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# An evaluation of wearable sensors and their placements for analyzing construction worker's trunk posture in laboratory conditions

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ABSTRACT

This study investigates the effect of sensor placement on the analysis of trunk posture for construction activities using two off-the-shelf systems. Experiments were performed using a single-parameter monitoring wearable sensor (SPMWS), the ActiGraph GT9X Link, which was worn at six locations on the body, and a multi-parameter monitoring wearable sensor (MPMWS), the Zephyr BioHarness™3, which was worn at two body positions. One healthy male was recruited and conducted 10 experiment sessions to repeat measurements of trunk posture within our study. Measurements of upper-body thoracic bending posture during the lifting and lowering of raised deck materials in a laboratory setting were compared against video-captured observations of posture. The measurements from the two sensors were found to be in agreement during slow-motion symmetric bending activities with a target bending of $\leq 45°$. However, for asymmetric bending tasks, when the SPMWS was placed on the chest, its readings were substantially different from those of the MPMWS worn on the chest or under the armpit.



## 1. Introduction

### 1.1. Work-related musculoskeletal disorders in construction

Construction workers are exposed to physically demanding tasks that require repetitive lifting, carrying, and installing of materials with non-neutral postures (Spielholz et al., 2006). These activities result in lower-back pain and injury (Frymoyer et al., 1980). For instance, rodmen have been found to be 3.9 times more likely to suffer from lower-back injuries compared to non-construction workers. Their full-flexion posture was found to contribute to their high injury rate (Rose et al., 2001). Tak et al. (2011) observed various levels of ergonomic hazards for workers in several construction trades and found that tilers, carpenters, and plasterers were exposed to back flexion for 40% of the observed time. Repetitive lifting tasks intensify muscular tension and are the cause of most work-related musculoskeletal disorders (WMSDs) among construction workers particularly in the lower back (Holmström et al., 1992). Lower back disorders are reported as the major cause of early retirement and turnover owing to disability and absenteeism (Burdorf and Sorock, 1997). These issues strongly affect the construction industry and are exacerbated by a post-recession workforce migration to other industries that amounted to about 20% of pre-recession workers (Barker, 2011).

### 1.2. Traditional ergonomic risk exposure assessment tools

Observation-based methods, such as the rapid upper limb assessment (RULA), Ovaco working postures assessment system (OWAS), posture, activity, tools, and handling (PATH), and rapid entire body assessment (REBA), have been traditionally used to assess the working posture. These methods rely upon direct observation and rating onsite or video recording and rating offsite (Valero et al., 2016; Vieira and Kumar, 2004). However, these methods are time-consuming and are potentially biased due to the subjective judgment of the raters (Vieira and Kumar, 2004). Therefore, the methods are recommended to be used by certified professional ergonomists or raters who are trained in ergonomics and industrial hygiene. But the practitioners experienced difficulties when using them in real-work conditions (Diego-Mas et al., 2015). Furthermore, the adoption of these methods is restricted by the nature of the construction industry. Video recording of construction activities is difficult due to the dynamic nature of construction activities, which involve multiple moving workers who

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are not limited to a stationary area. Workers, heavy equipment, and materials also share the same space, creating interferences and occlusions for human raters and video recording. Moreover, there are safety concerns that limit access to onsite raters.

### 1.3. Technology-based systems for occupational health and safety research

New wearable sensor technologies are emerging for occupational health and safety (OHS) research and can be classified into two main categories: (a) simple systems that are based on signal sensor/single-body location designs that only monitor body motion, and (b) complex systems involving multiple sensors that collect motion and physiologic measures. The first category of wearable sensors can be exemplified by current accelerometry-based monitors, which we refer to as “single-parameter monitoring wearable sensor” (SPMWS) systems. One of the examples is the accelerometer which is used to track a human's physical activity and motion by measuring the person's three-axis acceleration parameters at a single body location and estimating the person's physical activity, vibration, and inclination based on the measured acceleration data. Another example of the SPMWS systems for the collection of a body motion parameter is the inertial measurement unit (IMU) sensor which collects acceleration, gyroscope, and magnetometer data. IMU sensors can be worn on the wrist, waist, back, hip, thigh, or ankle by using wrist bands, waist loops, sticker patches, or belt pouches. Most SPMWS systems can log data to an internal memory as well as transmit real-time data to a personal computer through a gateway.

Accelerometer-based systems have been found to be useful and more practically applicable for assessing workers' exposures in terms of the degree and intensity of flexion during working hours. These systems have been used to assess the level and frequency of WMSDs exposure for various occupations by measuring inclinations of body parts. Estill et al. (2000) measured the arm acceleration of workers in assembly lines by using a single-axis accelerometer worn on the wrist to assess the WMSD exposure levels of upper limb motions. Paquet et al. (2001) used accelerometers to assess the trunk, shoulder, and leg postures of simulated construction job tasks including carrying wood beams and moving bricks and concrete blocks. Bernmark et al. (2011) evaluated a triaxial accelerometer as a tool to analyze the head movement inclination in computer work tasks. Thamsuwan and Johnson (2015) used tri-axial accelerometers for evaluating non-neutral work postures of the upper arms and back required by orchard workers' apple harvesting activities. Dahlqvist et al. (2016) validated a low-cost tri-axial accelerometer for measuring the inclination angles and velocities of the head, upper back, and upper arm movements with painting, computer work, furniture polishing, and elevated arm activities.

The second major category of wearable sensors consists of composite motion and physiological status monitors collecting multiple streams of data, which we refer to as “multi-parameter monitoring wearable sensor” (MPMWS) systems. Environmental and occupational exposures are often multifactorial and require multiple measures. Composite sensors provide a rich and holistic dataset compared with SPMWSs. For instance, MPMWS systems, besides tracking an activity, can also perform electrocardiogram (ECG) monitoring and respiratory rate measurement. Despite offering advantages of collecting various types of data, few validation studies have been conducted for MPMWS systems. Moreover, there are limitations when using the systems, as their designs often assume that they are worn in specific body locations specified by the sensor manufacturers. However, securing the systems with affixation aids, such as chest belts or compression shirts, is often not an option, despite the fact that they may improve wearer comfort, reduce interferences, and ensure data quality, because construction activities often involve vigorous movements.

MPMWS and SPMWS systems also differ based on the number of pivotal parameters they cover (Zhu et al., 2015). Generally for OHS research in construction, MPMWS systems are more desirable if the research objective is to investigate the construction worker's biomechanics in an integrated manner. SPMWS systems may be used in more integrated research studies, but would require separate physiological monitoring devices, such as a HR monitor, which introduces additional complexity and cost during data collection and analysis.

### 1.4. Purpose of the research

MPMWS systems have been used in several OHS research studies (Cheng et al., 2013; Dolezal et al., 2014; Lee and Migliaccio, 2016; Smith et al., 2014). The reliability and validity of the MPMWS for physiological measurements including the HR and BR have been studied (Gatti et al., 2014; Johnstone et al., 2012; Villar et al., 2015). However, previous studies have not validated the MPMWS system for analyzing the ergonomic postures of construction workers even though some models such as the Zephyr BioHarness™3 (ZB) (Medtronic, Dublin, Ireland) collect 3-axis acceleration data and estimate torso inclination. This study compares the accelerometer measurements from the ZB against a reference SPMWS system, the AG accelerometer (ActiGraph, LLC, Pensacola, FL), as well as against posture assessments from video recordings to determine the quality of thoracic bending measurements from exemplary MPMWS and SPMWS systems.

Specifically, in this study, we focus on measurements of upper body thoracic bending posture during material lifting and lowering. The results from past studies have shown that accelerometer locations are critical to the validity and reliability of the physical activity and sleep measurements (Gatti et al., 2016; Schall et al., 2016; Slater et al., 2015). The placement of sensors for ergonomic trunk posture has not yet been fully evaluated, although Faber et al. (2009) studied the optimal locations in the placement of a single inertial sensor on the posterior back for trunk inclination measurements. Our comparison among the selected MPMWS and SPMWS systems is therefore based on different sensor placements for analyzing non-neutral posture of the trunk body. Furthermore, the current study examines the error in bending angle measurements associated with different body placements for repetitive bending activities.

## 2. Method

### 2.1. Instruments

SPMWS accelerometer systems have been used widely for public health and occupational health research. For instance, the AG accelerometer described in Table 1, has been used to assess human activity levels and sedentary behavior (Matthews et al., 2008), energy expenditure (Plasqui and Westerterp, 2007), and sleep quality (Ancoli-Israel et al., 2003). The AG was originally developed to monitor physical activity and sleep for adults and children, generally. For instance, Donaire-Gonzalez et al. (2013) used the AG accelerometer (GT3X model) as a gold-standard for energy expenditure measurement for comparison smartphone-based energy expenditure measurement. Validation studies for ergonomic posture analysis have been conducted using the AG as well. The AG measurements were found to be correlated with a gold-standard motion analysis reference system for arm and trunk inclination in slow- and medium-speed simulated working tasks

(Korshøj et al., 2014). The AG was also used for assessing the musculoskeletal risk of upper body inclination and arm movement above the shoulder among blue-collar workers (Jørgensen et al., 2013).

Among the many off-the-shelf MPMWS systems, ZB has been applied in studies on construction workers' health and safety (Lee and Migliaccio, 2016). The features of this system are summarized in Table 1. In contrast with other systems, such as the Polar HR monitor (Polar Electro, Kempele, Finland) that relies on modules placed on the sternum, this system is particularly useful in construction studies because its sensor module is conveniently placed under the armpit and does not interfere with fall arrest systems. The popular chest belt type of HR monitor, such as the Polar H7 HR sensor, only collects ECG raw data; thus, it is considered a SPMWS system. However, ZB is a combined sensor system incorporating an internal BR sensor, an ECG sensor, and a tri-axial accelerometer. Built around a data logging module and fabric sensors mounted on a chest strap, ZB measures the HR, BR, and physical activity, which can be converted into energy expenditure during physical activity through validated algorithms. It should be noted that the MPMWS has a shorter battery life compared with the SPMWS system, likely due to the power requirements of logging or transmitting large amounts of data from multiple sensors as also shown in the examples in Table 1.

Previous literature indicates that the AG accelerometer is accurate and reliable for use in ergonomic posture analysis research. Whereas most of the literature is based on an early version of the AG (model GT3X), this study uses the current version of the system (model GT9X) that includes 3-axis gyroscope and magnetometer data, in addition to the accelerometer data that the GT3X collects. This model also collects measurements of ambient light, which is one of the variables related to assessment of sleep quality. Because we did not use the light sensor, we consider the AG GT9X in our study as an example of a SPMWS sensor.

Both the ZB and AG devices were set to sample at 100 Hz. The raw acceleration data were logged and stored in the internal memory of each sensor module. Each device was connected to a computer by using a universal serial bus cable, and the raw data were retrieved through the software supplied by the manufacturer of each device.

### 2.2. Experiment

A male university student with a typical build, but with no history of back pain or cardiovascular disease (height, 176 cm; weight, 80 kg; body mass index, 25.8) was recruited for the experiment. The participant concurrently wore multiple AGs. Several studies (Driel et al., 2013; Graham et al., 2009; Schall et al., 2015; Thamsuwan and Johnson, 2015; Veltink et al., 1996) have attached accelerometer sensors to the anterior torso between the sternum and the sternal notch for trunk flexion and lateral bending angle measurement. Therefore, the current study selected this location of the anterior torso (hereinafter referred to as "chest") as the reference placement for the upper body trunk flexion. Faber et al. (2009) studied the optimal locations in the placement of a single inertial sensor on the posterior back for trunk inclination measurements; thus the sensor mount on the back was considered to be the secondary reference placement. The head placement of the sensor has usually been considered for tracking construction workers for the purpose of posture analysis. For example, Yan et al. (2017) used an inertial sensor mounted on the head and posterior back to measure real-time posture angle, and thus, the current study also included the head placement. The shoulder placement is not usually used for trunk posture monitoring; however, the location has the potential of integrating the accelerometer system, which is used for patients' abnormal body movements (Manson et al., 2000) and for air pollutant monitoring sensors (Phillips et al., 2001). Since the AG system was originally validated for physical activity mounted on the waist (Chen and Bassett, 2005), the AG was also mounted on the waist for the current study. In addition to the (1) chest, sensors were worn at the (2) spine between the thoracic and lumbar vertebrae, (3) the center-waist, (4) the nondominant-side waist, (5) the head, and (6) the shoulder. The ZB sensor module was originally designed to be worn under the left

**Table 1**
Features of Zephyr BioHarness™3 and ActiGraph GT9X link.

| | Zephyr BioHarness™3 | ActiGraph GT9X Link |
|---|---|---|
| Sensor type classified based on number of parameter in raw data | Multi-parameter monitoring wearable sensors | Single-parameter monitoring wearable sensor |
| Raw data collected | | |
| *Body motion* (e.g., *3-Axis acceleration*) | O | o |
| *ECG sensor output* | O | × |
| *Breathing sensor output* | O | × |
| Selected measurements estimated | | |
| *Activity level* | O | o |
| *Energy burn* | × | o |
| *Heart rate* | O | × |
| *R–R interval* | O | × |
| *Heart rate variability* | O | × |
| *Breathing rate* | O | × |
| *Actual angle of inclination* [a] | O | × |
| *Sleep duration/efficiency* | × | o |
| Weight of sensor module | 18 g | 14 g |
| Size of sensor module | 28 (diameter) × 7 mm | 35 × 35 × 10 mm |
| Battery life | Up to 26 h per charge | Up to 14 days per charge |
| Memory | Logs and stores up to 20 days of data | 4 GB |
| Dynamic range | ±16 g | ±8 g (Primary accelerometer)/±16 g (Secondary accelerometer) |
| Data-logging sample rate | 100 Hz | 30–100 Hz |
| Reporting unit of raw output | Bits | g |
| Sensor module placement that manufacturer introduced | Chest, under armpit | Wrist, waist, ankle, upper arm, thigh, chest, back |
| Data analysis software | OmniSense | ActiLife |

Note: [a]The current research used the posture analysis software developed by the Ergonomics Laboratory at the University of Washington for estimating actual inclination angle. O: Provided × : Not Provided.

armpit with a chest strap; however, in addition to this location, a second ZB sensor was also concurrently placed on the chest using a compression shirt. Fig. 1 shows the placements of the two sensor types.

Two different tasks were designed to assess working posture. In the first experiment, the participant repetitively conducted single-axis symmetric bends while in a standing position. In the second experiment, the participant performed multi-axis, asymmetric bends while building a raised deck with pavers and pedestals. All experimental protocols were approved by the University of Washington Institutional Review Board.

### 2.2.1. Single-axis symmetric bending tasks

The single-axis symmetric bending task was designed with target bending angles and different levels of bending speeds. The task was designed to examine how the trunk flexion angle and speed affect the agreement between different sensor-placement combinations. The National Institute for Occupational Safety and Health (NIOSH) posture assessment guide introduced a recommended practice for classifying the extent of the worker's trunk flexion from a neutral to an increasingly non-neutral posture by over 30°, 60°, and 90° (NIOSH, 2014). Hoogendoorn et al. (2000) estimated the risk of trunk flexion in lifting work based on the percentage of the worker's time spent with trunk flexion above 30° and 60°. In the symmetric bending task experiment the participant was instructed to bend his upper torso to 45° and 90°, respectively. To guide the torso in moving to the targeted bending angles, a 45° cut wood frame and 90° table were placed in front of the participant (Fig. 2a1–a3). During the experiment, a research assistant provided oral feedback to the participant to inform him if he was bending at or beyond the designated 45° and 90° target angles. To assess if bending speed is a factor that matters to the agreements of the inclination angles measured by various sensor-placement combinations, the participant was instructed to bend at three different speeds. Fast bending was at 60 bends per minute (bpm; 1.00 Hz); medium bending was at 40 bpm (0.67 Hz), and slow bending was at 30 bpm (0.50 Hz). A metronome guided these three different bending speeds. The participant performed the bending activity 10 times for each combination of bending angle and speed.

### 2.2.2. Multi-axis asymmetric bending tasks

In the second experiment, the participant installed concrete pavers onto a raised deck to simulate a typical construction activity that requires repetitive, multi-axis, asymmetric bending of the upper torso. The installation task involves repetitive lifting, carrying, and lowering of 1-kg pavers to complete a raised deck with pedestals (Fig. 2b1–b3). The pavers were stored 2.5 m away from the installation area. Once the participant had installed 18 pavers on pedestals in the installation area, he disassembled the pavers and pedestals and moved them back to the inventory area. Then, the participant reinstalled the disassembled pavers and pedestals in the installation area once again. The tasks were performed for 50 min, and the participant was instructed to have a 2-min break between each 10-min work session of installing and disassembling the pavers and pedestals activities.

As the ZB and AG accelerometers have their own clocks, the participant was instructed to give out start/stop signals (i.e., flexing the trunk three times) at the beginning and end of each experiment task to help mark the timestamps for synchronization during data post-processing. Video cameras were also deployed to record all the experiment activities, with a timestamp as a back-up method of synchronizing the two different accelerometer devices.

Rothman et al. (2008) suggest that repeating a measurement within a study is one principle to reduce random error. Because only one subject participated in the study, the subject conducted 10 experiment sessions to repeat the measurements both in the single-axis systematic bending tasks and multi-axis asymmetric bending tasks. For the multi-axis asymmetric bending tasks especially, the subject had a 10-min break between each session. A research assistant checked and when necessary adjusted the sensors to make sure they were securely placed on the original sensor placement.

## 2.3. Data analysis

For signal processing of the 3-axis acceleration raw data, the posture analysis software developed by the Ergonomics Laboratory at the University of Washington was used. The software was written on LabVIEW and made up of two processing steps. The first step resampled the data at 10 Hz from the raw data collected at 100 Hz. The second step displayed various bins of postures as waveforms and calculated the trunk flexion/extension, lateral and vector sum angles, and raw triaxial accelerations. The calculated angle data were used to estimate the following: (1) the percentage of time bending in excess of the set threshold angles, (2) 10th, 50$^{th}$, 90$^{th}$, and 99th percentile bending angles, and (3) average angles. For step 2, an efficient method of estimating the inclination angle uses the ratio of two axes to determine the angle of the sagittal bending and lateral bending, respectively (Fisher, 2010). The angle between the gravity vector and z-axis was measured to determine the vector sum of the sagittal and lateral bending of the trunk (Fig. 3). The sagittal (forward) bending angle ($\alpha°$) was calculated as arctan ($Ay/Az$), and the vector sum of the lateral and sagittal bending ($\beta°$) was calculated as arctan $\left(\sqrt{A_x^2 + A_y^2}/A_z\right)$, where $Ax$ is the acceleration detected by the x-axis; $Ay$ is the acceleration detected by the y-axis, and $Az$ is the acceleration detected by the z-axis. The shaded face of the accelerometer in Fig. 3 was attached to the human anterior, posterior trunk, and head. The other faces of the accelerometer were attached to the shoulder, underarm, and side-waist placements; however, the three axes were rotated in accordance with the baseline three axes of acceleration shown in Fig. 3.

To test the agreement between the bending angle measurements using feature extractions (Lee et al., 2016), a preliminary data analysis was conducted by comparing the maximum bending angles of the bending trials. However, as the participant bent the trunk with a continuous movement for the task of symmetric bending, the continuous angular output was compared in the present study to investigate agreement with the various angle frames from −5° to over 90° as following the extent of risk levels from neutral to non-neutral trunk posture defined by Bao et al. (2007). The Pearson correlation coefficients for the continuous angular data point during the entire period of conducting the simulated activities were estimated in order to compare the measurements from the two sensors. The mean of sample-to-sample root mean square differences (RMSDs) was estimated using equation (1), where $\theta_i$ is trunk displacement measured by an alternative sensor and placement, and $\theta_i'$ is trunk displacement measured by the reference system worn on the chest.

$$RMSD = \sqrt{\sum_{i=1}^{n} \left(\theta_i - \theta_i'\right)^2 \Big/ n} \quad (1)$$

Bland–Altman plots were used to assess the agreement between the two devices (Bland and Altman, 1986; Gatti et al., 2014; Jones et al., 2011; Wundersitz et al., 2015; Hanneman, 2008). The angular data obtained by the ZB sensors worn on the chest and under the non-dominant armpit were compared with the data obtained from the AG placement combinations. The descriptive statistics of the percentage of time above the bending thresholds as

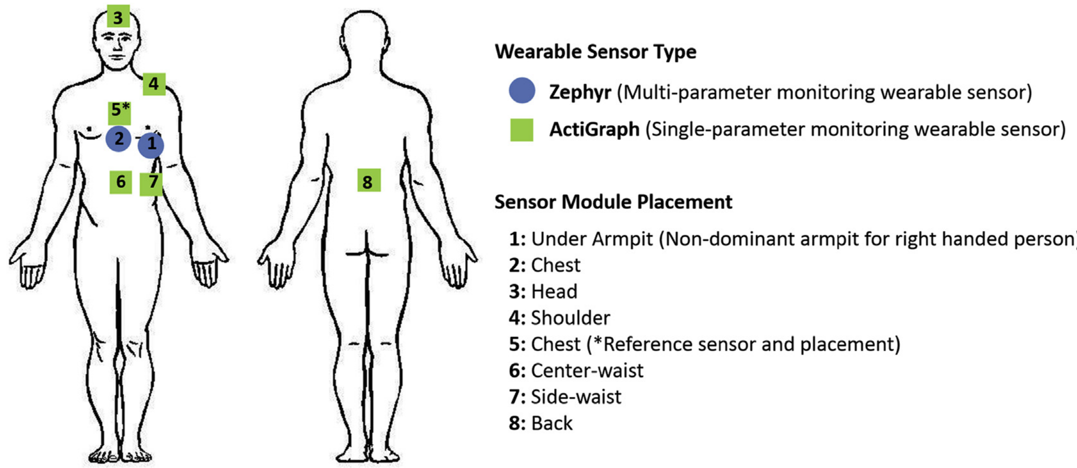


**Fig. 1.** Zephyr BioHarness ™ 3 and ActiGraph GT9X Link sensor placements (Background body map image courtesy of http://total-wellness.co.uk/body-map-front).

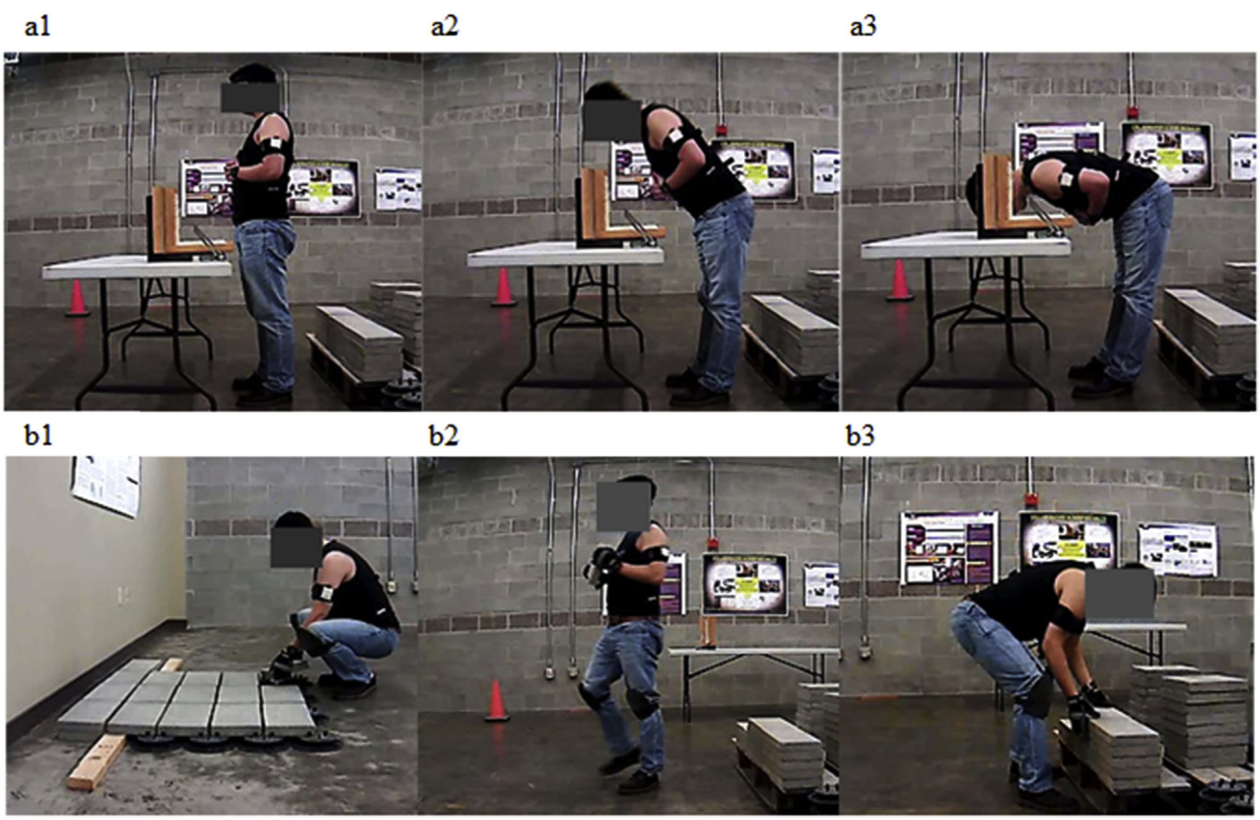


**Fig. 2.** Illustration of single-axis symmetric bending tasks (a1, a2, a3) and multi-axis asymmetric bending tasks (b1, b2, b3) in the designed experiment.

well as the 10th, 50$^{th}$ and 90$^{th}$ percentiles of the trunk flexion angle were estimated. The sample methods for data analysis were applied for the vector sum angles (β°) in the multi-axis asymmetric bending tasks except for the RMSDs. Descriptive statistics and the Bland–Altman analysis were conducted using STATA13 (College Station, TX, USA: StataCorp LP) and Microsoft Excel 2013 (Seattle, WA, USA: Microsoft).

### *2.4. Video-based observations*

As an additional reference for posture measurement, video recorded from a camera placed on the left side of the participant for the symmetric bending task experiment were analyzed using the modified RULA method introduced by Bao et al. (2007). Three raters independently evaluated the four risk levels of trunk flexion: $-5°$–$20°$ (risk level 1), extension (risk level 2), $20°$–$60°$ (risk level 3), and $\geq 60°$ (risk level 4). Video frame sequences were provided to each rater in random order. Material loading was not considered in the RULA analysis. The percentage of time in each category was estimated. The conformity of each rater's assessment and the measurements from sensors was assessed through the percentage of agreement, and by Kappa statistics (McHugh, 2012).

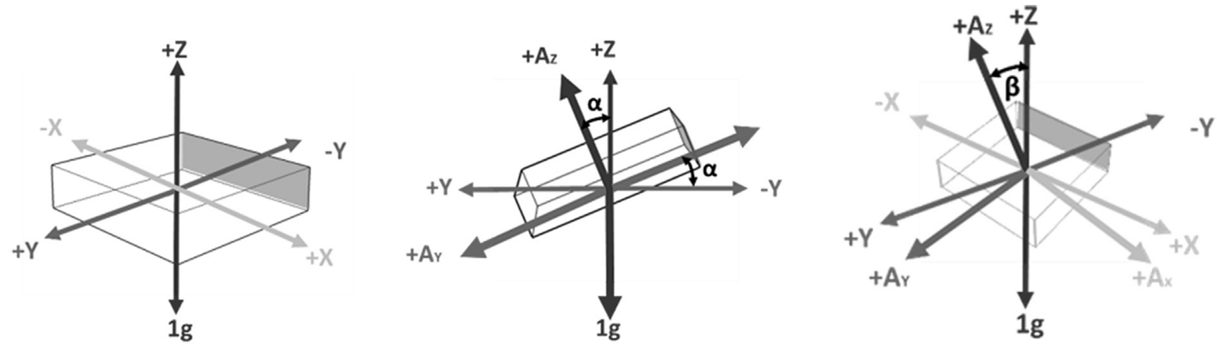


**Fig. 3.** Angle of trunk inclination (X–Z: Frontal plane, Y–Z: Sagittal plane).

## 3. Results

### 3.1. Single-axis symmetric bending tasks

A sample of truck flexion angle data collected from alternative sensors and placements is shown in Fig. 4, which illustrate similar cyclical patterns of repeated angles for the AG chest, back, and side-waist locations and both ZB locations. Although the other AG locations indicate different angles, cyclical patterns corresponding to each bend can be clearly identified in the data.

The summary statistics for Pearson correlation ($r$) and RMSDs for symmetric trunk bending tasks (Table 2) indicate that the AG worn on the back had the greatest agreement with the reference AG on the chest. The ZB on the chest also agreed with the reference system. The ZB under the armpit was also generally compatible with the reference.

The Bland-Altman plots between the reference AG at the chest and the chest ZB (Fig. 5 for 45° and 90° bending activities and 0.5 and 1.0 Hz bending frequencies, respectively) show that the difference between the two devices tended to increase during the torso bend. The magnitude of bias also increased along with the increase in velocity. Similar results were observed for the Bland-Altman plots comparing the reference chest AG and ZB in the under armpit location (Fig. 6). However, for the comparison of the chest AG and AG at the back location (Fig. 7), systematic bias was observed, with underestimates of 2 standard deviations for 45° and 90° bending angles when relying upon the AG at the back location.

Summary statistics for the trunk flexion angles of the single-axis symmetric bending tasks from ZB and AG are summarized in Tables 3 and 4 for different bending angles and speeds. It can be observed that the sample-to-sample RMSDs increased when the bending speed was increased from 0.5 Hz to 1.0 Hz. The RMSDs also increased when the target designated bending angle increased from 45° to 90°.

### 3.2. Multi-axis asymmetric bending tasks

For the asymmetric trunk bending experiment, the descriptive statistics for the percentage of time above the bending threshold as well as the 10th, 50$^{th}$, 90$^{th}$, and 99th percentiles of the vector sum angle (β°) combined sagittal and lateral bending are summarized in Table 5. The AGs worn on the center-waist, head, and shoulder tend to overestimate the bending posture angle when being compared with the AGs worn on the chest and back. The statistics from the ZBs agreed well with each other, although all of the angle statistics were higher than those of the chest-, back- and side waist-worn AGs and with a higher standard deviation. Based on the ZB data, the participant was more exposed to the non-neutral sagittal and lateral bending postures and spent more time bending over 20°, 30°, 60°, and 90°.

### 3.3. Comparison between observational and sensor methods

The Kappa coefficient of the three raters who conducted the RULA analysis was 0.87, indicating a strong agreement level. There was no case in which all three raters selected entirely different frame categories. The percentages of time in the four posture categories (i.e., four different risk levels) that were estimated by observation and independently, by accelerometer data (Table 6), indicate that estimates from the ZB sensors worn on the chest and under the armpit are comparable to the modified RULA in trunk flexion angles from −5° to 60°. In the trunk flexion that ranged from 20° to 60°, the estimates from the AG sensors worn on chest and back present as more comparable to the video observation estimates than the estimates by ZB worn on chest and under

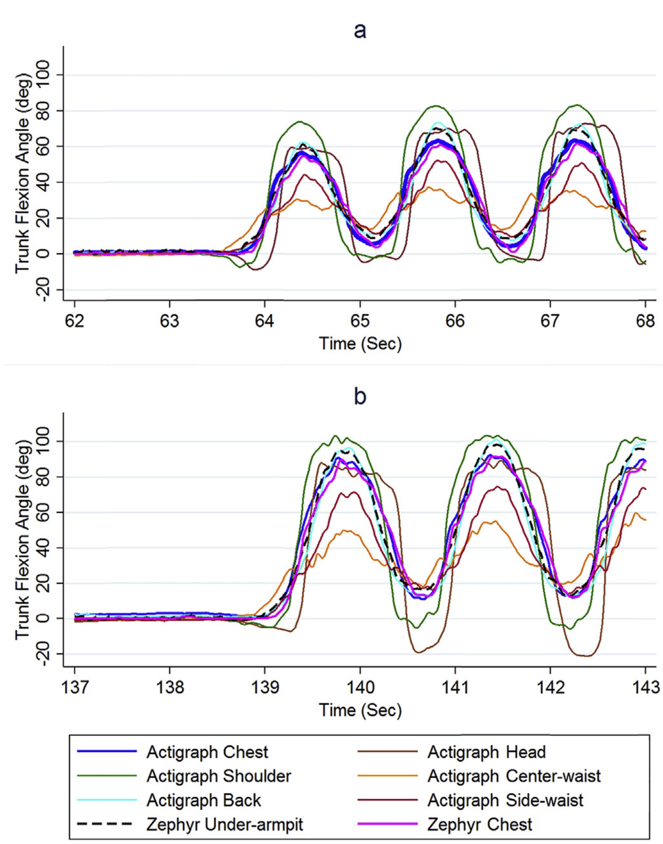


**Fig. 4.** Examples of trunk flexion angle waveforms for the two Zephyr and six ActiGraph measurements for single-axis symmetric bending tasks (a: 45° bending trials, b: 90° bending trials).

**Table 2**
Summary statistics for single-axis symmetric trunk bending tasks (all data).

| | ActiGraph Chest | Zephyr Chest | Zephyr under Armpit | ActiGraph Back | ActiGraph Side-Waist | ActiGraph Head | ActiGraph Shoulder | ActiGraph Center-waist |
|---|---|---|---|---|---|---|---|---|
| Mean (°) | 23.4 | 22.4 | 24.6 | 23.2 | 17.8 | 23.9 | 27.1 | 18.8 |
| Standard deviation (°) | 27.7 | 28.1 | 29.2 | 29.1 | 21.7 | 35.2 | 36.5 | 18.4 |
| 10th Percentile (°) | −1.1 | −1.3 | -0.35 | −0.8 | −2.2 | −7.1 | −0.3 | 0.2 |
| 50th Percentile (°) | 7.5 | 4.9 | 9.6 | 8.6 | 9.1 | 5.5 | 4.8 | 12.8 |
| 90th Percentile (°) | 69.1 | 68.3 | 70.6 | 70.4 | 49.9 | 82.4 | 91.2 | 45.8 |
| 99th Percentile (°) | 85.6 | 86.3 | 96.0 | 97.8 | 71.6 | 94.4 | 103.4 | 62.3 |
| Pearson correlation coefficient | Ref | 0.97 | 0.95 | 0.98 | 0.97 | 0.85 | 0.96 | 0.91 |
| Mean Bias (°) | Ref | 1.0 | −1.2 | 0.3 | 5.7 | −0.5 | −3.7 | 4.6 |
| Lower Limit of Agreement (°) | Ref | −13.6 | −18.8 | −12.5 | −11.5 | −37.4 | −29.3 | −21.8 |
| Upper Limit of Agreement (°) | Ref | 15.7 | 16.4 | 13.0 | 22.8 | 36.4 | 21.9 | 31.1 |
| Upper-Lower (°) | Ref | 29.3 | 35.2 | 25.5 | 34.3 | 73.8 | 51.2 | 52.9 |
| Sample to sample RMSD (°) | Ref | 7.4 | 8.9 | 6.4 | 10.3 | 18.5 | 13.3 | 14.0 |

Note: Ref = Reference device and placement.

armpit. The AG sensors worn on chest and back and ZB sensors worn on chest and under armpit underestimated the frequency of trunk flexion by $\geq 60°$ when contrasted with estimates taken by video observation. The measurements from AG worn on side waist, head, should, and center waist were not consistently comparable with the estimated measurements from video observation.

## 4. Discussion

### 4.1. Comparison between sensor systems and placements

This study measured trunk posture by using different sensors in different positions on the body. Similarly to Faber et al. (2009), our study also determined ideal placement for sensors, which can have

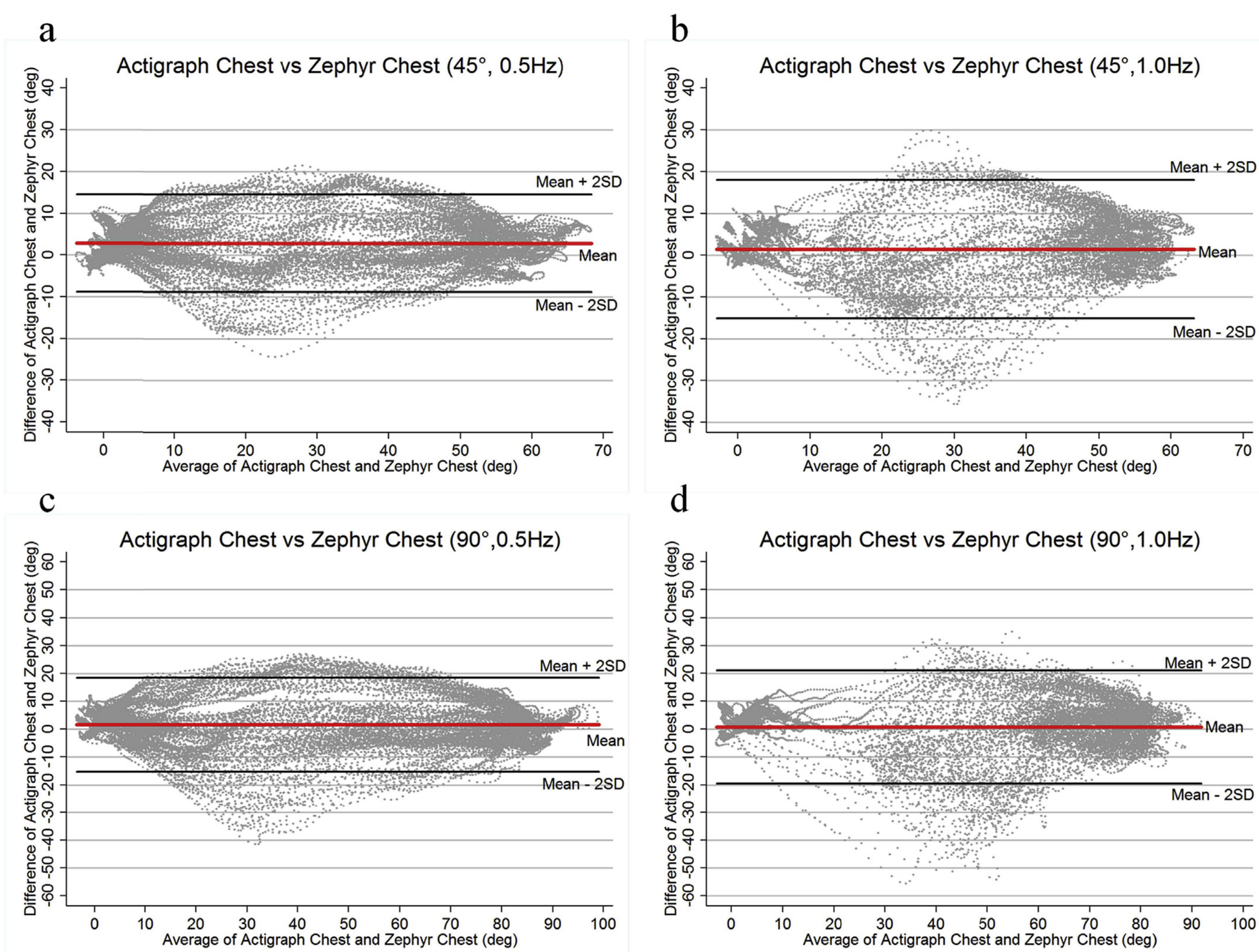


**Fig. 5.** Bland–Altman plots for ActiGraph and Zephyr at 45° and 90° bending with slow and fast bending speeds (a, b = x-axis ranged from 0° to 70°, y-axis ranged from −40° to 40°; c, d = x-axis ranged from 0° to 100°, y-axis ranged from −60° to 60°).

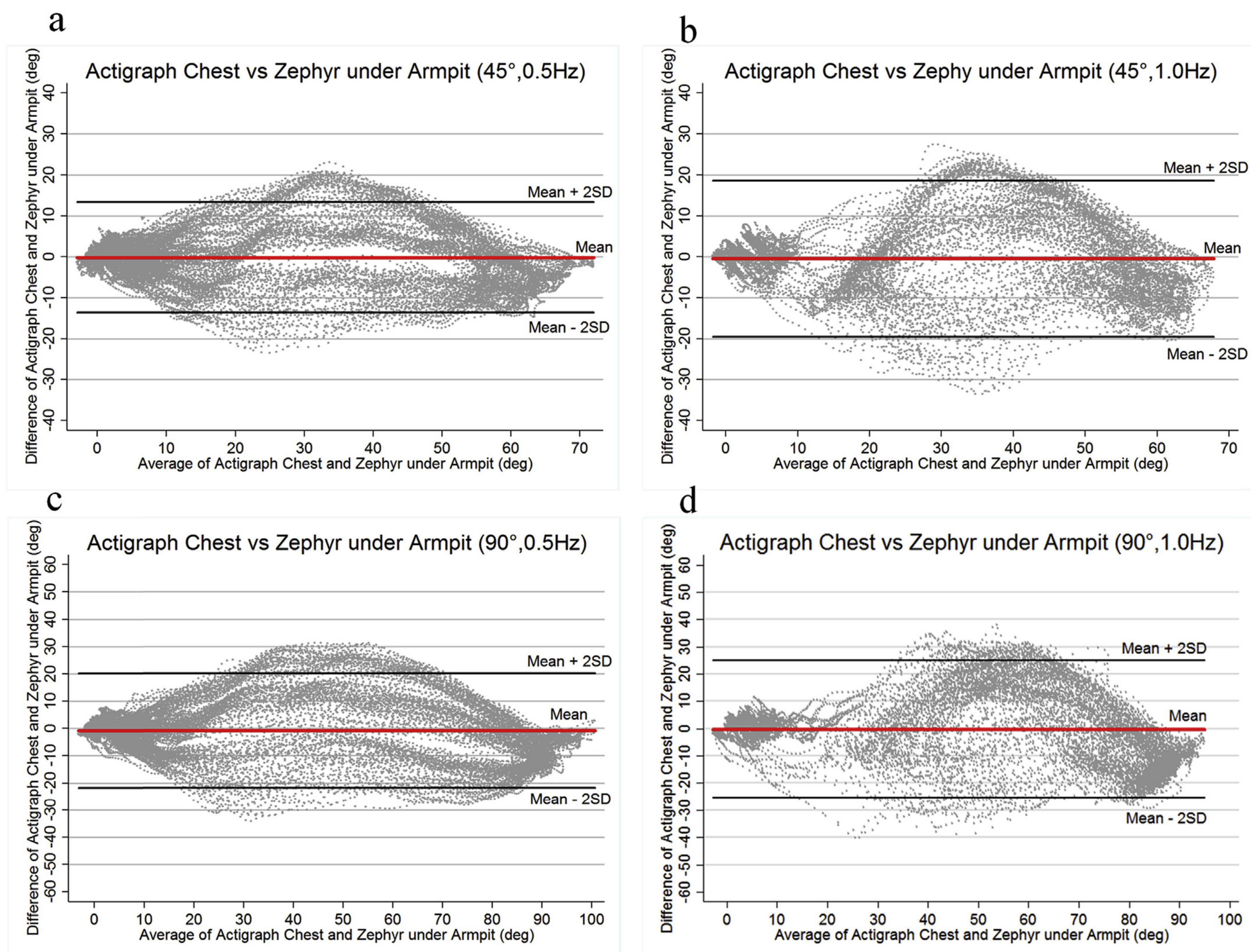


**Fig. 6.** Bland–Altman plots for ActiGraph and Zephyr at 45° and 90° bending with slow and fast bending speeds (a, b = x-axis ranged from 0° to 70°, y-axis ranged from −40° to 40°; c, d = x-axis ranged from 0° to 100°, y-axis ranged from −60° to 60°).

practical implications for studies of construction workers. Based on the sample-to-sample RMSDs in Tables 3 and 4, the bias of the angle measurement between the ZB and AG increases as the bending angle and speed increases. With a slow frontier–anterior bending of 0.5 Hz and a 45° target bending, readings from the chest-worn ZB have a good agreement with the reference sensor-placement, with a mean difference of −0.15°. However, the LOAs were larger, at approximately ±13°, suggesting that there may be large variations between the two devices when measuring individual bends. For the multi-axis asymmetric trunk bending tasks in Table 5, data collected by AG at the center-waist, head, and shoulder clearly indicated larger bending angles. This could be due to the necessary bending for the shoulder bones and muscles while performing the lifting and lowering of materials and while walking. Also, based on observations of the recorded video, the participant often bent his neck separately from the trunk flexion; thus, the AG worn on the head overestimated the trunk flexions. Other bodily movements, which were not relevant to the paver installation activity, such as nodding of the head when listening to the researcher's instructions during the experiment, also increased the error of the AG worn on the head. When the participant was installing the paver in a squatting posture, the belt worn by the participant severely interfered with the AG worn on the center-waist. For the multi-axis asymmetric bending tasks, the head, shoulder, and center-waist were not the optimal attachment locations because of the interference of the personal protective equipment expected to be worn by construction workers. A bias was observed between the two sensors that increased when the participant was in the process of torso bending; that is, when the angular velocity increased (Figs. 5 and 6). The magnitude of bias also increased along with the increase in velocity. For the AGs worn on the chest and back (Fig. 7), the error increased until the participant performed flexion and reached the maximum bending angle, and the error decreased while returning to the neutral position. The error was higher when the participant was bending forward than when he was returning to the original posture after bending. In addition, the higher the angular velocity, the higher the error value tended to be.

For the multi-axis asymmetric bending tasks posture analysis, both the chest- and non-dominant armpit-worn ZB accelerometers reported higher bending angles and percentages of times over the set threshold angles compared to the reference chest AG. When comparing the multi-axis asymmetric bending tasks vector sum

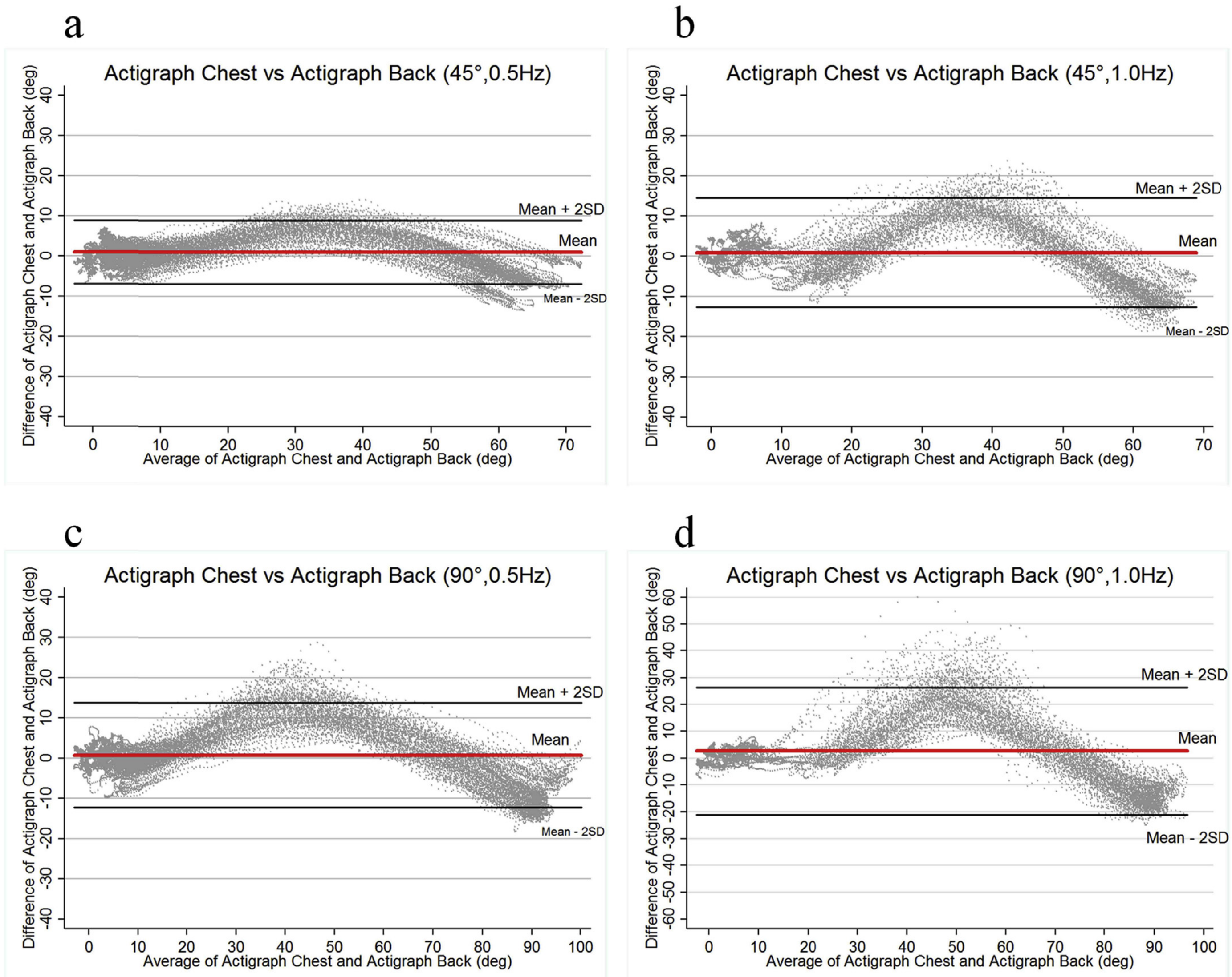


**Fig. 7.** Bland–Altman plots for ActiGraph worn on chest and back at 45° and 90° bending with slow and fast bending speeds (a, b = x-axis ranged from 0° to 70°, y-axis ranged from −40° to 40°; c, d = x-axis ranged from 0° to 100°, y-axis ranged from −60° to 60°).

estimation results in Table 5 with the symmetric posture results in Tables 3 and 4, there is a possible difference between the chest-worn AG and ZB caused by a slightly higher lateral bending value measured in the ZB than in AG. The measurements made by the AG on the side-waist and chest were most similar.

As for the AG worn on the chest and back, the sensors were installed on the relatively rigid part of the upper body. The rigidity of the armpit can vary depending on the body mass index of the subject. However, the ZB system worn on the armpit has been equipped with a shoulder belt to support a chest belt and prevent drift during continuous movement. Whereas the wearable attachment method of the ZB was intended for sports activity and occupational researches, the pouch and belt system of the AG were designed for the general population. For occupational research and the practical implications of the AG system for trunk posture measurement, a secured and wearable attachment should be designed for the construction industry which requires active trunk movement, as Thamsuwan and Johnson (2015) designed and applied in their research.

### 4.2. Video observation

The measurements from the AG worn on the chest and back, and from the ZB worn on the chest and armpit were found to be compatible with the RULA video analysis for trunk flexion less than 60° (Table 6). However, all the sensors, regardless of their placements except for the AG worn on the head and shoulder, underestimated the highest risk of trunk flexion over 60°, compared to video observations. This underestimate is an important consideration as our study utilized the chest AG as a reference for comparison with other AGs in alternative body locations and the ZB. The ZB system was actually slightly closer to the video-observed angles for single-bending postures (Table 6).

### 4.3. Limitations

Because only one participant was involved in the experiments, different anthropometric characteristics of the human body including body shape, body composition, flexibility, fitness level,

**Table 3**
Summary statistics for single-axis symmetric trunk bending (target bending degree: 45°).

| | ActiGraph Chest | Zephyr Chest | Zephyr under Armpit | ActiGraph Back | ActiGraph Side-Waist | ActiGraph Head | ActiGraph Shoulder | ActiGraph Center-waist |
|---|---|---|---|---|---|---|---|---|
| *Slow Bending 0.5Hz* | | | | | | | | |
| Mean (°) | 23.00 | 20.17 | 23.15 | 22.09 | 17.08 | 24.88 | 26.72 | 18.36 |
| Standard deviation (°) | 21.98 | 21.88 | 22.77 | 22.77 | 16.78 | 28.52 | 29.96 | 13.64 |
| 10th Percentile (°) | −4.18 | −0.35 | 0.47 | 0.24 | −1.70 | −3.25 | 0.92 | 0.88 |
| 50th Percentile (°) | 12.38 | 10.30 | 13.73 | 11.54 | 12.47 | 8.98 | 7.29 | 17.03 |
| 90th Percentile (°) | 59.87 | 53.79 | 60.20 | 60.46 | 43.28 | 67.75 | 75.48 | 36.85 |
| 99th Percentile (°) | 66.18 | 62.09 | 69.33 | 69.98 | 51.68 | 73.51 | 81.89 | 42.73 |
| Pearson correlation coefficient | Ref | 0.96 | 0.95 | 0.99 | 0.98 | 0.93 | 0.98 | 0.94 |
| Mean Bias (°) | Ref | 2.84 | −0.15 | 0.92 | 5.92 | −1.88 | −3.72 | 4.64 |
| Lower Limit of Agreement (°) | Ref | −8.87 | −13.64 | −6.97 | −7.36 | −24.94 | −22.67 | −16.14 |
| Upper Limit of Agreement (°) | Ref | 14.54 | 13.34 | 8.81 | 19.20 | 21.19 | 15.23 | 25.43 |
| Upper-Lower (°) | Ref | 23.41 | 26.98 | 15.78 | 26.56 | 46.13 | 37.90 | 41.57 |
| Sample to sample RMSD (°) | Ref | 6.50 | 6.75 | 4.05 | 8.90 | 11.69 | 10.18 | 11.38 |
| *Fast Bending 1.0 Hz* | | | | | | | | |
| Mean (°) | 29.17 | 27.78 | 29.66 | 28.27 | 21.82 | 28.93 | 32.10 | 21.53 |
| Standard deviation (°) | 21.71 | 21.17 | 22.16 | 23.29 | 15.54 | 34.30 | 34.99 | 13.42 |
| 10th Percentile (°) | 1.55 | 0.12 | 1.53 | 1.22 | −0.62 | −14.01 | −2.47 | 0.88 |
| 50th Percentile (°) | 27.84 | 30.09 | 26.24 | 22.99 | 26.16 | 15.66 | 10.31 | 26.43 |
| 90th Percentile (°) | 56.37 | 54.26 | 61.82 | 64.63 | 41.48 | 71.34 | 81.13 | 35.82 |
| 99th Percentile (°) | 62.17 | 59.70 | 69.50 | 71.70 | 48.13 | 78.57 | 86.05 | 43.28 |
| Pearson correlation coefficient | Ref | 0.93 | 0.91 | 0.96 | 0.91 | 0.74 | 0.91 | 0.65 |
| Mean Bias (°) | Ref | 1.39 | −0.49 | 0.90 | 7.35 | 0.24 | −2.93 | 7.64 |
| Lower Limit of Agreement (°) | Ref | −15.17 | −19.54 | −12.69 | −12.87 | −46.18 | −37.79 | −25.22 |
| Upper Limit of Agreement (°) | Ref | 17.95 | 18.57 | 14.49 | 27.57 | 46.65 | 31.92 | 40.50 |
| Upper-Lower (°) | Ref | 6.50 | 6.75 | 4.05 | 8.90 | 11.69 | 10.18 | 11.38 |
| Sample to sample RMSD (°) | Ref | 8.40 | 9.54 | 6.85 | 12.50 | 23.21 | 17.67 | 18.12 |

Note: Ref = Reference device and placement.

and direction of dominant hand that potentially affect the agreement of the two devices were not considered. The Bland–Altman analysis described the consistency of the two devices; however, did not explain whether the reliability of the subject device analysis was acceptable. Even though the AG is a valid and reliable instrument to measure physical activity, it may not be a gold-standard device for posture analysis. Indeed, in comparison to video observations, the ZB may be a better reference for some conditions (e.g., symmetric bends). However, the current study does help to quantify potential differences in trunk flexion measurements from the different devices. Additionally, our experiments were limited to certain trunk flexion angles.

### 4.4. MPMWS vs. SPMWS

In general, the MPMWS system is designed to be worn only on the manufacturer's designated placements that incorporate sensor modules with a chest fabric belt and patch or head. To use the MPMWS system for ergonomic risk analysis, the manufacturer's designated placement should be validated for the purpose. Another potential concern with MPMWS system is its shorter battery life. Most composite sensor systems allow the user to configure the type of sensing data and sampling rate, which are factors that affect the sensor system's battery life. The user needs to carefully configure the sensor for a given research study. As general fitness tracking devices are deployed in more OHS studies, and new research-focused devices become available, device settings will be important to consider and document in research. The higher cost of more complex MPMWS systems compared to SPMWS may also be a concern for research studies, which will often need to collect measurements for large numbers of workers, but a single MPMWS may be more cost-effective and accepted by workers than multiple SPMWS devices.

### 4.5. Implications

The goal of the study was to investigate the following: When do the errors of posture angle estimations that emerge from a MPMWS (in this research, the ZB system worn under the armpit) be more useful in the construction OHS research when compared with a SPMWS (in this research, the AG system)? We found the errors were associated with the level of flexion angle and the speed of trunk placement. Thus, we would like to provide a guideline for construction OHS researchers, noting that the ZB system—among available MPMWS—could be used in construction trades and activities which involve static or less swiftly repetitive trunk flexions, such as rebar tying and concrete pouring on the formwork platform (Tak et al., 2011; Rose et al., 2001). The MPMWS sensor suggested in this study can collect various physiological and activity data through the combination of diverse sensors. Thus, they can be useful in finding the relationship between an ergonomic posture and heart rate vital signals, and the relationship between posture and productivity. However, as they were not developed as an ergonomic posture analysis tool, the data analysis software from the sensors' manufacturers does not provide event- and time-based posture analysis results (e.g., the percentage of the worst postures in Bao et al., 2007). When applying ZB and/or AG wearable sensors for ergonomics hazards exposure measurements, additional procedural analysis and interpretation on the exposure are currently needed as we used LabVIEW posture-analysis software after processing the manufacturers' software to obtain raw triaxial accelerations data. The software of ZB system is limited and

**Table 4**
Summary statistics for single-axis symmetric trunk bending (target bending degree: 90°).

| | ActiGraph Chest | Zephyr Chest | Zephyr under Armpit | ActiGraph Back | ActiGraph Side-Waist | ActiGraph Head | ActiGraph Shoulder | ActiGraph Center-waist |
|---|---|---|---|---|---|---|---|---|
| *Slow Bending 0.5 Hz* | | | | | | | | |
| Mean (°) | 34.48 | 32.93 | 35.32 | 33.73 | 26.45 | 34.38 | 38.75 | 26.48 |
| Standard deviation (°) | 32.52 | 32.86 | 34.47 | 34.29 | 24.91 | 40.00 | 41.79 | 20.17 |
| 10th Percentile (°) | 1.11 | −0.08 | 0.62 | 0.31 | −0.86 | −7.87 | −13.27 | 1.39 |
| 50th Percentile (°) | 20.42 | 22.07 | 20.44 | 17.61 | 19.78 | 12.19 | 12.73 | 25.01 |
| 90th Percentile (°) | 82.87 | 81.93 | 92.15 | 91.88 | 67.51 | 87.38 | 100.85 | 56.66 |
| 99th Percentile (°) | 92.36 | 90.81 | 98.06 | 98.79 | 73.78 | 94.87 | 104.00 | 65.96 |
| Pearson correlation coefficient | Ref | 0.97 | 0.95 | 0.98 | 0.98 | 0.93 | 0.98 | 0.95 |
| Mean Bias (°) | Ref | 1.55 | −0.84 | 0.75 | 8.02 | 0.10 | −4.28 | 7.99 |
| Lower Limit of Agreement (°) | Ref | −15.38 | −21.86 | −12.23 | −10.90 | −29.60 | −27.12 | −21.89 |
| Upper Limit of Agreement (°) | Ref | 18.48 | 20.17 | 13.72 | 26.95 | 29.80 | 18.57 | 37.88 |
| Upper-Lower (°) | Ref | 33.86 | 42.03 | 25.95 | 37.85 | 59.40 | 45.69 | 59.77 |
| Sample to sample RMSD (°) | Ref | 8.61 | 10.54 | 6.53 | 12.41 | 14.85 | 12.20 | 16.95 |
| *Fast Bending 1.0 Hz* | | | | | | | | |
| Mean (°) | 42.49 | 41.74 | 42.72 | 39.84 | 31.26 | 37.17 | 43.73 | 31.84 |
| Standard deviation (°) | 31.83 | 32.05 | 33.83 | 34.61 | 24.67 | 50.96 | 46.40 | 21.42 |
| 10th Percentile (°) | 1.26 | 0.03 | 0.66 | 0.47 | −1.15 | −28.95 | −5.11 | 1.06 |
| 50th Percentile (°) | 49.36 | 52.98 | 41.89 | 32.37 | 36.46 | 13.83 | 18.45 | 40.16 |
| 90th Percentile (°) | 80.02 | 78.02 | 92.08 | 94.00 | 66.45 | 92.89 | 102.11 | 55.52 |
| 99th Percentile (°) | 86.98 | 85.12 | 96.67 | 100.22 | 72.31 | 115.99 | 104.97 | 62.90 |
| Pearson correlation coefficient | Ref | 0.97 | 0.95 | 0.98 | 0.98 | 0.94 | 0.98 | 0.95 |
| Mean Bias (°) | Ref | 0.75 | −0.23 | 2.64 | 11.22 | 9.32 | −1.25 | 10.65 |
| Lower Limit of Agreement (°) | Ref | −19.49 | −25.40 | −21.16 | −12.80 | −66.87 | −48.57 | −26.18 |
| Upper Limit of Agreement (°) | Ref | 20.98 | 24.95 | 26.45 | 35.25 | 85.52 | 46.08 | 47.48 |
| Upper-Lower (°) | Ref | 40.47 | 50.35 | 47.61 | 48.05 | 152.39 | 94.65 | 73.66 |
| Sample to sample RMSD (°) | Ref | 10.14 | 12.59 | 12.19 | 16.44 | 38.47 | 23.70 | 21.27 |

Note: Ref = Reference device and placement.

**Table 5**
Combined sagittal and lateral bending exposure variability by device and placement at multi-axis asymmetric trunk bending tasks.

| | ActiGraph Chest | Zephyr Chest | Zephyr under Armpit | ActiGraph Back | ActiGraph Center-Waist | ActiGraph Head | ActiGraph Shoulder | ActiGraph Side-Waist |
|---|---|---|---|---|---|---|---|---|
| Mean (°) | 18.7 | 23.7 | 21.3 | 20.8 | 36.4 | 28.1 | 29.4 | 17.6 |
| Standard Deviation (°) | 15.9 | 21.5 | 19.8 | 15.0 | 30.3 | 20.9 | 32.1 | 15.6 |
| 10th Percentile (°) | 4.1 | 4.4 | 3.6 | 6.4 | 9.4 | 5.3 | 3.8 | 3.7 |
| 50th Percentile (°) | 11.7 | 11.8 | 12.4 | 16.7 | 24.2 | 21.5 | 13.0 | 12.8 |
| 90th Percentile (°) | 40.0 | 51.2 | 43.5 | 36.5 | 86.4 | 55.3 | 64.7 | 34.9 |
| 99th Percentile (°) | 73.8 | 97.6 | 97.1 | 83.9 | 129.9 | 86.8 | 157.0 | 81.6 |
| % time above 20° | 35.7 | 40.6 | 39.1 | 37.5 | 59.8 | 51.9 | 42.4 | 35.8 |
| % time above 30° | 23.26 | 35.1 | 31.7 | 21.3 | 41.1 | 41.7 | 37.6 | 14.4 |
| % time above 60° | 2.26 | 4.7 | 4.1 | 3.1 | 20.3 | 6.3 | 12.4 | 3.1 |
| % time above 90° | 0.0 | 1.5 | 1.4 | 0.6 | 8.1 | 0.6 | 4.9 | 0.3 |

**Table 6**
Observation and accelerometer data of time spent in categorized trunk posture for the single-axis symmetric bending activity.

| Posture category (% of time) | Video observation | ActiGraph Chest | Zephyr Chest | Zephyr under Armpit | ActiGraph Back | ActiGraph Side-Waist | ActiGraph Head | ActiGraph Shoulder | ActiGraph Center Waist |
|---|---|---|---|---|---|---|---|---|---|
| Trunk extension | 0 | 0 | 2.3 | 0 | 0.1 | 1.9 | 14.2 | 2.3 | 0 |
| Trunk neutral −5° to 20° | 56.4 | 60.8 | 57.7 | 59.8 | 62.4 | 58.5 | 49.4 | 63.3 | 56.1 |
| Trunk flexion 20°–60° | 22.1 | 23.9 | 25.9 | 24.1 | 22.0 | 33.1 | 10.3 | 9.2 | 42.0 |
| Trunk flexion ≥ 60° | 21.5 | 15.3 | 14.1 | 16.1 | 15.7 | 6.5 | 26.1 | 25.2 | 1.9 |
| Number of samples | 330 | 173,226 | 173,226 | 173,226 | 173,226 | 173,226 | 173,226 | 173,226 | 173,226 |

provides the actual angle of inclination per unit time only for sagittal bending. In practice, tilers, plasterers, and laborers are exposed to severe flexion at work in heavy civil construction projects (Tak et al., 2011). Through the application of the accelerometer integrated with the time-and-motion study, practitioners, safe professionals and industrial hygienist in the field should be able to analyze which factors of work require the severe flexion and conduct exposure control through the changes in work platform, the work flow, and work-rest regimen. They ought to consider not only the flexion exposure of the accelerometer, but also the weight of the lifted object and the type of tool used altogether. If sensors are generalized, cheaper, lightened, and can be offered to workers in the field, it will be possible to routinely analyze and provide interactive feedback on safe ergonomic behaviors.

While numerous studies have started to apply wearables, such as the AG system, to OHS research, and many off-the-shelf systems can currently collect data over eight or more working hours, there are usability issues when workers are required to wear additional sensors in various placements to measure a combination of motion and physiologic variables. Wearing sensors during all working hours may cause discomfort and result in resistance to participate in OHS studies, particularly when workers are also required to wear safety equipment and carry or operate tools that could interfere with the sensor placement. Therefore, the availability of composite systems that can measure numerous variables over a prolonged period without intruding tasks in progress is an important technological development for OHS practices and research.

Although as an overall trend the sensors are becoming smaller, the usability and comforts of the sensor securing means such as the belt, straps and wristband should be considered altogether. This will allow practitioners to embrace the sensor applications and use the new wearable technologies for ergonomics control in the field and allow researchers to apply them to their ergonomics research. Lately, mainly through the efforts of recreational and medical bio-signal monitoring sensor startup companies, MPMWS systems are becoming more flexible and slimmer, and are being developed into patches which can be attached to the torso. Examples of such development are VitalPatch (Vital Connect) and Fitpal (Vivomi) that are being commercialized or will soon be commercialized. The patch type of sensors could be optimal because of how the sensors are secured. However, the risk of skin irritation caused by the adhesive and the absence of a data-logging function in the patch-type sensors should be solved before they can serve ergonomics practice and research purposes.

Wearable sensor systems are becoming more compact and integrated. Most of them are thriving in the consumer market for tracking an individual's personal health or exercise records while the data that is collected can be transmitted onto an individual's smartphone for customized advice. Ergonomic hazard assessment will be quicker and more individual-focused, and the hazard communication will be improved between practitioner and workers with the technology support.

## 5. Conclusions

Based on the findings of this study, the selected MPMWS (i.e., Zephyr) could be worn on the chest and under the armpit for assessing thoracic bending postures involved in construction tasks with low angular velocity, as it yielded similar results compatible with ones assessed by AG worn on the chest. However, because a high variability between the multi-parameter monitor and reference SPMWS (i.e., ActiGraph GT9X) measurements was observed, the authors do not recommend that either device be used to measure single bends. Since both the chest-worn MPMWS and SPMWS tend to agree with one another over a large number of trunk flexions, either may be useful for gauging longer-term cumulative bending levels such as the mean level of bending over an entire work shift. Even though the armpit-worn MPMWS overestimated the trunk flexion angle compared with the SPMWS, the measuring posture under the armpit has the advantage of being potentially less affected by body size or shape. The selected body placements (i.e., chest and non-dominant armpit) may be the most acceptable areas for construction workers who need to wear personal protective equipment. This study suggests that both the chest-worn and under-armpit MPMWS are potentially acceptable for slow tasks in non-neutral postures compared with the SPMWS in the single-axis symmetric posture. Because of the many limitations associated with direct observation and video analysis of real-world construction activities, wearable sensors hold a lot of promise for future OHS studies.

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