD differences between the accelerometry-based IMU on the chest and a complementary weighting algorithm-based sternum IMU relative to a sacrum IMU that did not exceed ~2° of flexion. In Lee et al (2017), RMSD differences between the Bioharness and a chest-mounted sternum were as high as 13° of trunk flexion.

Bland Altman analysis in the present study also indicated poor agreement between the Bioharness 3 and the Xsens for estimating trunk flexion and extension (Table 2). Based on suggestions from El-Zayat et al. (2013) and Schiefer et al. (2014) on agreement using Bland

Altman, the biggest absolute 95% limit of agreement (~ 20° of flexion) between the Bioharness 3 and Xsens was considered to be too large to establish acceptable agreement (Lee et a., 2016; El-Zayat et al., 2013; Schiefer et al., 2014). Schall et al. (2015a) reported 95% limits of agreements that were a lot lower than those reported in the present study. When comparing mean trunk flexion and extension estimates of IMUs to estimates from an electrogoinometry system, Schall et al. (2015a) reported the bigger absolute 95% limit of agreement to be ~11° of flexion for an accelerometry-based IMU on the chest and ~7° for a complementary weighting algorithm-based sternum IMU relative to a sacrum IMU. The differences between the two IMU methods for the absolute 95% limits of agreement were relatively small at about 4° of flexion. In Lee et al. (2017), the biggest absolute 95% limit of agreement between the Bioharness 3 and a chest-mounted accelerometer was more comparable to the present study at about ~25° of flexion. It should also be noted that despite the large 95% limits of agreement, Lee et al. (2017) concluded that the Bioharness 3 and the chest-mounted accelerometer had acceptable agreement solely based on the small mean differences (~1°) from the Bland Altman analysis. This method has not been suggested to be a proper way of interpreting Bland Altman results, however.

Normalized vs. non-normalized

Certain expected trends were also observed between the non-normalized and normalized values for the Bioharness 3. First, summary measures indicated that the estimates from the two measurement methods used for the Bioharness 3 differed upon the severity of trunk flexion and extension. Estimates measured using the non-normalized method (BH1) were similar to the estimates from Xsens only when participants entered relatively high trunk flexion (30° or greater) (Table 1 and 5). In contrast, the estimates from the normalized method (BH2) were similar to those of Xsens only when participants entered relatively low trunk flexion (30° or less) (Table 1 and 5). Based upon the findings of the present study, the manufacturer of the Bioharness 3 should consider establishing a wireless calibration procedure to estimate subjects' neutral trunk position prior to collecting data. Currently, the Bioharness 3 has a calibration procedure but it can only be initiated by connecting it to a computer via a USB cord and running the manufacturer-supplied software. Without calibrating the system while the user is wearing the system, neutral positions of participants can often be characterized by overestimated trunk extension (5°-15°). Previous research has supported the effects of individuals' anthropometrics on the quality of exposure data (Feito et al., 2011). With a calibration procedure integrated as part of the Bioharness 3, health and safety professionals can access trunk posture estimates that are more representative of the exposure of workers to awkward trunk exposures.

Implications

The findings of the present study have a number of implications for health and safety professionals. The results indicated that the Bioharness 3 was capable of measuring low trunk flexion and extension values similarly to the Xsens system which can be useful in specific MMH jobs. The ranges of trunk flexion and extension observed in the present study are similar to postures seen in different industries, including nursing and manufacturing (Punnett et al., 1991; Keyserling et al., 1992; Schall et al. (2015b). For example, the Bioharness 3 can provide useful posture information on tasks where workers are primarily handling materials on a single level such as handling parts and tools on an assembly line or handling products where workers rely on overhead reaching to complete a task. Other industries where posture information from the Bioharness could be useful include office work, commercial driving, and retail where prolonged trunk postures (i.e. standing, sitting) are common. The results of the present study also suggested that the Bioharness had acceptable agreement for estimating practical measures of trunk postures, including percentiles and percent time in posture categories, and can be interchangeable to the Xsens system if those metrics are the focus of the exposure assessment.

The Bioharness 3 has the ability to simultaneously quantify multiple physical and physiological parameters to evaluate exposure to working conditions. For example, evaluating heart rate, activity levels through acceleration, and trunk posture data using a single device has been suggested to be key in providing health and safety professionals with a more complete representation of work-environment interaction (Cheng et al., 2013; Migliaccio et al., 2012; Gatti et al., 2014). The application of fused multi-parameter data can aid in identifying tasks that not only may expose workers to awkward trunk postures, but also possible physiological stress including cardiovascular strain and high metabolic demands. The small size and user-friendly interface of the Bioharness 3 may make it a more acceptable tool to be used by health and safety professionals over a more complex wearable measurement system.

The human factors of modern wearable measurement systems have been recognized to be just as important as their ability to accurately and reliably measure work postures. Human factors, the study of interactions between people and the environment/products, is a key aspect that needs to be addressed when designing wearable technology (Moti and Caine, 2014). If wearable measurement systems are not designed to be simple and be centered around the needs of the user or wearer (e.g. occupational professionals, workers), they can become a source of stress. Ferraro et al. (2017) claims that the stress that results from poor interfaces, uncomfortable fitting, and overwhelming amounts of data can often leave wearers disorganized and confused. A straightforward and intuitive design can enhance the usability levels of wearable measurement systems and help increase and maintain the levels of engagement of users (Siewiorek, Smailagic, and Starner, 2008). A wearable measurement system should be designed to have options to facilitate interaction, consider human cognitive capabilities for data processing, and provide convenient sensor locations that aid user comfort (Cho, 2010; Siewiorek, Smailagic, and Starner, 2008). The Bioharness 3, with its simple and instinctual design, possess a lot of these traits, making it more welcoming to use than complex systems like Xsens. With a better grasp on human factors, the Bioharness can be more accepted by safety and health professionals and encourage continues engagement from users and wearers alike.

Sensor Placement

The study investigated the effect of sensor placement to estimate trunk postures by comparing an IMU on the sternum (X-ST) and an IMU on the right shoulder (X-SH) to reference method represented by an IMU on the sternum relative to an IMU on the sacrum (X-SST).

Sternum and Shoulder IMUs

The findings of the study indicated that trunk posture estimates of the IMU on the sternum were the most comparable to the estimates derived from the IMU on the sternum relative to an IMU on the sacrum. Similar summary measures and strong associations between summary measures were observed between the two measurement methods (Table 1 and 2). Acceptable agreement for measuring percent time across a range of trunk postures between the sternum IMU and the sternum IMU relative to sacrum IMU was also observed (Table 6). Despite being too large to establish comparability or agreement, the sternum IMU had the smallest mean RMSD values (~9.0°), mean differences (~1.0°), and absolute 95% limit of agreement (~15°) when compared to the reference method. Although not directly comparable, previous studies have reported comparable results for IMU methods similar to the ones used in the present study. Schall et al. (2016) compared a complementary weighting algorithm-based IMU secured to the sternum and complementary weighting algorithm-based IMUs secured to the sternum and sacrum. The RMSDs reported in Schall et al. (2016) differed by ~1° of flexion between the IMU on the sternum and the two on IMUs on the sternum and sacrum. In Schall et al. (2015a), where the same IMU methods were compared to a electrogoinometry system, summary measures reported were higher for the IMU on the sternum than the IMUs on the sacrum and sternum. RMDS values were similar between the two IMU methods when compared to the electrogoinometry system and had a small difference of ~2° of flexion. The level of agreement via Bland Altman analysis was also reported in the study. Schall et al. (2015a) reported mean differences and biggest absolute 95% limits of agreement for the sternum IMU (mean differences = ~4° of flexion, 95% limits of agreement ~11° of flexion) and

IMUs on the sternum and sacrum (mean differences = ~1° of flexion, 95% limits of agreement ~7° of flexion). The difference between the 95% limits of agreement from the two IMU methods was relatively small at ~5° of flexion.

The findings of the study revealed that the shoulder IMU was not as comparable to the sternum IMU relative to sacrum IMU. Differences between the methods were largest when participants experienced extreme trunk flexion and extension (Table 1). These discrepancies could be due to possible movement artifact from the Xsens shirt, scapular movement, and shoulder posture. Although considerably large, mean RMSD estimates (~10° of flexion) and Bland Altman 95% limits of agreement (approximately ±15° of flexion) were closer to those of the sternum IMU than any of the other methods (Table 2). The shoulder as a landmark to place motion sensors is new in the research and has not been tested enough to provide comparable results to the present study. Although it may not be directly comparable, these results appeared to be lower than reported values in a previous study. Lee et al. (2017) tested an accelerometer on the shoulder against an accelerometry mounted on the chest during MMH tasks. Results from Lee et al. (2017) indicated that the RMSD values for the sensor on the shoulder ranged between approximately 12° to 23° of trunk flexion. Bland Altman analysis revealed that the biggest absolute 95% limits of agreement ranged was ~46° of trunk flexion. Differences suggest that although an IMU on the shoulder may not consistently measure trunk flexion and extension, it is more accurate method than using an accelerometer secured to the shoulder alone. Similar to sternum IMU, estimates for the key percentiles and percent time metrics from the shoulder IMU showed to have acceptable agreement with estimates from the IMU on the sternum relative to an IMU on the sacrum. Agreement mostly occurred in low flexion variables (10^{th} percentile, 50^{th} percentile) and time spent in Category 2 (0°-30°), Category 3 (31°-60°), Category 4 (>61°), suggesting that this method could be a consistent alternative for sensor placement in exposure assessments (Table 4 and 5).

Implications

Since commercial wearable measurement systems are often designed only to be worn on specific parts of the body prescribed by the manufacturer, it is critical that the placement of these systems is evaluated. If the system is designed only to function under specific placement of sensors on the body, it is also important to explore how to safety professionals can make wearable devices more adaptable to situations where recommended placement may not be possible. The information from an IMU on the sternum can be primarily helpful when needing wearable measurement systems to secure sensors on workers. For instance, in industries such as construction, workers use bulky tool belts, oxygen tanks, concrete vibrators, fall protection harnesses, and back belts in a daily basis which often cover certain parts of the trunk. Placing an inertial sensor under equipment or harnesses may be unconformable for workers, create artifact error from unnecessary movement, and incorrectly quantify exposure to awkward trunk postures. Being able to put an inertial sensor on the shoulder or sternum alone can serve as an alternative to estimate trunk posture when placing sensors on the sacrum and sternum is not feasible. In situations where worker anthropometrics (e.g. weight, size) makes it difficult to locate certain landmarks or are more prone to movement artifact from skin, muscles, or other tissues, having the option to place an inertial sensor on other landmarks can also help assure quality data in exposure assessments. Issues regarding wearable devices not being able to be used by individuals with various anthropometrics have been acknowledged in previous studies (Sazonov et al., 2011; Gemperle et al., 1998; Feito et al., 2011). Improving the adaptability of wearable measurement systems may also help address parts of the privacy issues regarding wearable technology. In certain scenarios, placing inertial sensors on the chest or sacrum may be intrusive for workers and be perceived as a violation of their personal space. Placing an inertial sensor on a less intrusive area such as the shoulder may help workers feel more comfortable and willing to wear the sensors.

Strengths and Limitations

The present study is one of the first efforts to the knowledge of the researchers to compare two commercially-available wearable measurement systems for measuring trunk postures in a simulated MMH tasks in a laboratory setting. The study was intended to improve the knowledge of how these types of systems can be used by occupational health and safety professionals looking to assess exposure to work postures. The results of the study contribute to the growing literature on wearable measurement systems used to assess exposure to occupational trunk postures.

A number of strengths in the present study need to be recognized. The study had a relatively larger sample size (n =30) compared to previous studies which helps improve its statistical stability and generalizability (Schall et al., 2015a; Schall et al., 2016; Lee et al., 2017). The sample size also had an almost even split of females and males partaking in the study (53% male, 47% females), which is similar to gender distribution of the workface in the U.S. (BLS, 2016c). The simulated MMH tasks in the study were performed at a pace and with a lifting technique that felt natural and comfortable to the participants so it could be representative of how people are likely to handle materials in the job. The study followed data processing and statistical procedures presented in previous studies which allows more direct comparisons of the methods and results (Schall et al., 2015a; Schall et al., 2016; Lee et al., 2017).

The findings of the study also need to be interpreted under a number of limitations. Although the Xsens system has been tested against ‘gold-standard’ systems for posture analysis, there is not enough consensus in the literature to consider it a ‘gold standard’ system. The Xsens system was used as the reference system to determine if a more user-friendly Bioharness 3 could serve as an alternative to a complex system. Therefore, RMSD estimates and other comparative measures are expected to be higher if the Bioharness 3 was to be tested against a more validated tool such as an optoelectronic system. Systematic error for the Xsens might have been introduced via variability of the sensor placement techniques by researchers, shifting of sensors during the simulated MMH task, and the presence of ferromagnetic interference from the surrounding structures in the laboratory.

Other factors such as fatigue or participants changing lifting techniques through the MMH task might have affected the trunk posture estimates. Participants were asked to execute the tasks at a self-selected pace which might have induced inconsistent movements for the Bioharness 3 to recognize correctly. The lack of a controlled speed for the simulated MMH tasks may have affected the trunk posture estimates from the Bioharness 3. Inconsistent speeds of body movements have been proposed to increase the angle error in accelerometer estimates (Lee et al., Korshøj et al., 2014; Hansson et al., 2001). Hansson et al. (2001) indicated that high angle errors from accelerometers commonly occur because accelerometers are sensitive to radial and tangential accelerations. This issue does not apply to IMU-based systems, however, as the accelerometer imbedded inside an IMU relies on additional aiding sensors (e.g. magnetometers, gyroscopes) to correct the orientation of the device and helps reduce error.

The lightweight loads being handled in the study and the short duration of the study also may prevent the results to be generalized to tasks that involve heavier loads and longer handling time, which is common in many industries. Weights handled in other studies that focused on using motion sensors for quantifying exposure during MMH tasks have ranged between 500 grams to 18 kilograms (Kim and Nussbaum, 2013; Faber et al., 2009; Lee et al., 2017; Schall et al., 2015a; Robert-Lachaine et al., 2016). Since MMH tasks were designed to focus on specific movements, results from this study may not be generalizable for other MMH tasks that are more asymmetrical and more static in nature. Previous studies have also focused on trunk postures that involved lateral bending in the frontal/coronal and axial rotation in the transverse plane (Wong and Wong, 2008; Robert-Lachaine et al., 2016; Kim and Nussbaum, 2013; Schall et al., 2015a; Schall et al., 2017; Schepers et al., 2009).

Future work

More extensive research on the use of wearable measurement systems to assess the exposure to awkward trunk postures in MMH tasks continue to be needed. Research on how wearable measurement system perform under different conditions is very important in particular. Testing these wearable devices in a number of simulated and field-based tasks, on workers across different industries, and against properly validated systems should be considered for future work. Wearable measurements systems are entering the market quickly, offering to identify and measure exposure to physical hazards but lacking sufficient research studies to support their use in daily health and safety practices. Most importantly, as wearable technology continues to improve, a significant switch to IMUs and inertial measurement systems is predicted to grow. It is important that these systems not only become more accurate and reliable for measuring work postures, but also make it easier for professionals to apply them in the field. If accurate and reliable systems continue to become more user-friendly, wearable measurement systems in exposure assessments can experience a high demand and engagement from professionals in the field.

Ensemble averages

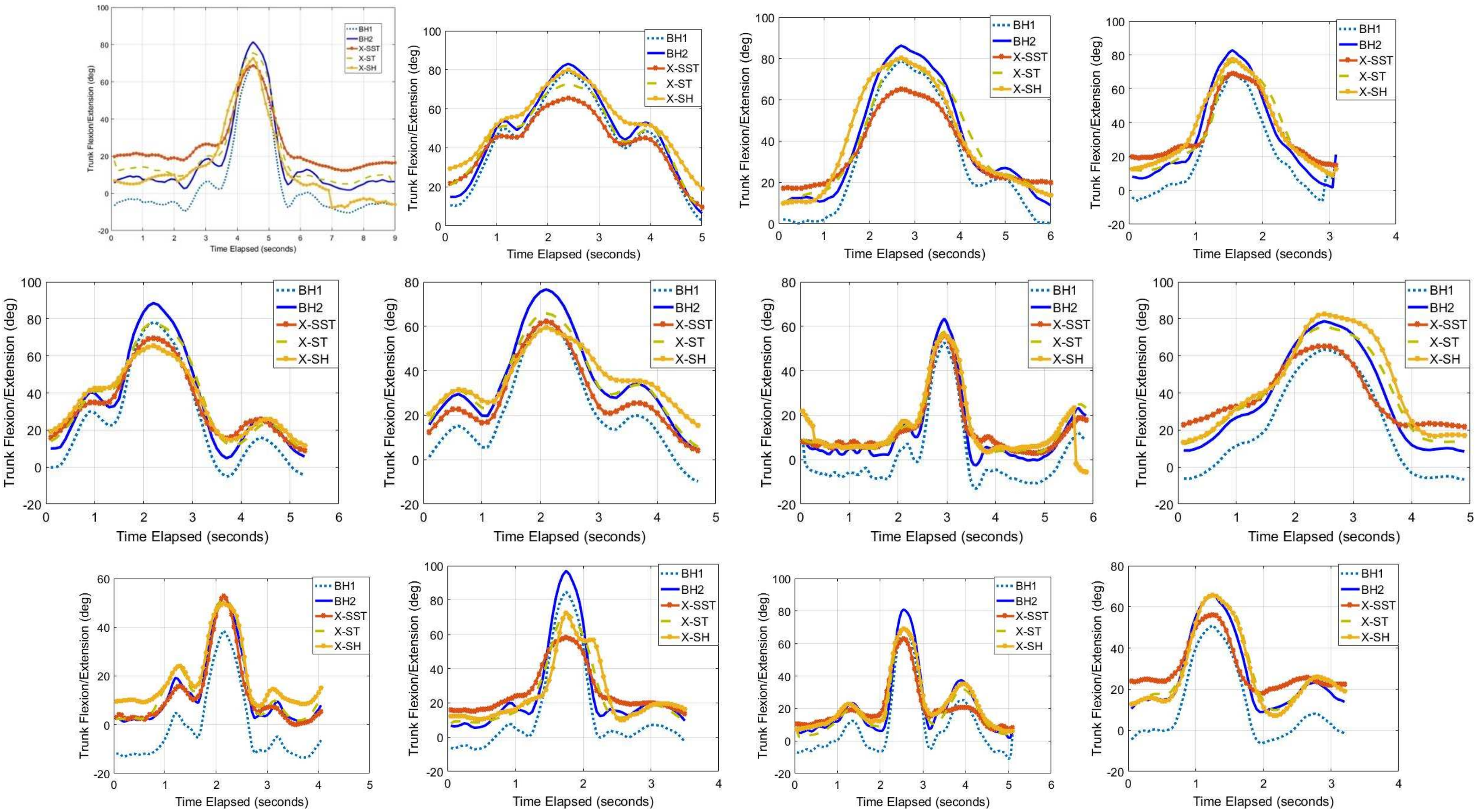

Figure 11: Ensemble average of trunk flexion and extension for participants 1 to 12 (top left to bottom right).

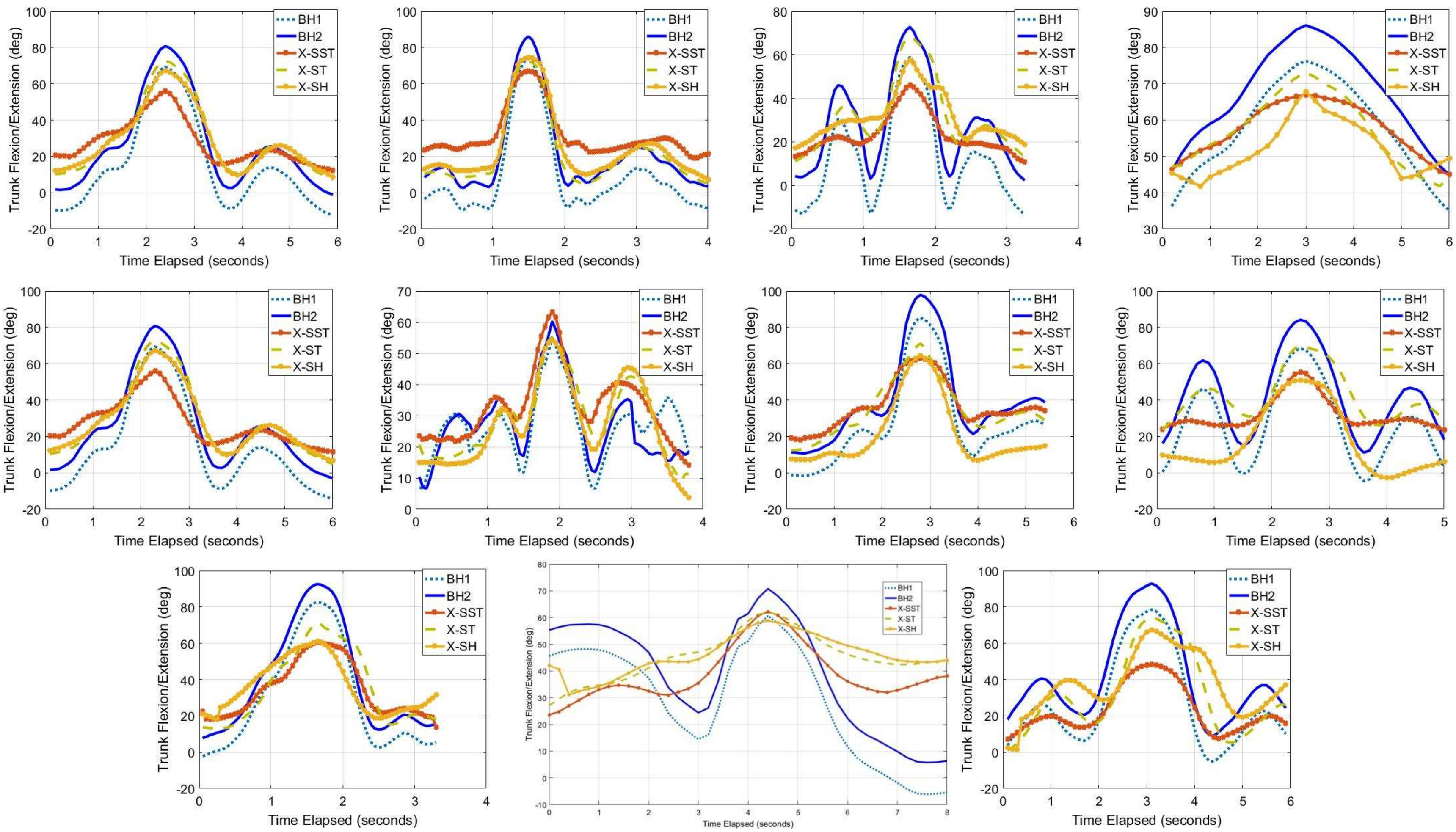

Figure 12: Ensemble average of trunk flexion and extension for participants 13 to 23 (top left to bottom right).

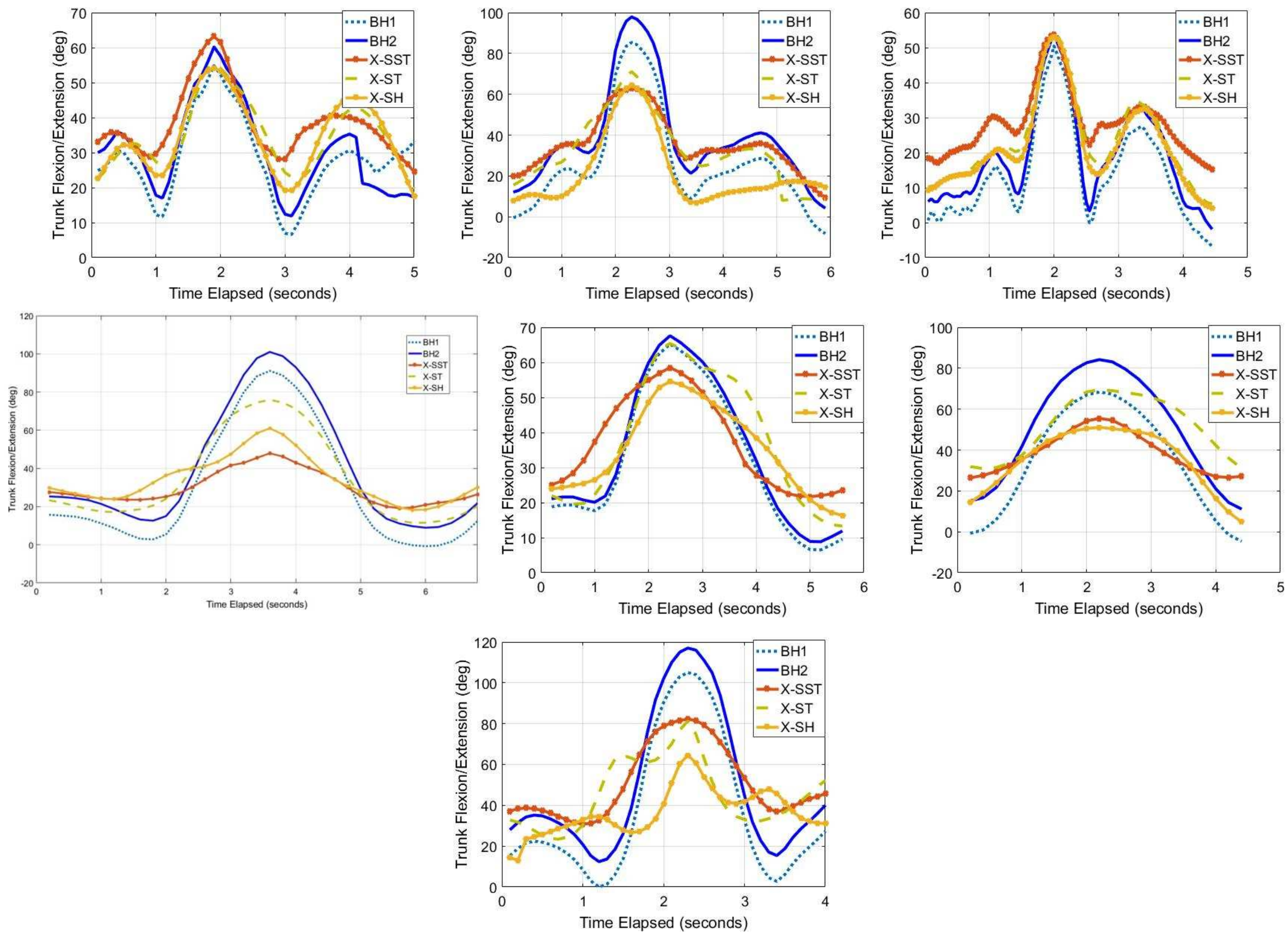

Figure 13: Ensemble average of trunk flexion and extension for participants 23 to 30 (top left to bottom right).

REFERENCES

Adams. M. A., Hutton. W. C. and Stott. J. R. R. (1980) The resistance to flexion of the lumbar intervertebral joint. *Spine 5*, 245-253.

Åkesson, I., Hansson, G. Å., Balogh, I., Moritz, U., and Skerfving, S. (1997). Quantifying work load in neck, shoulders and wrists in female dentists. *International archives of occupational and environmental health*, *69*(6), 461-474.

Amasay, T., Zodrow, K., Kincl, L., Hess, J., and Karduna, A. (2009). Validation of tri-axial accelerometer for the calculation of elevation angles. *International Journal of Industrial Ergonomics*, 39(5), 783-789.

American Federation of Labor and Congress of Industrial Organizations (AFL-CIO) (2012). Report on 'Death on the Job, the Toll of Neglect: a National and State-bystate Profile of Worker Safety and Health in the United States'.

Andersen, J. H., Haahr, J. P., and Frost, P. (2007). Risk factors for more severe regional musculoskeletal symptoms: A two-year prospective study of a general working population. *Arthritis and Rheumatology*, *56*(4), 1355-1364.

Andersson, G. B. (1997), The epidemiology of spinal disorders, in J. W. Frymoyer (ed.), The Adult Spine: Principles and Practice, 2nd edition; Philadelphia: Lippincott-Raven; 93-141.

Ayoub, M. M. and Mital, A. (1989). Manual Materials Handling. Taylor and Francis Inc.

Bachmann, E. R. (2000). Inertial and magnetic tracking of limb segment orientation for inserting humans into synthetic environments. Naval Postgraduate School Monterey, CA.

Balogh, I., Ohlsson, K., Hansson, G. Å., Engström, T., and Skerfving, S. (2006). Increasing the degree of automation in a production system: consequences for the physical workload. *International Journal of Industrial Ergonomics*, *36*(4), 353-365.

Bao, S. S., Kapellusch, J. M., Merryweather, A. S., Thiese, M. S., Garg, A., Hegmann, K. T., and Silverstein, B. A. (2016). Relationships between job organizational factors, biomechanical and psychosocial exposures. *Ergonomics*, *59*(2), 179-194.

Bao, S., Mathiassen, S. E., and Winkel, J. (1996). Ergonomic effects of a management-based rationalization in assembly work—a case study. *Applied ergonomics*, *27*(2), 89-99.

Bauer, C. M., Rast, F. M., Ernst, M. J., Kool, J., Oetiker, S., Rissanen, S. M., and Kankaanpää, M. (2015). Concurrent validity and reliability of a novel wireless inertial measurement system to assess trunk movement. *Journal of Electromyography and Kinesiology*, *25*(5), 782-790.

Bernmark, E., and Wiktorin, C. (2002). A triaxial accelerometer for measuring arm movements. *Applied Ergonomics*, 33(6), 541-547.

Berquer, R., Smith, W. D., and Davis, S. (2002). An ergonomic study of the optimum operating table height for laparoscopic surgery. *Surgical Endoscopy*, 16(3), 416-421.

Bigos, S. J., Spengler, D. M., Martin, N. A., Zeh, J., Fisher, L., Nachemson, A., and Wang, M. H. (1986). Back Injuries in Industry: A Retrospective Study: II. Injury Factors. *Spine*, 11(3), 246-251.

Bland, J. M., and Altman, D. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet*, 327(8476), 307-310.

Bouten, C. V. C., Sauren, A. A. H. J., Verduin, M., and Janssen, J. D. (1997). Effects of placement and orientation of body-fixed accelerometers on the assessment of energy expenditure during walking. *Medical and Biological Engineering and Computing,* 35(1), 50-56.

Brinckmann, P., Biggemann, M., and Hilweg, D. (1988). Fatigue fracture of human lumbar vertebrae. *Clinical Biomechanics*, 3, 1-23.

Burdorf, A. (1995). Reducing random measurement error in assessing postural load on the back in epidemiologic surveys. *Scandinavian Journal of Work, Environment and Health*, 15-23.

Burdorf, A., and Van Der Beek, A. (1999). Exposure assessment strategies for work-related risk factors for musculoskeletal disorders. *Scandinavian Journal of Work, Environment and Health*, 25-30.

Burdorf, A., Derksen, J., Naaktgeboren, B., and van Riel, M. (1992). Measurement of trunk bending during work by direct observation and continuous measurement. *Applied Ergonomics*, 23(4), 263-267.

Burdorf, A., Govaert, G., and Elders, L. (1991). Postural load and back pain of workers in the manufacturing of prefabricated concrete elements. *Ergonomics*, 34(7), 909-918.

Bureau of Labor Statistics. (2016a). Nonfatal occupational injuries and illnesses requiring days away from work, 2015. Retrieved from https://www.bls.gov/news.release/pdf/osh2.pdf. Accessed on August 2017.

Bureau of Labor Statistics (BLS) (2016b). Number of nonfatal occupational injuries and illnesses involving days away from work by part of body and selected natures of injury or illness, private industry, 2015. Author, Washington, DC. Available at www.bls.gov/iif/oshwc/osh/case/ostb4771.pdf. Accessed on August 2017.

Bureau of Labor Statistics. (2016c). Employed persons by detailed occupation, sex, race, and Hispanic or Latino ethnicity, 2016. Retrieved from https://www.bls.gov/cps/cpsaat11.pdf. Accessed on September 2017.

California Department of Industrial Relations (CDIR). (2007). Ergonomic guidelines for manual materials handling (NIOSH Publication No. 2007-131). Washington, DC: U.S. Department of Health and Human Services (DHHS), Center of Disease Control and Prevention, National Institute for Occupational Health and Safety.

Chaffin, D. B., Andersson, G., and Martin, B. J. (1999). *Occupational Biomechanics* (pp. 91-130). New York: Wiley.

Chaffin, D., Heidl, R., Hollenbeck, J. R., Howe, M., Yu, A., Voorhees, C., and Calantone, R. (2017). The promise and perils of wearable sensors in organizational research. *Organizational Research Methods*, *20*(1), 3-31.

Chan, M., Estève, D., Fourniols, J. Y., Escriba, C., and Campo, E. (2012). Smart wearable systems: Current status and future challenges. *Artificial Intelligence in Medicine*, 56(3), 137-156.

Cheng, T., Teizer, J., Migliaccio, G. C., and Gatti, U. C. (2013). Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data. *Automation in Construction*, *29*, 24-39.

Chiasson, M. È., Imbeau, D., Aubry, K., and Delisle, A. (2012). Comparing the results of eight methods used to evaluate risk factors associated with musculoskeletal disorders. *International Journal of Industrial Ergonomics*, 42(5), 478-488.

Christie, H. J., Kumar, S., and Warren, S. A. (1995). Postural aberrations in low back pain. *Archives of Physical Medicine and Rehabilitation*, *76*(3), 218-224.

Cho, G. (Ed.). (2009). *Smart clothing: technology and applications*. CRC Press.

Ciriello, V. M., Snook, S. H., Hashemi, L., and Cotnam, J. (1999). Distributions of manual materials handling task parameters. *International Journal of Industrial Ergonomics*, *24*(4), 379-388.

Ciuti, G., Ricotti, L., Menciassi, A., and Dario, P. (2015). MEMS sensor technologies for human centered applications in healthcare, physical activities, safety and environmental sensing: a review on research activities in Italy. *Sensors*, 15(3), 6441-6468.

Clarkson, H. (2000). Musculoskeletal assessment (2nd ed.). Philadelphia, PA: Lippincott, Williams and Wilkins.

Coenen, P., Kingma, I., Boot, C. R., Twisk, J. W., Bongers, P. M., and van Dieën, J. H. (2013). Cumulative low back load at work as a risk factor of low back pain: a prospective cohort study. *Journal of Occupational Rehabilitation*, 23(1), 11-18.

Colombo, G., De Vecchi, G., Regazzoni, D., and Rizzi, C. (2012, August). Motion capture and virtual humans to enhance ergonomic design and validation of refrigerated display units. In ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference; 663-671. *American Society of Mechanical Engineers.*

Cooper, G. (2015). Lower Back Pain: An Overview of the Most Common Causes. In Non-

Operative Treatment of the Lumbar Spine (pp. 11-13). Springer International Publishing.

Cuesta-Vargas, A. I., Galán-Mercant, A., and Williams, J. M. (2010). The use of inertial sensors system for human motion analysis. *Physical Therapy Reviews*, 15(6), 462-473.

da Costa, B. R., and Vieira, E. R. (2010). Risk factors for work-related musculoskeletal disorders: a systematic review of recent longitudinal studies. *American Journal of Industrial Medicine*, 53(3), 285-323.

Dagenais, S., Caro, J., and Haldeman, S. (2008). A systematic review of low back pain cost of illness studies in the United States and internationally. *Spine Journal*, 8(1), 8-20.

David, G. C. (2005). Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. *Occupational Medicine*, 55(3), 190-199.

De Vries, W. H. K., Veeger, H. E. J., Baten, C. T. M., and Van Der Helm, F. C. T. (2009). Magnetic distortion in motion labs, implications for validating inertial magnetic sensors. *Gait and Posture*, 29(4), 535-541.

Dinu, D., Fayolas, M., Jacquet, M., Leguy, E., Slavinski, J., and Houel, N. (2016). Accuracy of Postural Human-motion Tracking Using Miniature Inertial Sensors. *Procedia Engineering*, 147, 655-658.

Dolan, P., and Adams, M. A. (1998). Repetitive lifting tasks fatigue the back muscles and increase the bending moment acting on the lumbar spine. *Journal of Biomechanics*, *31*(8), 713-721.

Driel, R. V., Trask, C., Johnson, P. W., Callaghan, J. P., Koehoorn, M., and Teschke, K. (2013). Anthropometry-corrected exposure modeling as a method to improve trunk posture assessment with a single inclinometer. *Journal of Occupational and Environmental Hygiene*, *10*(3), 143-154.

Ettinger, L., Kincl, L., Johnson, P., Carter, C., Garfinkel, S., and Karduna, A. (2013). Workday Arm Elevation Exposure: A Comparison Between Two Professions. *Occupational Ergonomics and Human Factors*, 1(2), 119-127.

Evanoff, B., Abedin, S., Grayson, D., Dale, A. M., Wolf, L., and Bohr, P. (2002). Is disability underreported following work injury?. *Journal of Occupational Rehabilitation*, 12(3), 139-150.

Faber, G. S., Chang, C. C., Kingma, I., Dennerlein, J. T., and van Dieën, J. H. (2016). Estimating 3D L5/S1 moments and ground reaction forces during trunk bending using a full-body ambulatory inertial measurement system. *Journal of Biomechanics*, 49(6), 904-912.

Faber, G. S., Chang, C. C., Rizun, P., and Dennerlein, J. T. (2013). A novel method for assessing the 3-D orientation accuracy of inertial/magnetic sensors. *Journal of Biomechanics*, 46(15), 2745-2751.

Faber, G. S., Kingma, I., and van Dieën, J. H. (2010). Bottom-up estimation of joint moments during manual lifting using orientation sensors instead of position sensors. *Journal of Biomechanics*, 43(7), 1432-1436.

Faber, G. S., Kingma, I., Bruijn, S. M., and van Dieën, J. H. (2009). Optimal inertial sensor location for ambulatory measurement of trunk inclination. *Journal of Biomechanics*, 42(14), 2406-2409. 41(Supplement 1), 5527-5528.

Fahrenberg, J., Foerster, F., Smeja, M., and Muller, W. (1997). Assessment of posture and motion by multichannel piezoresistive accelerometer recordings. *Psychophysiology*, 34(5), 607-612.

Feito, Y., Bassett, D. R., Tyo, B., and Thompson, D. L. (2011). Effects of body mass index and tilt angle on output of two wearable activity monitors. *Medicine and Science in Sports and Exercise*, *43*(5), 861-866.

Fethke, N. B., Gant, L. C., and Gerr, F. (2011). Comparison of biomechanical loading during use of conventional stud welding equipment and an alternate system. *Applied Ergonomics*, 42(5), 725-734.

Fisher, C. J. (2010). Using an accelerometer for inclination sensing. *AN-1057, Application note, Analog Devices*.

Foerster, F., Smeja, M., and Fahrenberg, J. (1999). Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring. *Computers in Human Behavior*, *15*(5), 571-583.

Forsman, M., Hansson, G. Å., Medbo, L., Asterland, P., and Engström, T. (2002). A method for evaluation of manual work using synchronised video recordings and physiological measurements. *Applied Ergonomics*, *33*(6), 533-540.

Gallagher, A., Matsuoka, Y., and Ang, W. T. (2004, October). An efficient real-time human posture tracking algorithm using low-cost inertial and magnetic sensors. In Proceedings of Intelligent Robots and Systems, 2004 IEEE/RSJ International Conference on (Vol. 3, pp. 2967-2972).

Garg, A. (1986). Methods for estimating physical fatigue. In R. L. Shell (ed.), Work Measurement Principles and Practice, Industrial Engineering and Management Press, Atlanta, pp. 125–132.

Garg, A., and Kapellusch, J. M. (2009). Applications of biomechanics for prevention of work-related musculoskeletal disorders. *Ergonomics*, 52(1), 36-59.

Gatti, U. C., Migliaccio, G. C., and Schneider, S. (2011). Wearable Physiological Status Monitors for Measuring and Evaluating Workers' Physical Strain: Preliminary Validation. In *Computing in Civil Engineering (2011)* (pp. 194-201).

Gatti, U. C., Schneider, S., and Migliaccio, G. C. (2014). Physiological condition monitoring of construction workers. *Automation in Construction*, *44*, 227-233.

Gemperle, F., Kasabach, C., Stivoric, J., Bauer, M., and Martin, R. (1998, October). Design for wearability. In *Wearable Computers, 1998. Digest of Papers. Second International Symposium on* (pp. 116-122). IEEE.

Giansanti, D., Maccioni, G., and Macellari, V. (2005). The development and test of a device for the reconstruction of 3-D position and orientation by means of a kinematic sensor assembly with rate gyroscopes and accelerometers. *IEEE Transactions on Biomedical Engineering*, *52*(7), 1271-1277

Godfrey, A. C., Conway, R., Meagher, D., and ÓLaighin, G. (2008). Direct measurement of human movement by accelerometry. *Medical Engineering and Physics,* 30(10), 1364-1386.

Godwin, A., Agnew, M., and Stevenson, J. (2009). Accuracy of inertial motion sensors in static, quasi-static, and complex dynamic motion. *Journal of Biomechanical Engineering*, 131(11), 114501.

Goodvin, C., Park, E. J., Huang, K., and Sakaki, K. (2006). Development of a real-time three-dimensional spinal motion measurement system for clinical practice. *Medical and Biological Engineering and Computing*, *44*(12), 1061-1075.

Graham, R. B., Agnew, M. J., and Stevenson, J. M. (2009). Effectiveness of an on-body lifting aid at reducing low back physical demands during an automotive assembly task: Assessment of EMG response and user acceptability. *Applied Ergonomics*, *40*(5), 936-942.

Grant, K. A., Johnson, P. W., and Galinsky, T. L. (1995). Evaluation of an accelerometric activity monitor as an exposure assessment tool in ergonomic studies. *Applied Occupational and Environmental Hygiene*, 10(5), 461-466.

Guo, H. R., Tanaka, S., Halperin, W. E., and Cameron, L. L. (1999). Back pain prevalence in US industry and estimates of lost workdays*. American Journal of Public Health*, 89(7), 1029-1035.

Hansson, G., Asterland, P., Holmer, N. G., and Skerfving, S. (2001). Validity and reliability of triaxial accelerometers for inclinometry in posture analysis. *Medical and Biological Engineering and Computing*, 39(4), 405-413.

Hansson, G. Å., Balogh, I., Ohlsson, K., Granqvist, L., Nordander, C., Arvidsson, I., and Skerfving, S. (2010). Physical workload in various types of work: Part II. Neck, shoulder and upper arm. *International Journal of Industrial Ergonomics*, *40*(3), 267-281.

Hernandez, N., Cowings, P., and Toscano, W. (2012). Psychophysiological Assessment of Fatigue in Commercial Aviation Operations. NASA Ames Research Center; Moffett Field, CA, United States.

Hess, J. A., Kincl, L., Amasay, T., and Wolfe, P. (2010). Ergonomic evaluation of masons laying concrete masonry units and autoclaved aerated concrete. *Applied Ergonomics*, 41(3), 477-483.

Hoogendoorn, W. E., Bongers, P. M., De Vet, H. C. W., Ariens, G. A. M., Van Mechelen, W., and Bouter, L. M. (2002). High physical work load and low job satisfaction increase the risk of sickness absence due to low back pain: results of a prospective cohort study. *Occupational and Environmental Medicine,* 59(5), 323-328.

Hoogendoorn, W. E., van Poppel, M. N., Bongers, P. M., Koes, B. W., and Bouter, L. M. (1999). Physical load during work and leisure time as risk factors for back pain. *Scandinavian Journal of Work, Environment and Health*, 387-403.

Hoogendoorn, W. E., Bongers, P. M., de Vet, H. C., Douwes, M., Koes, B. W., Miedema, M. C., and Bouter, L. M. (2000). Flexion and rotation of the trunk and lifting at work are risk factors for low back pain: results of a prospective cohort study. *Spine*, *25*(23), 3087-3092.

Hoy, D., Brooks, P., Blyth, F., and Buchbinder, R. (2010). The epidemiology of low back pain. *Best Practice and Research Clinical Rheumatology*, 24(6), 769-781.

Howarth, S. J., Grondin, D. E., La Delfa, N. J., Cox, J., and Potvin, J. R. (2016). Working position influences the biomechanical demands on the lower back during dental hygiene. *Ergonomics*, *59*(4), 545-555.

Jäger, M., Jordan, C., Luttmann, A., Laurig, W., and Dolly Group. (2000). Evaluation and assessment of lumbar load during total shifts for occupational manual materials handling jobs within the Dortmund Lumbar Load Study–DOLLY. *International Journal of Industrial Ergonomics*, *25*(6), 553-571.

Jansen, J. P., Morgenstern, H., and Burdorf, A. (2004). Dose-response relations between occupational exposures to physical and psychosocial factors and the risk of low back pain. *Occupational and Environmental Medicine*, 61(12), 972-979.

Jasiewicz, J. M., Treleaven, J., Condie, P., and Jull, G. (2007). Wireless orientation sensors:

their suitability to measure head movement for neck pain assessment. *Manual Therapy*, 12(4), 380-385.

Jonker, D., Rolander, B., and Balogh, I. (2009). Relation between perceived and measured workload obtained by long-term inclinometry among dentists. *Applied ergonomics*, *40*(3), 309-315.

Jonsson, B. (1978). Kinesiology: with special reference to electromyographic kinesiology. *Electroencephalography and clinical neurophysiology. Supplement*, (34), 417-428.

Jonsson, B. (1988). The static load component in muscle work. *European Journal of Applied Physiology and Occupational Physiology*, 57(3), 305-310.

Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., and Garrett, A. T. (2012a). BioHarness multivariable monitoring device. Part II: reliability. *Journal of Sports Science and Medicine*, 11(3), 409-417.

Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., and Garrett, A. T. (2012b). BioHarness multivariable monitoring device. Part I: validity*. Journal of Sports Science and Medicine*, 11(3), 400-408.

Johnstone, J. A., Ford, P. A., Hughes, G., Watson, T., Mitchell, A. C., and Garrett, A. T. (2012c). Field based reliability and validity of the BioHarness™ multivariable monitoring device. *Journal of Sports Science and Medicine*, 11(4), 643.

Jorgensen, M. J., and Viswanathan, M. (2005, September). Ergonomic field assessment of bucking bars during riveting tasks. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 49, No. 14, pp. 1354-1358). Sage CA: Los Angeles, CA: SAGE Publications.

Josephson, M., and Vingård, E. (1998). Workplace factors and care seeking for low-back pain among female nursing personnel. *Scandinavian Journal of Work, Environment and Health*, 465-472.

Joshua, L., and Varghese, K. (2010). Accelerometer-based activity recognition in construction. *Journal of Computing in Civil Engineering,* 25(5), 370-379.

Jovanov, E., Milosevic, M., and Milenković, A. (2013, July). A mobile system for assessment of physiological response to posture transitions. In Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE (pp. 7205-7208). IEEE.

Juul-Kristensen, B., Hansson, G. Å., Fallentin, N., Andersen, J. H., and Ekdahl, C. (2001). Assessment of work postures and movements using a video-based observation method and direct technical measurements. *Applied Ergonomics*, 32(5), 517-524.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Journal of Basic Engineering*, 82(1), 35-45.

Karantonis, D. M., Narayanan, M. R., Mathie, M., Lovell, N. H., and Celler, B. G. (2006). Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Transactions on Information Technology in Biomedicine, 10(1), 156-167.

Kazmierczak, K., Mathiassen, S. E., Forsman, M., and Winkel, J. (2005). An integrated analysis of ergonomics and time consumption in Swedish ‘craft-type’car disassembly. *Applied Ergonomics*, *36*(3), 263-273

Keyserling, W. M., Brouwer, M., and Silverstein, B. A. (1992). A checklist for evaluating ergonomic risk factors resulting from awkward postures of the legs, trunk and neck. *International Journal of Industrial Ergonomics*, 9(4), 283-301.

Kim, S. (2012). Development and Evaluation of Methods to Assess Physical Exposures in the Workplace using Wearable Technologies (Doctoral dissertation, Virginia Polytechnic Institute and State University).

Kim, S., and Nussbaum, M. A. (2013). Performance evaluation of a wearable inertial motion capture system for capturing physical exposures during manual material handling tasks. *Ergonomics*, *56*(2), 314-326.

Konz, S., and Johnson, S. (2007). Work design: occupational ergonomics. Holcomb Hathaway. Scottsdale, AZ.

Korshøj, M., Skotte, J. H., Christiansen, C. S., Mortensen, P., Kristiansen, J., Hanisch, C., and Holtermann, A. (2014). Validity of the Acti4 software using ActiGraph GT3X+ accelerometer for recording of arm and upper body inclination in simulated work tasks. *Ergonomics*, 57(2), 247-253.

Kumar, S. (2001). Theories of musculoskeletal injury causation. *Ergonomics*, 44(1), 17-47.

LaScalza, S., Arico, J., and Hughes, R. (2003). Effect of metal and sampling rate on accuracy of Flock of Birds electromagnetic tracking system. *Journal of Biomechanics*, 36(1), 141-144.

Lee, J., Koh, D., and Ong, C. N. (1989). Statistical evaluation of agreement between two methods for measuring a quantitative variable. *Computers in Biology and Medicine*, *19*(1), 61-70.

Lee, W., Seto, E., Lin, K. Y., and Migliaccio, G. C. (2017). An evaluation of wearable measurement systems and their placements for analyzing construction worker's trunk posture in laboratory conditions. *Applied Ergonomics*.

Li, G., and Buckle, P. (1999). Current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture-based methods. *Ergonomics*, 42(5), 674-695.

Liberty Mutual (2017). The 2017 Liberty Mutual Safety Index. Available at: https://www.libertymutualgroup.com/about-liberty-mutual-site/news-site/Pages/2017-Liberty-Mutual-Workplace-Safety-Index.aspx. Accessed on August 11, 2017.

Luo, X., Pietrobon, R., Sun, S. X., Liu, G. G., and Hey, L. (2004). Estimates and patterns of direct health care expenditures among individuals with back pain in the United States. *Spine*, *29*(1), 79-86.

Marklin, R. W., and Cherney, K. (2005). Working postures of dentists and dental hygienists. *Journal of the California Dental Association*.

Marras, W. S. (2000). Occupational low back disorder causation and control. *Ergonomics*, 43(7), 880-902.

Marras, W. S., Lavender, S. A., Leurgans, S. E., Fathallah, F. A., Ferguson, S. A., Gary-Allread, W., and Rajulu, S. L. (1995). Biomechanical risk factors for occupationally related low back disorders. *Ergonomics*, 38(2), 377-410. Chicago

Marras, W. S., Cutlip, R. G., Burt, S. E., and Waters, T. R. (2009). National occupational research agenda (NORA) future directions in occupational musculoskeletal disorder health research. *Applied Ergonomics*, 40(1), 15-22.

Marras, W. S., Lavender, S. A., Ferguson, S. A., Splittstoesser, R. E., and Yang, G. (2010). Quantitative dynamic measures of physical exposure predict low back functional impairment. *Spine*, 35(8), 914-923.

Matsui, H., Maeda, A., Tsuji, H., and Naruse, Y. (1997). Risk indicators of low back pain among workers in Japan: association of familial and physical factors with low back pain. *Spine*, 22(11), 1242-1247.

McGill, S. M. (1997). The biomechanics of low back injury: implications on current practice in industry and the clinic. *Journal of Bomechanics*, 30(5), 465-475.

Meskers, C. G. M., Fraterman, H. V., Van der Helm, F. C. T., Vermeulen, H. M., and Rozing, P. M. (1999). Calibration of the “Flock of Birds” electromagnetic tracking device and its application in shoulder motion studies. *Journal of Biomechanics*, 32(6), 629-633.

Migliaccio, G. C., Teizer, J., Cheng, T., and Gatti, U. C. (2012). Automatic identification of unsafe bending behavior of construction workers using real-time location sensing and physiological status monitoring. In *Construction Research Congress 2012: Construction Challenges in a Flat World* (pp. 633-642).

Milosevic, M., Jovanov, E., Frith, K. H., Vincent, J., and Zaluzec, E. (2012, August). Preliminary analysis of physiological changes of nursing students during training. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE* (pp. 3772-

3775). IEEE.

Mital, A. (1997). Guide to manual materials handling. CRC Press.

Morlock, M. M., Bonin, V., Deuretzbacher, G., Müller, G., Honl, M., and Schneider, E. (2000). Determination of the in vivo loading of the lumbar spine with a new approach directly at the workplace–first results for nurses. *Clinical Biomechanics*, 15(8), 549-558.

Motti, V. G., and Caine, K. (2014, September). Human factors considerations in the design of wearable devices. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 58, No. 1, pp. 1820-1824). Sage CA: Los Angeles, CA: SAGE Publications.

Muaremi, A., Seiter, J., Tröster, G., and Bexheti, A. (2013, September). Monitor and understand pilgrims: Data collection using smartphones and wearable devices. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication* (pp. 679-688). ACM.

Mukaka, M. M. (2012). A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal*, *24*(3), 69-71.

Nahavandi, D., Iskander, J., Hossny, M., Haydari, V., and Harding, S. (2016, October). Ergonomic effects of using Lift Augmentation Devices in mining activities. In Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference (pp. 2012-2019). IEEE.

National Institute for Occupational Health and Safety (NIOSH) (2016). Exposure Assessment. Available at https://www.cdc.gov/niosh/programs/expa/. Accessed on August 2017.

National Research Council (NRC) (2001). Musculoskeletal disorders and the workplace: low back and upper extremities. National Academies Press.

Occupational Safety and Health Administration (OSHA) (2016a). Prevention of Musculoskeletal Disorders in the Workplace. Available at https://www.osha.gov/SLTC/ergonomics/. Accessed on August 2017.

Occupational Safety and Health Administration (OSHA) (2016b). OSHA Technical Manual: Back Disorders and Injuries. Available at https://www.osha.gov/dts/osta/otm/otm_vii/otm_vii_1.html.

Accessed on August 2017.

Plamondon, A., Delisle, A., Larue, C., Brouillette, D., McFadden, D., Desjardins, P., and Larivière, C. (2007). Evaluation of a hybrid system for three-dimensional measurement of trunk posture in motion. *Applied Ergonomics*, 38(6), 697-712.

Punnett, L., Fine, L. J., Keyserling, W. M., Herrin, G. D., and Chaffin, D. B. (1991). Back disorders and non-neutral trunk postures of automobile assembly workers. *Scandinavian Journal of Work, Environment and Health*, 337-346.

Punnett, L., and Wegman, D. H. (2004). Work-related musculoskeletal disorders: the epidemiologic evidence and the debate. *Journal of Electromyography and Kinesiology*, 14(1), 13-23.

Putz-Anderson, V. and Bernard, B. (1997). *Musculoskeletal Disorders and Workplace Factors: A Critical Review of Epidemiologic Evidence for Work-Related Musculoskeletal Disorders of the Neck, Upper Extremity, and Low Back*. U.S. Department of Health and Human Services, Public Health Service, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, (Second, Vol. 97–141). Cincinnati.

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

Ribeiro, D. C., Sole, G., Abbott, J. H., and Milosavljevic, S. (2011). Cumulative postural exposure measured by a novel device: a preliminary study. *Ergonomics*, *54*(9), 858-865.

Robert-Lachaine, X., Mecheri, H., Larue, C., and Plamondon, A. (2016). Validation of inertial measurement units with an optoelectronic system for whole-body motion analysis. *Medical and Biological Engineering and Computing*, 1-11.

Roetenberg, D., Luinge, H. J., Baten, C. T., and Veltink, P. H. (2005). Compensation of magnetic disturbances improves inertial and magnetic sensing of human body segment orientation. IEEE Transactions on neural systems and rehabilitation engineering, 13(3), 395-405.

Roetenberg, D., Luinge, H., and Slycke, P. (2009). Xsens MVN: full 6DOF human motion tracking using miniature inertial sensors. Xsens Motion Technologies BV, Tech. Rep.

Roetenberg, D., Luinge, H., and Veltink, P. (2003, October). Inertial and magnetic sensing of human movement near ferromagnetic materials. In *Mixed and Augmented Reality, 2003. Proceedings. The Second IEEE and ACM International Symposium on* (pp. 268-269). IEEE.

Różanowski, K., Sondej, T., and Lewandowski, J. (2015, June). First approach for design of an autonomous measurement system to aid determination of the psychological profile of soldiers. In Mixed Design of Integrated Circuits and Systems (MIXDES), 2015 22nd International Conference (pp. 53-57). IEEE.

Sabatini, A. M. (2006). Quaternion-based extended Kalman filter for determining orientation by inertial and magnetic sensing. IEEE Transactions on Biomedical Engineering, 53(7), 1346-1356.

Sazonov, E. S., Fulk, G., Hill, J., Schutz, Y., and Browning, R. (2011). Monitoring of posture allocations and activities by a shoe-based wearable sensor. *IEEE Transactions on Biomedical Engineering*, *58*(4), 983-990.

Schall, M. C., Fethke, N. B., Chen, H., and Gerr, F. (2015a). A comparison of instrumentation methods to estimate thoracolumbar motion in field-based occupational studies. *Applied Ergonomics*, 48, 224-231.

Schall Jr, M. C., Chen, H., and Fethke, N. (2015b, September). Comparing Fatigue, Physical Activity, and Posture among Nurses in Two Staffing Models. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 59, No. 1, pp. 1269-1273). Sage CA: Los Angeles, CA: SAGE Publications.

Schall, M. C., Fethke, N. B., Chen, H., Oyama, S., and Douphrate, D. I. (2016). Accuracy and repeatability of an inertial measurement unit system for field-based occupational studies. *Ergonomics*, *59*(4), 591-602.

Schepers, H. M., Roetenberg, D., and Veltink, P. H. (2010). Ambulatory human motion tracking by fusion of inertial and magnetic sensing with adaptive actuation. *Medical and Biological*

Engineering and Computing, 48(1), 27.

Schmuntzsch, U., Yilmaz, U., and Rötting, M. (2013, July). Combining motion capture and digital human modeling for creating instructions in industrial settings. In International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management (pp. 124-133). Springer Berlin Heidelberg.

Siewiorek, D., Smailagic, A., and Starner, T. (2008). Application design for wearable computing. *Synthesis Lectures on Mobile and Pervasive Computing*, *3*(1), 1-66.

Snook, S. H. (1978). The Ergonomics Society: The design of manual handling tasks. *Ergonomics*, 21(12), 963-985.

Spielholz, P., Silverstein, B., Morgan, M., Checkoway, H., and Kaufman, J. (2001). Comparison of self-report, video observation and direct measurement methods for upper extremity musculoskeletal disorder physical risk factors. *Ergonomics*, 44(6), 588-613.]

Stenerson, M., Cameron, F., Wilson, D. M., Harris, B., Payne, S., Bequette, B. W., and Buckingham, B. A. (2014). The impact of accelerometer and heart rate data on hypoglycemia mitigation in type 1 diabetes. *Journal of Diabetes Science and Technology*, *8*(1), 64-69.

Taylor, R. (1990). Interpretation of the correlation coefficient: a basic review. *Journal of diagnostic medical sonography*, *6*(1), 35-39.

Teschke, K., Trask, C., Johnson, P., Chow, Y., Village, J., and Koehoorn, M. (2009). Measuring posture for epidemiology: comparing inclinometry, observations and self-reports. *Ergonomics*, 52(9), 1067-1078.

Trask, C., Bath, B., Johnson, P. W., and Teschke, K. (2016). Risk factors for low back disorders in Saskatchewan farmers: field-based exposure assessment to build a foundation for epidemiological studies. *JMIR Research Protocols*, *5*(2).

Trost, S. G., McIver, K. L., and Pate, R. R. (2005). Conducting accelerometer-based activity assessments in field-based research. *Medicine and Science in Sports and Exercise*, 37(11), S531.

Tubach, F., Leclerc, A., Landre, M. F., and Pietri-Taleb, F. (2002). Risk factors for sick leave due to low back pain: a prospective study. *Journal of Occupational and Environmental Medicine*, 44(5), 451-458.

Tulen, J. H., Bussmann, H. B., van Steenis, H. G., Pepplinkhuizen, L., and Man't Veld, A. J. (1997). A novel tool to quantify physical activities: ambulatory accelerometry in psychopharmacology. *Journal of Clinical Psychopharmacology*, 17(3), 202-207.

Unge, J., Ohlsson, K., Nordander, C., Hansson, G. Å., Skerfving, S., and Balogh, I. (2007). Differences in physical workload, psychosocial factors and musculoskeletal disorders between two groups of female hospital cleaners with two diverse organizational models. *International archives of occupational and environmental health*, *81*(2), 209-220.

Van Driel, R., Teschke, K., Callaghan, J. P., Trask, C., Koehoorn, M., and Johnson, P. W. (2009, August). A Comparison of Trunk Posture Movements: A Motion Capture System and a New Data-Logging Inclinometer. In *IEA 2009, 17thWorld Conference on Ergonomics. Beijing, China*.

Vasseljen, O., and Westgaard, R. H. (1997). Arm and trunk posture during work in relation to shoulder and neck pain and trapezius activity. *Clinical Biomechanics*, *12*(1), 22-31.

Vieira, E. R., and Kumar, S. (2004). Working postures: a literature review. *Journal of Occupational Rehabilitation*, *14*(2), 143-159.

Vignais, N., Miezal, M., Bleser, G., Mura, K., Gorecky, D., and Marin, F. (2013). Innovative system for real-time ergonomic feedback in industrial manufacturing. *Applied Ergonomics*, 44(4), 566-574.

Viikari-Juntura, E., Rauas, S., Martikainen, R., Kuosma, E., Riihimäki, H., Takala, E. P., and Saarenmaa, K. (1996). Validity of self-reported physical work load in epidemiologic studies on musculoskeletal disorders. *Scandinavian Journal of Work, Environment and Health,* 251-259.

Villumsen, M., Samani, A., Jørgensen, M. B., Gupta, N., Madeleine, P., and Holtermann, A. (2015). Are forward bending of the trunk and low back pain associated among Danish bluecollar workers? A cross-sectional field study based on objective measures. *Ergonomics*, 58(2), 246-258.

Wahlström, J., Mathiassen, S. E., Liv, P., Hedlund, P., Ahlgren, C., and Forsman, M. (2010). Upper arm postures and movements in female hairdressers across four full working days. *Annals of occupational hygiene*, *54*(5), 584-594.

Wai, E. K., Roffey, D. M., Bishop, P., Kwon, B. K., and Dagenais, S. (2010). Causal assessment of occupational bending or twisting and low back pain: results of a systematic review. *The Spine Journal*, 10(1), 76-88.

Walker, D. J., Heslop, P. S., Plummer, C. J., Essex, T., and Chandler, S. (1997). A continuous patient activity monitor: validation and relation to disability. *Physiological Measurement*, 18(1), 49.

Wang, D., Dai, F., and Ning, X. (2015). Risk assessment of work-related musculoskeletal disorders in construction: state-of-the-art review*. Journal of Construction Engineering and Management*, 141(6), 04015008.

Wang, X., Liu, S., Qin, C., Yuan, J., and Lin, M. (2015, June). Real-time localization and information acquisition system based on wireless communication. In Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), 2015 IEEE International Conference on (pp. 1293-1298). IEEE.

Wang, Z., and Fu, S. (2016). Evaluation of a strapless heart rate monitor during simulated flight tasks. *Journal of Occupational and Environmental Hygiene*, 13(3), 185-192.

Waters, T. R., Dick, R. B., Davis-Barkley, J., and Krieg, E. F. (2007). A cross-sectional study of risk factors for musculoskeletal symptoms in the workplace using data from the General Social Survey (GSS). *Journal of Occupational and Environmental Medicine*, 49(2), 172-184.

Winkel, J. and Mathiassen, S. E. (1994). Assessment of physical work load in epidemiologic studies: concepts, issues and operational considerations. Ergonomics, 37(6), 979-988.

Wong, W. Y., and Wong, M. S. (2008). Trunk posture monitoring with inertial sensors. *European*

Spine Journal, 17(5), 743-753.

Wong, W. Y., and Wong, M. S. (2009). Measurement of postural change in trunk movements using three sensor modules. IEEE Transactions on instrumentation and measurement, 58(8), 2737-2742.

Wu, G., Van der Helm, F. C., Veeger, H. D., Makhsous, M., Van Roy, P., Anglin, C., and Werner, F. W. (2005). ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part II: shoulder, elbow, wrist and hand. *Journal of Biomechanics*, 38(5), 981-992.

Wu, G., Siegler, S., Allard, P., Kirtley, C., Leardini, A., Rosenbaum, D., and Schmid, O. (2002). ISB recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion—part I: ankle, hip, and spine. *Journal of Biomechanics*, 35(4), 543-548

Xsens Technologies B.V. (2015). *MVN User Manual.* Enschede, Netherlands.

Wuellner, S. E., Adams, D. A., and Bonauto, D. K. (2016). Unreported workers' compensation claims to the BLS Survey of Occupational Injuries and Illnesses: Establishment factors. *American Journal of Industrial Medicine,* 59(4), 274-289.

Yan, X., Li, H., Li, A. R., and Zhang, H. (2017). Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention. *Automation in Construction*, *74*, 2-11.

Yang, C. C., and Hsu, Y. L. (2010). A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors*, 10(8), 7772-7788.

Yayaram, U., Jayaram, S., Shaikh, I., Kim, Y.J., Palmer, C., (2006). Introducing quantitative analysis methods into virtual environments for real-time and continuous ergonomic evaluations. *Computers in Industry*, 57(3), 283-296.

Yip, V. Y. B. (2004). New low back pain in nurses: work activities, work stress and sedentary lifestyle. *Journal of Advanced Nursing,* 46(4), 430-440.

Zephyr Technology (2012). *BioHarness 3 User Manual*. Retrieved from www.zephyranywhere.com/products/bioharness-3. Accessed in May 2017.

Zhang, J. T., Novak, A. C., Brouwer, B., and Li, Q. (2013). Concurrent validation of Xsens MVN measurement of lower limb joint angular kinematics. Physiological measurement, 34(8), N63.

Zimmermann, C. L., and Cook, T. M. (1997). Effects of vibration frequency and postural changes on human responses to seated whole-body vibration exposure. *International Archives of Occupational and Environmental Health*, 69(3), 165-17