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Evaluation of four sensor locations for physical activity assessment

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Direct measurements of physical activity (PA) obtained with inertial measurement units (IMUs) secured to the upper arms and trunk of 36 registered nurses working a full shift were compared to measurements obtained with a commercially-available PA monitor (ActiGraph wGT3X-BT) worn at the waist. Raw accelerations from each device were summarized into PA counts/min and metabolic equivalent (METs) categories using standard definitions. Differences between measurements were examined using repeated measures one-way analyses of variance (ANOVA) and agreement was assessed using Bland-Altman plots. Statistically significant differences were observed between all sensor locations for all PA summary metrics except for between the left and right arm for percentages of work time in the light and moderate counts/min categories. Bland-Altman plots suggested limited agreement between measurements obtained with the IMUs and measurements obtained with the wGT3X-BT waist-worn PA monitor. Results indicate that PA measurements vary substantially based on sensor location.

1. Introduction

Musculoskeletal health outcomes of the low back and neck/shoulder are among the most prevalent and burdensome of all occupational injuries. Estimates from the Global Burden of Disease 2010 study suggest that low back pain causes more global disability than any other condition, accounting for 83 million disability-adjusted life years (DALYs) in 2010 alone (Hoy et al., 2012, 2014a). Low back pain arising from occupational exposure to physical risk factors caused 21.7 million DALYs; an increase of 22% between 1990 and 2010 (Driscoll et al., 2014; Murray et al., 2013). Neck/shoulder pain was estimated to account for 33.6 million DALYs in 2010, ranking it the 4th highest in terms of disability and 21st in terms of overall burden (Hoy et al., 2014b).

Occupational exposure to non-neutral postures has been associated with musculoskeletal health outcomes of the low back and neck/shoulder (da Costa and Vieira, 2010; van Rijn et al., 2010; Vieira and Kumar, 2004). Methods for assessing exposure to non-neutral working postures in a field setting include self-report, observational, and direct measurement (Burdorf and Van Der Beek, 1999; David, 2005). The standard approach for directly measuring occupational exposure to non-neutral postures of the low back and shoulder is with piezoresistive accelerometers or, more recently, inertial measurement units (IMUs) secured to the trunk and/or upper arms (David, 2005; Li and Buckle, 1999; Teschke et al., 2009).

An IMU is a solid-state device that measures and reports an object's spatial orientation and motion characteristics using multiple electromechanical sensors (i.e., accelerometers, gyroscopes, and/or magnetometers). They are considered advantageous to accelerometers for posture assessment as fusion of the components of an IMU may address limitations of each individual sensor component (Luinge and Veltink, 2005; Roetenberg et al., 2007). For example, gyroscope measurements can be used to compensate for accelerometer-based measurements that are known to be negatively affected by dynamic and complex motions (Amasay et al., 2009; Godwin et al., 2009). Several recent studies have indicated that IMUs are reasonably stable and accurate when estimating trunk and upper arm postures in comparison to “gold-standard” optoelectric motion capture systems (Cuesta-Vargas et al., 2010; El-Gohary and McNames, 2012; Kim and Nussbaum, 2013; Schall et al., 2015a) and a field-capable reference device (Schall et al., 2015b).

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Additionally, the small size and increasing affordability of IMUs make them practical instruments for measuring posture in field-based research.

In addition to posture, an IMU's accelerometer may be used to measure other aspects of worker health that are typically difficult to observe, such as intensity of physical activity (PA). Although leisure-time PA is widely considered beneficial to overall health (Haskell et al., 2007; Warburton et al., 2006), and some studies have observed favorable effects of PA on musculoskeletal pain among worker populations (Hildebrandt et al., 2000), high intensity occupational PA has been associated with increased risk of several chronic health conditions and may be deleterious to health (Harari et al., 2015; Heneweer et al., 2011; Holtermann et al., 2012a, 2012b, 2010; Sitthipornvorakul et al., 2011). Moreover, some investigators have suggested a U-shaped relationship between intensity of PA and undesirable health outcomes (i.e. both inactivity and excessive activity may increase risk; Heneweer et al., 2009; Sesso et al., 2000). Recent work has thus emphasized the need for more accurate ascertainment of exposure to occupational and leisure-time PA using objective and validated field measurement instruments to better establish future public and occupational health recommendations (Holtermann, 2015; Prince et al., 2008).

Modern PA monitors are portable, electronic devices used to measure and track fitness-related metrics such as energy expenditure, caloric consumption, sleep patterns, and total activity. PA monitors are commonly used in epidemiological research because of their small size, freedom from biases associated with self-report, and accuracy and precision in estimating intensity of activity (Freedson et al., 2012; Matthews et al., 2012). Most PA monitors are worn at the waist or wrist and use single or multi-axis accelerometers to provide summary metrics of the quantity and intensity of movements during set time intervals (Taraldsen et al., 2012; Troiano et al., 2008; Van Remoortel et al., 2012). PA monitors have been used extensively to promote workplace health, with promising results (Bravata et al., 2007; Freak-Poli et al., 2011; Pal et al., 2009; van Sluijs et al., 2006).

Because IMUs and commercially available PA monitors incorporate fundamentally identical hardware (accelerometers), the use of small numbers of sensors in anatomic locations to capture both biomechanically meaningful posture information and PA information may be possible. Commercially available PA monitors positioned on the upper arms and on the upper back provide valid inclination data for direct long-term field measurements of upper arm and trunk inclinations in comparison to a magnetic tracking device (Korshøj et al., 2014) and a universal goniometer (Hirschhorn et al., 2015). However, the extent to which PA measurements obtained from sensors located on the upper arms or on the trunk agree with PA measurements obtained from PA monitor worn at the waist is not known. The objective of this study was, therefore, to estimate the agreement between measures of PA obtained with IMUs attached to the upper arms and to the trunk and measures of PA obtained with a commercially available PA monitor worn at the waist.

2. Methods

2.1. Participants and study design

A convenience sample of 36 healthy, female registered nurses (mean age = 30.8 years, SD = 10.1; mean body mass index [BMI] = 24.1, SD = 4.4) was recruited from two medical surgical inpatient units in the University of Iowa Hospitals and Clinics. Participants self-reported 1) no history of physician-diagnosed MSDs in the neck/shoulder or back regions, 2) no neck/shoulder or back pain two weeks prior to enrollment, and 3) no history of neurodegenerative disease (e.g., Parkinson's disease). All participants were right-hand dominant. Study procedures were approved by the University of Iowa Institutional Review Board and the University of Iowa Hospitals and Clinics Nursing Review Committee. Informed consent was obtained prior to participation.

2.2. Physical activity data processing

Direct measurements of PA from each participant were obtained using three IMUs and one wGT3X-BT PA monitor (ActiGraph, Pensacola, Florida, USA). Each IMU (ArduIMU v3, 3D Robotics Inc., Berkeley, CA) was a small wireless, battery-powered unit that was set to measure and store acceleration (triaxial, ±8 g) information. One IMU was secured to the posterior trunk at approximately the level of the 4th thoracic vertebral body and one IMU was secured to the lateral aspect of both upper arms approximately one-half the distance between the lateral epicondyle and the acromion (Fig. 1). The raw acceleration data streams of the wGT3X-BT (triaxial, ±8 g) and each IMU were sampled at 50 Hz for a continuous duration of 12 h. All devices stored the raw acceleration data to on-board flash memory. A combination of custom LabVIEW (version 2014, National Instruments Inc., Austin, TX) and Matlab (r2014a, The Mathworks, Natick, MA) programs were used to synchronize the data from each device (using time stamps recorded with the data) and process the raw acceleration information to PA summary metrics.

The raw acceleration information from each IMU and the wGT3X-BT were summarized using two approaches. For the first approach, the raw acceleration information was transformed from units of gravity (i.e., g) to a unitless metric describing the intensity of the acceleration (i.e., "counts") (Chen and Bassett, 2005; John and Freedson, 2012). First, the raw acceleration values were converted into an omnidirectional measure of acceleration by calculating the vector magnitude of the three accelerometer axes. The resulting acceleration signal was then band-pass filtered (zero-phase, 6th order Butterworth) at a bandwidth of 0.25–2.5 Hz and full-wave rectified (John and Freedson, 2012). The filtered acceleration signal was then converted to activity counts, defined as any activity that was measured above a predefined threshold of 0.016317 m/s^2

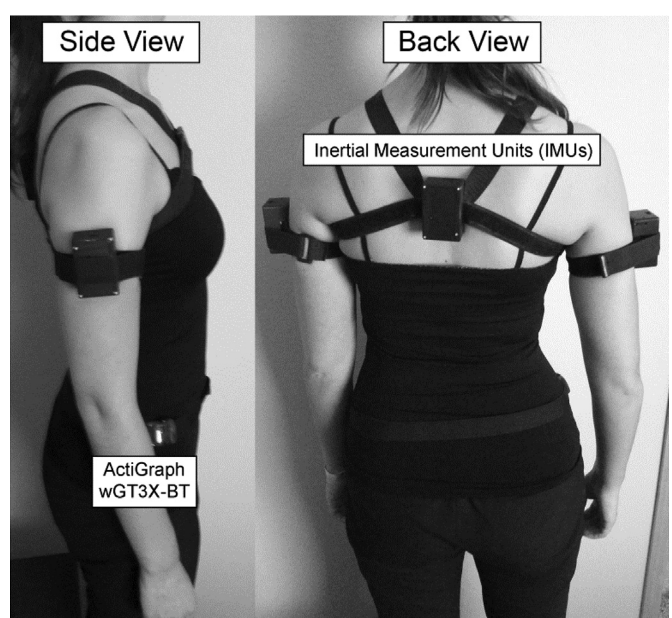

Fig. 1. The four sensor locations.

(Arias et al., 2015; Umukoro et al., 2013). The counts at each data sample were summed across non-overlapping epochs of 1-min in duration, providing results in terms of counts/min. Finally, the counts/min at each epoch was categorized into different intensities of PA. We used definitions from Freedson et al. (1998) to categorize PA as "sedentary" (0–100 counts/min), "light" (101–1952 counts/min), "moderate" (1953–5724 counts/min), vigorous (5725–9498 counts/min), and "very vigorous" (>9498 counts/min). For each participant and sensor, we then computed the total number of minutes assigned to each PA category across the full sampling duration.

For the second approach, the raw acceleration information was transformed to reflect metabolic equivalents (METs) expressing the energy cost of physical activities following the recommendations of Hildebrand et al. (2014). Specifically, the raw acceleration values were converted into an omnidirectional measure of acceleration by calculating the vector magnitude of the three accelerometer axes and then subtracting the value of gravity (g), after which, negative values were rounded up to zero. The resulting value has been referred to as the Euclidian norm minus one (ENMO) (van Hees et al., 2013). Data were then further reduced by calculating the average acceleration values per 1-s epoch and then finding the average of these 1-s epoch values over 1-min intervals. The resulting acceleration averages per 1-min epoch were then used to predict METs based on the relationship between acceleration and oxygen consumption (VO_2) (Hildebrand et al., 2014). We used standard definitions to categorize PA as "light" ($\leq$3.0 METs), "moderate" (>3.0 METs), or "vigorous" (>6.0 METs) intensity activity.

2.3. Statistical analysis

Differences between percentages of work time in each PA summary metric category by sensor location (IMUs on the trunk and each upper arm and the wGT3X-BT on the waist) were examined using repeated measures one-way analyses of variance (ANOVA), with device as a fixed effect. A separate analysis was performed for each PA category, and post-hoc pairwise comparisons were performed using a Bonferroni correction.

Agreement between the counts/min and METs obtained by the IMUs and the wGT3X-BT was also assessed using Bland–Altman analyses (Bland and Altman, 2007). Specifically, for each epoch, we calculated the average of the IMU and wGT3X-BT measurements and the difference between the IMU and wGT3X-BT measurements. Estimates of the mean (fixed) bias of the IMU measurement in comparison to the wGT3X-BT measurement and upper and lower limits of agreement were obtained using calculations that considered both repeated measures and a time-varying "true" value of the measurement (Bland and Altman, 2007).

Due to the large number of 1-min epochs in the data set (36 participants $\times$ 720 1-min epochs $=$ 25,920 total epochs), a "summarized" Bland-Altman plot was also developed to qualitatively assess inter-method agreement. Specifically, across all epochs for each participant, we calculated the mean and standard deviation of the average of the IMU and the wGT3X-BT measurements and the mean and standard deviation of the differences between the IMU and the wGT3X-BT measurements. We then plotted the means of the differences against the means of the averages and assessed the strength of the linear relationship between the means of the averages and the means of the differences using Pearson correlation coefficients. Linear regression lines were fit to check for proportional bias and hyperbolic, 95% prediction limits were plotted around the line of best fit (Armitage et al., 2008; Ludbrook, 2010).

3. Results

Complete ActiGraph data were obtained on all 36 participants. Instrumentation failure (IMUs) led to the loss of one participant's trunk data, three participants' left upper arm data, and three participants' right upper arm data. All but three participants worked a 12 h shift (two worked for eight hours and one worked for 11 h). Twenty-one participants worked day shifts (starting at 7 am) and 15 participants worked night shifts (starting at 7pm). Overall, a small percentage of work time was spent performing moderate PA across all participants regardless of sensor location. On average, participants spent less than 0.25% of their work day performing any vigorous activity (>5725 counts/min or >6 METS). Due to the small percentage of work time spent performing vigorous activity, the percentage of work time spent performing vigorous or very vigorous activity was combined with the percentage of work time performing moderate activity for all analyses.

Statistically significant differences were observed between all sensor locations for all PA summary metrics except for between the left and right arm for percentages of work time in the light and moderate counts/min categories (Table 1). In general, the IMU worn on the dominant (right) arm displayed the greatest range and mean percentage of work time performing moderate intensity PA, followed by the non-dominant (left) arm, the waist, and the trunk (e.g., percentage of work time METs moderate; Fig. 2).

Bland–Altman evaluations used to assess agreement between the PA measurements from each IMU and the wGT3X-BT further suggested that PA measurements from the trunk and each upper arm were substantially different (Table 2). Mean bias estimates indicated that the IMUs worn on the upper arms both estimated about 200 counts/min more, on average, than the wGT3X-BT (195 counts/min for the left arm and 208 for the right arm). In addition, estimates for the limits of agreement indicated potentially large differences between measurements. The IMU worn on the right (dominant) upper arm had a greater range for the limits of agreement (2229 counts/min) in comparison to that of the left upper arm (1743 counts/min). The IMU worn on the trunk had a smaller mean bias than the upper arm IMUs, estimating about 8 counts/min fewer, on average, than the wGT3X-BT. Despite the smaller mean bias, however, the IMU worn on the trunk displayed the greatest range of the limits of agreement (2581 counts/min). A similar pattern of mean bias and limits of agreement results was observed for METs, although the greatest range of the limits of agreement occurred with the right (dominant) upper arm (1.33 METs) rather than the trunk.

Qualitative assessment of the summarized Bland-Altman plots (Fig. 3) indicated that, in general, as the mean of the average of two

Table 1
The percentage of work time in each PA summary metric category [mean (SD)] by sensor location and results of one-way repeated measures analyses of variance.

Summary metric	Sensor location			
	Waist	Trunk	Left arm	Right arm
Counts (% of work day)				
Sedentary[a]	34.9 (6.1)	29.3 (6.7)	12.8 (4.2)	11.4 (4.7)
Light[b]	58.2 (6.0)	64.6 (6.8)	78.9 (4.3)	79.6 (5.6)
Moderate[b]	7.0 (2.1)	6.1 (2.1)	8.4 (2.8)	9.0 (3.4)
METs (% of work day)				
Light[a]	96.8 (1.5)	99.3 (0.6)	94.0 (3.3)	89.4 (5.0)
Moderate[a]	3.2 (1.5)	0.7 (0.6)	6.0 (3.3)	10.6 (5.0)

Note: The effect of sensor location on each summary metric was statistically significant ($p < 0.05$).
[a] All post-hoc pairwise comparisons statistically significant with $p < 0.01$.
[b] All post-hoc pairwise comparisons statistically significant with $p < 0.01$ except the difference between the left and right arm sensor locations ($p > 0.05$).

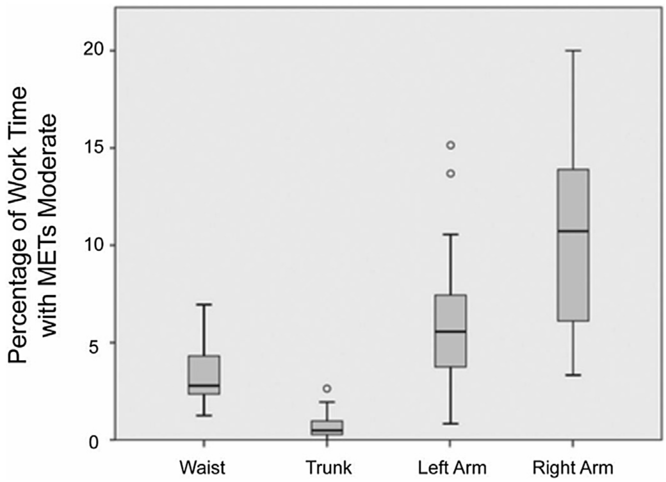

Fig. 2. Percentage of work time performing at least moderate PA as measured using Hildebrand et al. (2014) prediction of metabolic equivalents (METs) for the four different sensor locations.

measurement approaches increased, the difference between the measurement approaches also increased. An exception was an observed decrease in the difference in METs between the IMU at the trunk and the wGT3X-BT with an increase in the average METs of these two sensors. Within-subject variability of both the averages of the measurement approaches and the differences between them also generally increased as the average increased. The existence of proportional bias, especially for the upper arms, suggests that PA measurements (i.e., counts/min and METs) from the IMUs at the trunk and upper arms did not agree equally through the full range of measurements with PA measurements from the wGT3X-BT at the waist. This observation was most pronounced when comparing the IMUs on the upper arms with the wGT3X-BT.

4. Discussion

While participation in moderate- or vigorous-intensity leisure-time PA is considered an important aspect of good overall health (Haskell et al., 2007; Warburton et al., 2006), large amounts of both low intensity (i.e., sedentary) and high intensity occupational PA may be detrimental to health (Harari et al., 2015; Heneweer et al., 2011, 2009; Holtermann et al., 2012a, 2010; Sitthipornvorakul et al., 2011). Further development of objective, field capable measurement devices are needed to more accurately ascertain exposure to occupational and leisure-time PA and understand their relationship with health outcomes (Holtermann, 2015). Several recent studies and systematic reviews have assessed the validity and/or reliability of PA monitors among participants in controlled laboratory environments and/or during free-living conditions (Aguilar-Farías et al., 2014; Brazeau et al., 2014; Grydeland et al., 2014; Jarrett et al., 2014; John et al., 2010, 2013; Kelly et al., 2013; Kowalski et al., 2012; Van Remoortel et al., 2012; Thiese, 2014; Vanhelst et al., 2010; Welk et al., 2012; Yang and Hsu, 2010). Results have generally suggested a high level of heterogeneity (Van Remoortel et al., 2012), indicating a need for researchers to cautiously select monitors and summary metrics that are appropriate for their research questions (Kowalski et al., 2012). Recommendations and protocols for evaluating and using wearable monitors for researchers, developers, and end users have thus been developed in an effort to control for differences among monitors and summary metrics (Brazendale et al., 2015; Freedson et al., 2012; Welk et al., 2012).

IMUs are reasonably stable and accurate instruments capable of simultaneously measuring multiple components of worker health such as exposure to high intensity PA and non-neutral working postures. Despite the large number of studies comparing various PA monitors and activity outcomes, the current study represents the first effort we are aware of to estimate the agreement between measures of PA obtained with IMUs attached to the upper arms and to the trunk to measures of PA obtained with an ActiGraph wGT3X-BT worn at the waist. Overall, results suggested that PA measurements obtained from the four sensor locations evaluated in this study (the waist, trunk, and each upper arm) varied substantially. The IMU worn on the dominant (right) arm displayed the greatest amount of moderate intensity PA for all summary metrics evaluated, followed by the non-dominant (left) arm, the waist, and the trunk.

Accelerometers worn on the waist may underestimate the energy expenditure of free-living individuals because of an inability to detect arm movements and upper body work (Bassett et al., 2000; Hendelman et al., 2000; Matthews, 2005; Matthews et al., 2012). Given this limitation, it is worth considering if PA measurements for individuals performing complex, high intensity upper body activities should be assessed using PA monitors worn on the upper arm instead of the waist. Patient care workers, for example, have been observed to report a substantially greater duration of moderate to vigorous PA during a work week than what is directly measured by PA monitors worn at the waist (Umukoro et al., 2013). Although nurses may perceive their work as physically-demanding, PA monitors worn at the waist may not be sensitive to the tasks potentially culpable for the sentiment (e.g., extremes of posture during patient transfers). The results of the current study imply that an IMU worn on the upper arm may provide more representative estimates of PA than a waist-worn PA monitor for field-based occupational research. However, while we have observed a greater range and higher percentage of work time performing moderate PA for IMUs located on the upper arms in comparison to the waist-worn PA monitor, it is unknown what specific tasks participants were doing that led to this observation.

An additional incentive to wearing PA monitors on the upper arm is the ability to capture information regarding exposure to non-neutral shoulder postures, a risk factor for the development of work-related musculoskeletal health outcomes (da Costa and Vieira, 2010; Miranda et al., 2001; Ohlsson et al., 1994; Bernard, 1997; Silverstein et al., 2008, 2006; Svendsen et al., 2004a,b; van Rijn et al., 2010; van der Windt et al., 2000). Estimates of arm and trunk inclination obtained with PA monitors have been observed to compare favorably to estimates from a magnetic tracking device (Korshøj et al., 2014) and universal goniometer (Hirschhorn et al., 2015). While PA monitors have been used to

Table 2
Bland–Altman results [mean bias (lower limit of agreement, upper limit of agreement)] for each 1-min epoch of observation by sensor location.

Summary metric	Sensor location		
	Trunk	Left arm	Right arm
Counts	−8.3 (−1298.8, 1282.2)	195.2 (−676.2, 1066.7)	207.7 (−906.7, 1322.1)
METs	−0.16 (−0.66, 0.35)	0.24 (−0.22, 0.70)	0.35 (−0.33, 1.00)

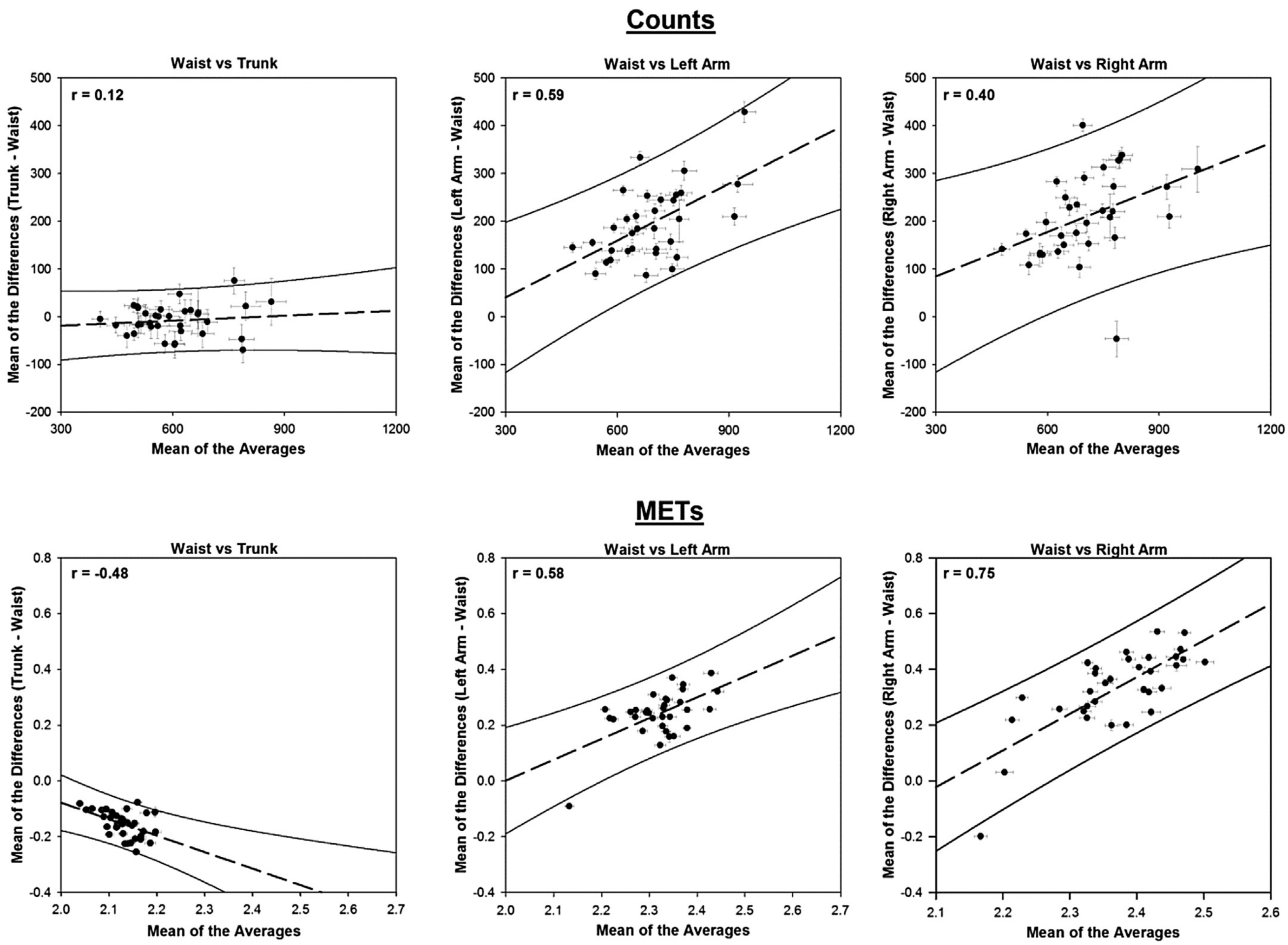

Fig. 3. Summarized Bland-Altman plots for each sensor location, with linear regression lines and hyperbolic, 95% "prediction" limits. Pearson correlation coefficients assessing the strength of the proportional bias is presented in the upper left corner of each plot. Error bars represent standard errors of the mean of the averages and mean of the differences for each participant.

assess PA levels in the context of worker health promotion (Malik et al., 2014) and have strong potential for posture measurement, few studies have simultaneously measured occupational exposure to working postures and PA. This study provides a critical step towards understanding the potential limitations of using IMUs worn on the trunk and upper arms to simultaneously measure PA and exposure to non-neutral working postures.

Limitations of the study include the lack of a wrist-worn PA monitor and the collection of PA data during a single work shift. Several studies have recommended multiple measurement days for reliable accelerometer estimates of habitual daily PA (Berlin et al., 2006; Trost et al., 2000; Welk et al., 2012). Agreement between sensor locations may have improved had measurements been obtained over multiple days. Additionally, while we used raw acceleration to measure PA and summarized our estimates of PA using two approaches, the use of traditional PA count cut points is becoming less common (John et al., 2013). Finally, it is important to note that while the IMU worn on the dominant (right) arm displayed greater levels of moderate intensity PA for all summary metrics evaluated, on average, than the non-dominant (left) arm, it is unknown if this result was a function of worker handedness or if the work itself required more right arm movement. Further research on the effects of worker handedness and the design of the work environment on PA estimation is needed.

5. Conclusions

Efficient estimation of the physical demands of work remains somewhat limited by the need for multiple sensors to capture different aspects of physical demands (e.g., ActiGraph or other commercially available monitors to capture PA and a separate accelerometer or IMU to measure posture). The results of this study indicate that the location of the sensor used to obtain acceleration information may substantially affect PA estimates when compared to estimates from a waist-worn PA monitor. Additional research is needed to better understand how PA measurements obtained from the upper arm and trunk relates to measurements obtained from waist and wrist-worn PA monitors. Specifically, validation studies conducted in controlled laboratory environments or using systematic observation of field-based activities are needed to develop conversion algorithms intended to relate or synthesize PA estimates from various studies (e.g., Brazendale et al., 2015). Standardized, non-proprietary metrics and procedures for using ambulatory sensors such as IMUs in field-based research must also continue to be developed and evaluated (Freedson et al., 2012).

While PA measurements obtained from the upper arm and trunk may not agree with measurements obtained from the waist, they may provide more representative PA estimates for demanding work tasks than a waist-worn PA monitor. The existence of a potential interaction between intensity of PA and non-neutral working postures should, therefore, also be further investigated. Such research may provide valuable insight into the association between physical risk factors in the workplace and musculoskeletal health outcomes.

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