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Mind the gap – development of conversion models between accelerometer- and IMU-based measurements of arm and trunk postures and movements in warehouse work

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ABSTRACT

Sensor type (accelerometers only versus inertial measurement units, IMUs) and angular velocity computational method (inclination versus generalized velocity) have been shown to affect the measurements of arm and trunk movements. This study developed models for conversions between accelerometer and IMU measurements of arm and trunk inclination and between accelerometer and IMU measurements of inclination and generalized (arm) velocities. Full-workday recordings from accelerometers and IMUs of arm and trunk postures and movements from 38 warehouse workers were used to develop 4 angular (posture) and 24 angular velocity (movement) conversion models for the distributions of the data. A power function with one coefficient and one exponent was used, and it correlated well ($r^2 > 0.999$) in all cases to the average curves comparing one measurement with another. These conversion models facilitate the comparison and merging of measurements of arm and trunk movements collected using the two sensor types and the two computational methods.

1. Introduction

Work-related diseases and disorders are a major global health problem. Musculoskeletal disorders (MSDs) are one of the main causes of quality-years lost due to ill health and disability (Murray, 2018) and account for 4/10 of the global compensation costs of occupational and work-related accidents and diseases (ILO, 2015). In addition to heavy manual handling, vibration and psychosocial factors, awkward postures, repetitive movements and movements at high velocities are considered risk factors for MSDs (Balogh et al., 2019; Lötters et al., 2003; Nordander et al., 2016; Punnett, 2014; Sluiter et al., 2001; van Rijn et al., 2010). These latter MSD risk factors are also common in the working population (Eurofound, 2012, 2016). Assessments of physical workload, postures and movements are usually estimated using self-reports or systematic observations (Burdorf, 2010; Coenen et al., 2018; Violante et al., 2016; Yung et al., 2019). These methods are versatile, can collect information about exposures retrospectively and have, at least in the past, allowed for collecting data from large samples at a relatively low cost when compared to technical measurements (Burdorf et al., 1997; Trask et al., 2014). However, self-reports and systematic observations usually produce crude exposure estimates, and often, the accuracy (Koch et al., 2016) and reliability of estimations of upper arm movements or postures are low (Forsman, 2017; Lind et al., 2019, 2020; Rhén and Forsman, 2020; Takala et al., 2010). The use of technical measurement instruments such as accelerometer-based inclinometers has drastically increased in the last two decades. Such instruments can record kinematic data with high precision and continuous data that can be used for comparisons of occupational groups and for studying exposure-effect relationships (Balogh et al., 2019; Nordander et al., 2016). In the last 5–10 years, an increasing number of studies have shifted from using inclinometers based on triaxial accelerometers (hereafter referred to as ‘accelerometers’) to inclinometers that use inertial measurement units (IMUs), which combine accelerometers with gyroscopes, and sometimes magnetometers (Fan et al., 2021), for their comparatively high accuracy (Chen et al., 2018; Yang et al., 2017).

Currently, many research groups are monitoring the exposure of occupational groups using inclinometers based on either accelerometers

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Abbreviations

IMUs	inertial measurement units
MSDs	Musculoskeletal disorders
acc	accelerometers
RMSE	Root mean square error

or IMUs (Table 1). Recent lab-based studies have indicated that estimates of angular velocities from instruments based on accelerometers are not comparable to those of optical-based motion capture systems, which are regarded as the gold standard in the measurement of movements, and that measurements based on accelerometers combined with gyroscopes substantially improve the accuracy (Chen et al., 2018; Yang et al., 2017). It is because optical-based motion capture systems calculate angles and velocities based on the changes of a vector between two markers on a body segment, while accelerometer-based systems calculate those parameters based on the changes of the gravitation vector determined from readings of three accelerometers. Since the accelerometers are inherently sensitive not only to gravitation but also to accelerations, kinematic results from those systems are less accurate at higher velocities. Additionally, in a field-based study, Fan et al. (2021) observed statistically significant deviations in the measurements of the angular velocities of the trunk and arms obtained using accelerometers combined with gyroscopes (the average median inclination velocity was 15.9°/s for the arms and 7.6°/s for the trunk) when compared to measurements derived solely from accelerometers (the corresponding velocities were 32.9°/s and 20.2°/s, i.e. more than double as high). The study also found statistically significant deviations in the estimates of angles expressed as percentiles or accumulated time in different angular ranges, but these deviations were marginal. The study indicates the need for the possibility of converting measurements of arm and trunk angular velocities based on accelerometers to those obtained by accelerometers combined with gyroscopes. To the best of our knowledge, such conversion models have not yet been presented in the scientific literature. Additionally, two different types of angular velocities (i.e., the inclination velocity and generalized velocity) are currently used to report angular velocities of the arm in the scientific literature in field studies (Table 1). For the arms, generalized velocity includes both inclinational velocity and axial rotation velocity; therefore, these types of angular velocity computational methods produce different results (Fan et al., 2021). As a result, conversion models are also needed between these different velocities. However, to the best of our knowledge, such a conversion model has not been presented in the scientific literature. Hence, both the sensor type, such as accelerometers versus IMUs, and the angular velocity computational methods such as generalized velocity and inclination velocity are two important factors to adjust for when comparing the results between two studies.

To overcome the difficulties of comparing or merging kinematics data derived from different sensor types and angular velocity computational methods, the aim of this study was illustrate a possible solution that facilitates comparisons or merging of data by conversion models based on full work days of one occupational group (warehouse order pickers), which can be used for the conversion of distributions of accelerometer-based data of postures (i.e., arm and trunk inclination angles) and movements, i.e., inclination velocities (arm and trunk) and generalized velocities (arm) to those from IMUs, and vice versa.

2. Material and methods

For this study, conversion models were developed based on full-workday accelerometer-based data and IMU-based data from a

Table 1
Examples of field studies and laboratory-based studies using inclinometers based solely on triaxial accelerometers (acc) or inertial measurement units (IMUs) to monitor movements of the arm or trunk.

Study (nr)	Sensor type (acc, IMU[1] or IMU[2])	Arm movements (inclination velocity or generalized velocity)	Trunk movements (sagittal or lateral inclination velocity)	Type of work	Origin(i.e., in which country the study was carried out)
Moriguchi et al. (2011)	acc	Generalized velocity	Sagittal	Real work tasks	Brazil
(Byström et al., 2002; Christmansson et al., 2002; Heiden et al., 2019; Kazmierczak et al., 2005; Wahlström et al., 2016)	acc	Generalized velocity	Sagittal	Real work tasks	Sweden
(Heilskov-Hansen et al., 2014; Juul-Kristensen et al., 2001)	acc	Generalized velocity	No trunk	Real work tasks	Denmark
(Arvidsson et al., 2006a, 2006b, 2012; Balogh et al., 2006, 2016, 2019; Dahlqvist et al., 2018; Hansson et al., 2006, 2010; Jonker et al., 2009, 2011, 2013; Nordander et al., 2008, 2016; Unge et al., 2007; Wahlström et al., 2010; Åkesson et al., 2012)	acc	Generalized velocity	No trunk	Real work tasks	Sweden
(Dahlqvist et al., 2016; Rislund et al., 2013)	acc	Generalized velocity	No trunk	Simulated work tasks	Sweden
Veiersted et al. (2008)	acc	Inclination velocity	No trunk	Real work tasks	Norway
(Douphrate et al., 2012; Ettinger et al., 2013; Hess et al., 2010)	acc	Inclination velocity	No trunk	Real work tasks	USA
Nourollahi-Darabad et al. (2020)	acc	Inclination velocity	No trunk	Real work tasks	Iran
Yang et al. (2017)	IMU[1]	Generalized velocity	No trunk	Simulated work	Sweden
(Fethke et al., 2020; Schall et al., 2021)	IMU[1]	Inclination velocity	Both	Real work tasks	USA
(Granzow et al., 2018; Kersten and Fethke, 2019; Schall et al., 2016)	IMU[1]	Inclination velocity	No trunk	Real work tasks	USA
(Chen et al., 2018, 2020)	IMU[1]	Inclination velocity	No trunk	Simulated work tasks	USA
Peppoloni et al. (2016)	IMU[2]	Inclination velocity	No trunk	Simulated work tasks	Italy

Note: IMU[1] refers to inertial measurement units that fuse triaxial accelerometer data with gyroscope data, and IMU[2] refers to inertial measurement units that fuse triaxial accelerometer data with gyroscope data and magnetometer data.

randomly selected sample of a population of manual material handlers (Fan et al., 2021). In the development of the conversion models, angles and velocity amplitudes up to the 95th percentiles were used, including arm accelerometer-based inclination angles up to 73° and trunk accelerometer-based sagittal inclination angles from −28° to 50°. Furthermore, accelerometer-based generalized velocities up to 254°/s were used for the arm, and accelerometer-based inclination velocities up to 150°/s were used for the trunk.

2.1. Participants

The participants' personal characteristics are displayed in Table 2. Their self-rated work ability was recorded using a single-item question on work ability (Ahlström et al., 2010), where "0" indicates not being able to work and "10" corresponds to having a work ability at its best. Prior to participating in the study, all participants gave written informed consent, and the study was approved by the Regional Ethics Committee in Stockholm, Sweden (2017/1586–31/4).

The participants performed either order picking (N = 28) or palletizing (N = 10), and both tasks (Fig. 1) involved frequent movements of the arm and trunk. The order picking tasks involved frequent manual handling of packages weighing 0.22–11 kg. The packages were picked from shelves between ankle height and shoulder height and placed in cardboard boxes at waist level on a hand cart. The cardboard boxes (0.40–12 kg) were thereafter transported to a conveyer belt to which they were manually transferred. To complete one order, which included approximately 50–60 packages, took approximately 5–10 min. The participants who performed palletizing received the cardboard boxes via the conveyer belt. At the palletizing station, the cardboard boxes were manually lifted off the conveyer belt to a pallet placed on the floor approximately 1 m from the conveyer belt. The cardboard boxes were manually stacked up to a level of 180–190 cm. The palletizers handled approximately 45–50 orders per workday.

2.2. Study design and measurements

2.2.1. Inclinometer measurements

Full-workday accelerometer recordings of the dominant arm and the trunk of the participants were used. The movements of the dominant arm and the trunk were recorded with two inertial measurement units (AX6, Axivity Ltd, Newcastle, UK, dimensions: 23 × 32.5 × 8.9 mm, mass 11 g). The AX6 has been used previously for measurements of arm postures (Wærsted et al., 2019) and builds on the AX3 (Axivity Ltd, Newcastle, UK), which has been validated for estimating physical activity level (Godinho et al., 2016; Schmal et al., 2018). The AX3 and AX6 include a triaxial accelerometer, but the AX6 also has a triaxial gyroscope and a triaxial magnetometer. For this study, a sampling frequency of 25 Hz, an acceleration range of ±8 g and a gyroscope range of ±1000°/s were used. The magnetometer was disabled similar to most reviewed studies (Table 1) due to potential magnetic interference in industrial settings (Robert-Lachaine et al., 2017).

Table 2
Personal characteristics of the participants.

N	38
Men, n (%)	25 (66)
Women, n (%)	13 (34)
Right-hand dominant, n (%)	35 (92)
Left-hand dominant, n (%)	3 (8)
Age[a], median (range)	24 (19–59) years
Body mass[a], median (range)	77 (52–93) kg
Stature[a], median (range)	178 (163–196) cm
BMI, median[a] (range)	24.2 (18.6–30.8) kg/m^2
Self-rated work ability[a], median (range)	9 (5–10)
≤2 years' work experience in order picking[a], n (%)	17 (49%)
≥3 years' work experience in order picking[a], n (%)	18 (51%)

[a] 3 subjects did not provide information regarding their personal characteristics.

The IMU that was used to record trunk movements was positioned to the right side of the thoracic spine at the level of the thoracic vertebrae 1–2 (Skotte et al., 2014). The IMU that was used to record dominant upper arm movements was positioned on the dominant arm with its superior edge just distal to the insertion of the medial deltoid muscle (Hansson et al., 2006). The IMUs were attached to the skin using double-sided adhesive tape and covered with a polyurethane film (Opsite Flexifix, Smith & Nephew AB, Mölndal, Sweden) (Fiona and Robert, 2013).

The reference position for the arm (0° arm elevation) was recorded as the median value of 3 s while the participants were seated and leaning their trunk laterally over the backrest of a chair with their arm hanging vertically while holding a 2 kg dumbbell in the hand (Hansson et al., 2006). The reference position for the trunk (0° flexion/extension) was also based on the median value of a 3-s time window, with the participant standing still in full balance in an upright position after having returned from a toe stand (Fan et al., 2021). To determine the sagittal direction (flexion/extension), the triaxial median value of a 3-s window was measured when the participants bent forward at an arbitrary angle (Hansson et al., 2006).

2.3. Data processing

The computation of the inclination angles and the velocities are described in detail in Fan et al. (2021).

2.3.1. Postures – inclination angles

The inclination angle of the trunk and the arm was calculated as the angle between the sensor direction of each sample and the sensor direction at the reference posture. The accelerometer data inclination angles were computed as described by Hansson et al. (2001, 2006) with a low-pass filter for accelerometer signals of 5 Hz (Hansson et al., 2001) and 3 Hz (Chen et al., 2018). For the IMU signals, the Kalman filter validated by Chen et al. (2018) was used with the same recommended coefficients. The Kalman filter was used to integrate the gyroscope signals with the accelerometer signals. For the arm, the inclination included both abduction and flexion postures and movements, while for the trunk, the inclination only comprised the inclination in the sagittal plane, with the forward projection being positive (Hansson et al., 2001).

2.3.2. Movements – computational methods of generalized and inclination angular velocity

The generalized velocity was computed as described by Hansson et al. (2001). A triaxial accelerometer measures acceleration and gravitation in its three axial directions. For instance, if an accelerometer is held statically in a vertical direction, the full vector of gravitation is in the z-axis. If the vector is normalized to 1 g, the coordinates of the gravitational vector in the accelerometer (x,y,z) is (0,0,1). If it is rotated a little and held statically again, the x and/or y values will increase while the z-value decreases. When it remains static, the total normalized amplitude of the vector will be 1 (as in both above cases). But during movements, the total amplitude will be above or below 1 (since the acquired vectors then also include accelerations, which can be positive or negative). The vector therefore needs to be divided with its amplitude, so that it becomes normalized and reaches the unit sphere. In the computation, for all times, the vectors are normalized to the amplitude of 1, i.e., reaching the unit sphere. The generalized velocity was then computed (in degrees per second) as the angle between two samples divided by the time between those two samples. The angle between two samples can be calculated by seeing the distance between the two vectors' endpoints on the unit sphere as the base of an equilateral triangle with two sides of the length one. If we call that distance l and the angle between two sample ΔS, we have

Fig. 1. Samples of work tasks for (a) order picking and (b) palletizing.

$$\Delta S = 2\arcsin(l/2), \ with\ l = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2 + (z_1 - z_0)^2} \tag{1}$$

where (x_0, y_0, z_0) and (x_1, y_1, z_1) are coordinates of S_0 and S_1 which are the gravitation vectors transformed to the body coordinate system at an initiative time point and a later time point (see Fig. 2). This generalized velocity includes the rotations around all three of the sensor axes. The inclination velocity was computed as the absolute value of the change in the inclination angle between two samples divided by the time between those two samples. It may be hard to explain how the axial rotation is included, and if the arm is rotated around its own axis when the arm is hanging vertically (zero degrees inclination), there is an axial rotation around the vertical line (the z-axis) that will not be measured by the accelerometer, since the gravity vector will be constantly, and only, in the z-direction. If, however, the arm is in an inclination angle of for example 45° and is rotated, for instance 1°, around its own axis (i.e. axial rotation), there will be a deltaS above zero. The z-component of the gravity vector will stay constant during that rotation, but there will be changes in the x- and y-components. This axial rotation will be included in the generalized velocity – since there is a change in the gravitational axis, but not in the inclination velocity – since the inclination angle is unchanged. Therefore, the only case where the axial rotation is not included in the generalized velocity, is in that specific case of a vertical arm. In short, the inclinational velocity is the difference in inclinational angles between two samples (divided by the sampling time), while the generalized velocity is the angular difference of the gravitation vector, on the unit circle, between two samples (divided by the sampling time).

For the arm, both the generalized velocity and the inclination velocity were computed since they have both been frequently used in the research literature (see Table 1). For the trunk, only the (sagittal) inclination velocity was computed, since only that computational method has been used in research studies.

2.4. Development of conversion models

Distribution-based conversion models were developed to facilitate the conversion of measurements obtained from one sensor type to another sensor type, as well as (for the arm) from one angular computational method to another. In this development, for each subject, the data of each included sensor type and computational method were ordered and placed in columns next to each other. Then, distribution comparison curves were plotted by going from 0 to the value (° or °/s) of the 95th percentile, in 1000 equidistant steps on the x-axis, finding the row of that angle or velocity in the x-axis column, and taking the y-axis value from the same row. For instance, the upper arm had two such distributions computed for the postures (angles; see Fig. 5) and four

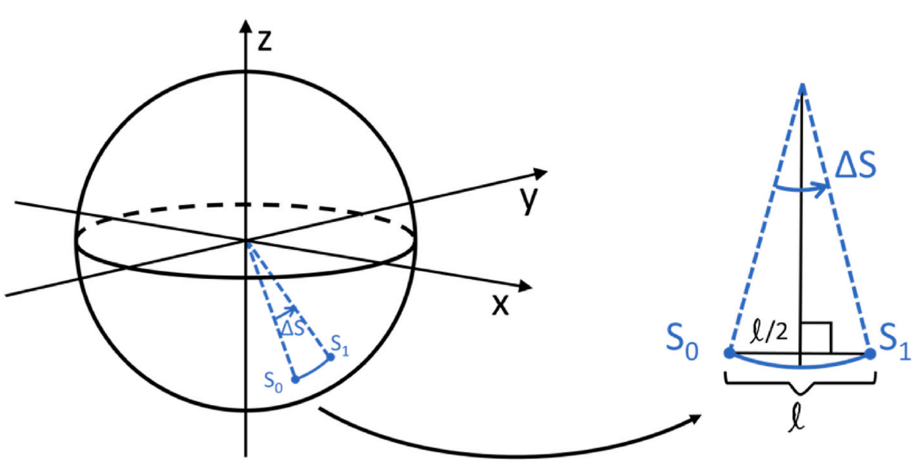

Fig. 2. Illustration of a generalized angle ΔS with S_0 and S_1 being the gravitation vectors transformed to the body coordinate system from sample 0 and sample 1, and l being Cartesian distance from S_0 to S_1. The sphere is a unit sphere.

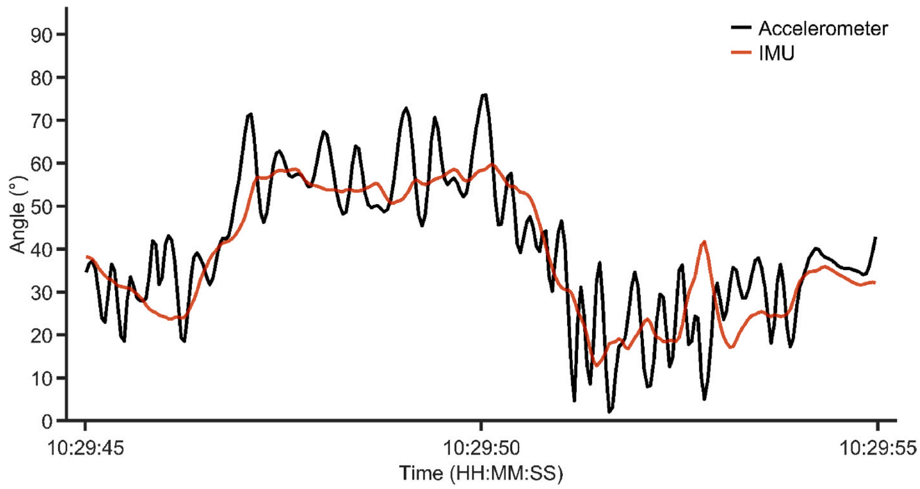

Fig. 3. A representative sample of the inclination angle signals from the accelerometers with a 5-Hz low-pass filter (in black) and from the IMU (in red) from one subject.

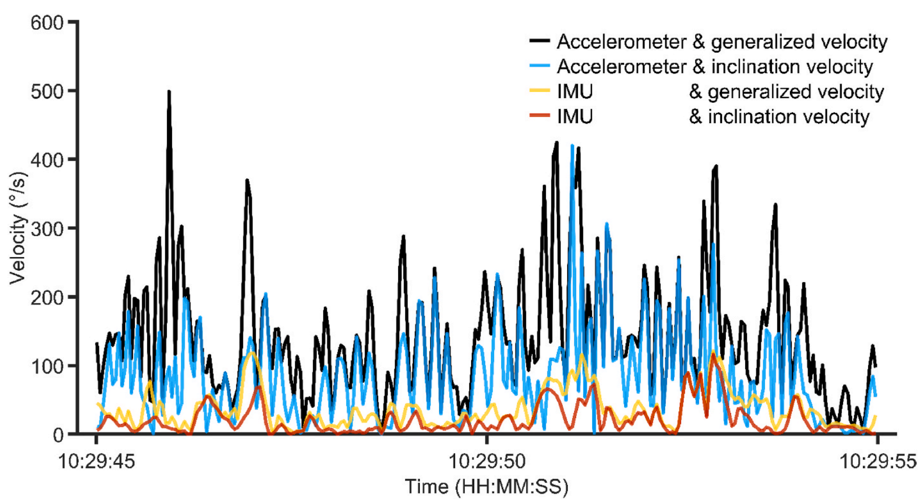

Fig. 4. A representative sample of the angular velocity signals of the generalized velocity from the accelerometer with a 5-Hz low-pass filter (in black), the inclination velocity from the accelerometer (in blue), the generalized velocity from the IMU (in yellow), and the inclination velocity from the IMU (in red) from one subject (same as in Fig. 3).

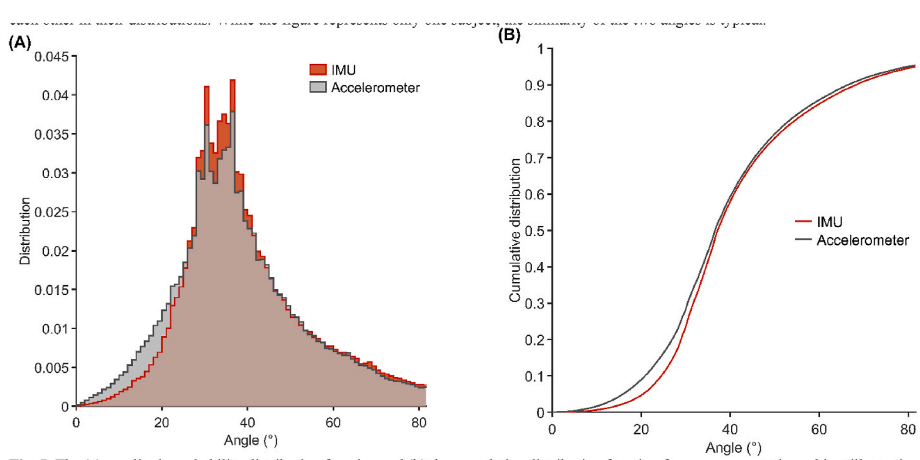

Fig. 5. The (a) amplitude probability distribution function and (b) the cumulative distribution function from a representative subject illustrating the deviations of the inclination angle using measurements based on only accelerometers with a 5-Hz low-pass filter (in gray) versus IMUs (in red). Angles up to the 95th percentile of the accelerometer-based angles are included in the graphs and in the development of conversion models.

distributions for the movements (angular velocities; Fig. 6). Then, the distributions between different sensor types and computational methods of the same measure were paired on an individual level to form a conversion curve, e.g., each x-axis value of the upper arm elevation measured by the accelerometer was paired with the corresponding value in the ordered upper arm elevation data measured by the IMU of the same person. After pairing was performed for each individual, a group mean conversion curve was computed between each pair of methods/sensor types by averaging all individual conversion curves on each x-axis value (see Figs. 7–9).

After initial analyses of three fitting models, a second-degree polynomial model, a third-degree polynomial model and a power function model as approximations of the conversion curves, the power function model was chosen (see Eq. (2)); with two parameters, it was a sufficiently good approximation for all conversions.

$$y = bx^m \tag{2}$$

where x is a value in the group mean conversion of one sensor type and/or velocity computational method, and y is the corresponding value of another sensor type and/or velocity computational method. For the trunk sagittal inclination, where there are positive and negative angles, the amplitude was used to fit the power function, but the sign was kept for the conversion from one sensor type to another.

The model was fitted for each comparison combination, and the prediction curves of these models are shown in red in Figs. 7–9.

3. Results

Data were acquired from all 38 participants. On average, 7.3 (range: 3.8–8.4) hours were collected per participant during the measurement day.

3.1. Examples of posture and angular velocity traces

Fig. 3 shows a short time window of the arm inclination angle from the performed measurements with an accelerometer and with an IMU (Kalman filtered accelerometer and gyroscope fusion). Typically, as in this example, the accelerometer signal fluctuates largely around the IMU signal.

As shown in Fig. 4, the velocity varies both due to sensor type (i.e., accelerometers only versus IMUs) and due to the angular velocity computational method (i.e., inclination versus generalized velocity). As Fig. 4 shows, the highest velocity is generally produced from the generalized velocity from the accelerometers, followed by the inclination velocity from the accelerometers, the generalized velocity from the IMUs, and the lowest for the inclination velocity from the IMUs. The velocities of the other two combinations are usually, as in this example, in the middle. The figure shows two black peaks (the generalized velocity from the accelerometer), of which the first peak is also a peak for the blue trace (the inclination velocity from the accelerometer). The first peak can, hence, be assumed to be a rapid inclination movement, while the second peak may include axial rotation of the arm.

3.2. Examples of distribution functions

The amplitude probability distribution function and the cumulative distribution function of the upper arm angle of one subject's full-workday measurement and of the two sensor types are shown in Fig. 5. The two angle signals, which are similar in their traces of Fig. 3, are also close to each other in their distributions. While the figure represents only one subject, the similarity of the two angles is typical.

The four velocities of the same subject (as in Fig. 5) are shown in Fig. 6. The figure illustrates clear deviations in the frequency distribution and the cumulative distribution between the four velocity types, and, as in Fig. 4, it shows that for this subject (who was typical), the generalized velocity from the accelerometer has the highest frequency of high velocities, while the inclination velocity from the IMU shows the highest frequency of low velocities.

3.3. Comparison and conversion of angles from two sensor types

Fig. 7 shows comparisons of the distributions of the upper arm angles measured with accelerometers and with IMUs. The figures show both the individual comparison curves and the average curves. As the average is close to the line of unity, the distributions of the two sensor types are similar. In each diagram, the curve of the fitted conversion formula is also shown. Table 3.

The model used for the conversion formulas was a power function, i.e., with one coefficient and exponent to be fitted. The fitted parameters are shown in Table 2, together with goodness of fit measures. It can be seen from Fig. 7 and Table 3 that the models show close fits to the average curves but also that the coefficients and exponents are close to one, which was expected since the average curves in these posture cases are close to the line of unity.

3.4. Comparison and conversion of the velocities of different sensor types and computational methods

Examples of the comparison curves of the different ways of measuring the velocity (i.e., sensor type and velocity computational method) are shown for the upper arm in Fig. 8 and for the trunk in Fig. 9. These comparisons show that, in contrast to the posture curves, the relations between the distributions of the angular velocity diverge clearly from the line of unity and show a power-type shape. Table 4.

The parameters of the power function (one coefficient and one

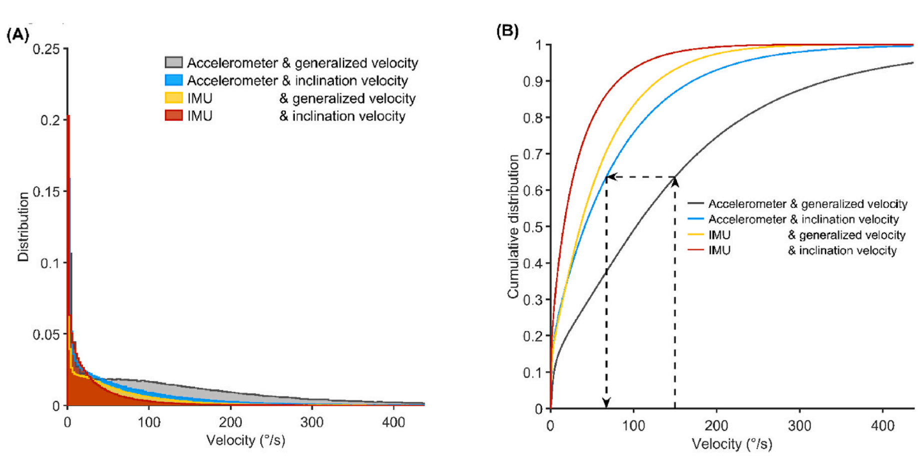

Fig. 6. The frequency distributions of the four velocities (a) and the cumulative distribution function (b) from a representative sample from one subject. The four arm velocities are from measurements with only accelerometers with a 5-Hz low-pass filter or with IMUs computed as inclination velocity or as generalized velocity. The arrows illustrate, schematically, how the individual comparison curves in Figs. 7–9 are computed. Velocities up to the 95th percentile of the generalized velocity from the accelerometer measurements are included in the graphs and in the development of the conversion models.

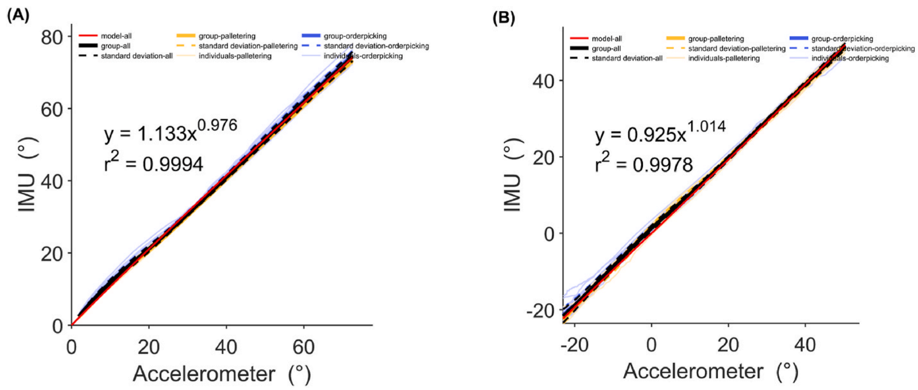

Fig. 7. Comparisons of the angular distributions of the accelerometers (with a 3-Hz low-pass filter) versus IMUs for the upper arm (left) and the trunk (right). The comparison curves of the distributions of individuals in a specific task (in thin colored solid lines), the average curves of individuals in a specific task (in thick colored solid lines), the average curves of all individuals (in black), and the result of the fitted power functions (in red) and standard deviations (in dashed lines)the parameters of which are shown (these parameters are also listed in).

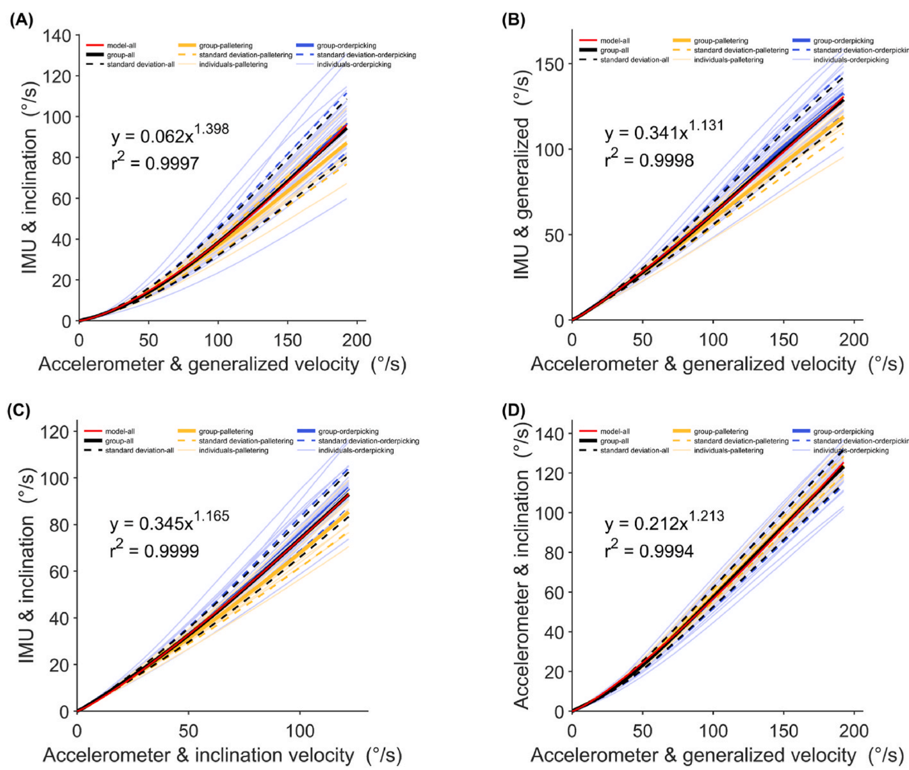

Fig. 8. Comparisons of the distributions of the angular velocities of the upper arm from different sensor-velocity combinations including accelerometers with a 3-Hz low-pass filter versus IMUs and inclination velocity versus generalized velocity. The comparison curves of the distributions of individuals in a specific task (in thin colored solid lines), the average curves of individuals in a specific task (in thick colored solid lines), the average curves of all individuals (in black), and the result of the fitted power functions (in red) and standard deviations (in dashed lines) – the parameters of which are shown (these parameters are also listed in.

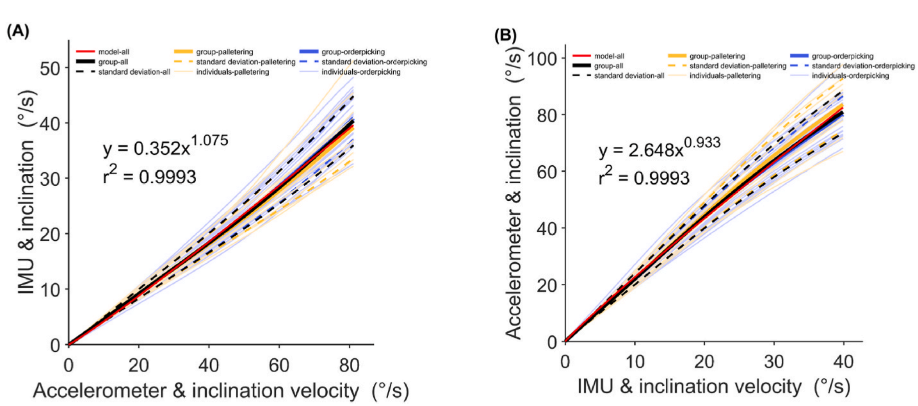

Fig. 9. Comparisons of the distributions of the inclination velocities of the trunk from the two sensors: (a) accelerometers (with a 3-Hz low-pass filter) versus IMUs and (b) IMUs versus accelerometers (with a 3-Hz low-pass filter). The comparison curves of the distributions of individuals in a specific task (in thin colored solid lines), the average curves of individuals in a specific task (in thick colored solid lines), the average curves of all individuals (in black), and the result of the fitted power functions (in red) and standard deviations (in dashed lines), the parameters of which are shown (these parameters are also listed in).

Table 3
Conversion model parameters, amplitude (b) and exponent (m), for postures (angles) and goodness of fit measures. The right column shows the average standard deviations around the average curves. For the trunk, the amplitude is converted using the corresponding formula, while the sign is kept through the conversion.

Angle	Converted from	Converted to	b	m	R-Square	RMSE	Average standard deviation[a]
	Sensor type	Sensor type					
Dominant arm, elevation	Accelerometer (5Hz)	IMU	1.11	0.98	0.9991	0.60	0.82
	IMU	Accelerometer (5Hz)	0.90	1.02	0.9992	0.58	0.80
	Accelerometer (3Hz)	IMU	1.13	0.98	0.9994	0.52	0.84
	IMU	Accelerometer (3Hz)	0.88	1.02	0.9994	0.50	0.82
Trunk, sagittal inclination	Accelerometer (5Hz)	IMU	0.87	1.03	0.9967	0.77	1.00
	IMU	Accelerometer (5Hz)	1.09	0.98	0.9970	0.80	0.87
	Accelerometer (3Hz)	IMU	0.93	1.01	0.9978	0.66	0.78
	IMU	Accelerometer (3Hz)	1.05	0.99	0.9978	0.70	0.78

[a] The average value of the standard deviations of all velocities around the average curve.

Table 4
The fitted parameters, the coefficient b and the exponent m of the power function, in the conversion models for the angular velocity of the upper arm, and goodness of fit descriptors.

Converted from		Converted to		b	m	R-Square	RMSE	Average standard deviation[a]
Sensor type	Computational method	Sensor type	Computational method					
accelerometer (5Hz)	generalized	accelerometer (5Hz)	inclinational	0.237	1.171	0.9992	1.27	5.91
accelerometer (5Hz)	generalized	IMU	inclinational	0.056	1.347	0.9995	0.68	7.61
accelerometer (5Hz)	generalized	IMU	generalized	0.308	1.094	0.9996	0.75	7.82
accelerometer (5Hz)	inclinational	accelerometer (5Hz)	generalized	3.564	0.845	0.9991	2.01	10.07
accelerometer (5Hz)	inclinational	IMU	inclinational	0.271	1.165	0.9999	0.20	5.26
accelerometer (5Hz)	inclinational	IMU	generalized	1.183	0.933	0.9998	0.50	5.78
IMU	inclinational	accelerometer (5Hz)	generalized	9.019	0.734	0.9995	1.45	21.26
IMU	inclinational	accelerometer (5Hz)	inclinational	3.081	0.861	0.9999	0.39	9.00
IMU	inclinational	IMU	generalized	3.328	0.805	1.0000	0.19	3.14
IMU	generalized	accelerometer (5Hz)	generalized	3.032	0.910	0.9997	1.16	16.23
IMU	generalized	accelerometer (5Hz)	inclinational	0.845	1.071	0.9998	0.62	7.53
IMU	generalized	IMU	inclinational	0.226	1.241	1.0000	0.12	2.23
accelerometer (3Hz)	generalized	accelerometer (3Hz)	inclinational	0.212	1.213	0.9994	0.91	4.36
accelerometer (3Hz)	generalized	IMU	inclinational	0.062	1.398	0.9997	0.49	6.32
accelerometer (3Hz)	generalized	IMU	generalized	0.341	1.131	0.9998	0.52	6.28
accelerometer (3Hz)	inclinational	accelerometer (3Hz)	generalized	3.719	0.817	0.9993	1.35	7.05
accelerometer (3Hz)	inclinational	IMU	inclinational	0.345	1.165	0.9999	0.31	4.27
accelerometer (3Hz)	inclinational	IMU	generalized	1.450	0.931	0.9996	0.68	4.95
IMU	inclinational	accelerometer (3Hz)	generalized	7.611	0.711	0.9998	0.78	13.14
IMU	inclinational	accelerometer (3Hz)	inclinational	2.488	0.861	0.9998	0.47	5.74
IMU	generalized	accelerometer (3Hz)	generalized	2.628	0.883	0.9999	0.62	9.62
IMU	generalized	accelerometer (3Hz)	inclinational	0.681	1.072	0.9997	0.66	5.04
accelerometer (5Hz)	generalized	accelerometer (3Hz)	inclinational	0.152	1.213	0.9994	0.91	4.36
accelerometer (3Hz)	inclinational	accelerometer (5Hz)	generalized	4.256	0.845	0.9991	2.01	10.07

[a] The average value of the standard deviations of all velocities around the average curve.

exponent) are shown for all conversions in Table 4 (arm: 24 conversion models) and Table 5 (trunk: 4 conversion models). Again, the fitted power functions correlate very well with the average curves. There are, however, relatively large variations between the individual curves and the average curves. Examples of standard deviation curves are shown in Figs. 8 and 9, and the average standard deviations are listed in Tables 4 and 5. These large standard deviations between the model curve and the individual curves show that the conversions, although they are the well-fitted functions of the average curves, do not converge exactly for each individual. Nevertheless, with the large deviations between the measurements (of different sensors and/or velocity computational methods), also at the individual level, the conversion models improve the individual accuracy, so it is better to use the conversion formulas. These deviations also illustrate that in cases where the accuracy of the velocity measure at the individual level is important (for example, when associations between exposure and health are investigated), IMUs should be preferred for the measurements. Table 5.

Table 5
The fitted parameters, the coefficient b and the exponent m of the power function, in the conversion models for the angular velocity of the trunk, and goodness of fit descriptors.

Converted from		Converted to		b	m	R-Square	RMSE	Average standard deviation[a]
Sensor type	Computational method	Sensor type	Computational method					
accelerometer (5Hz)	inclinational	IMU	inclinational	0.284	1.085	0.9994	0.27	2.07
IMU	inclinational	accelerometer (5Hz)	inclinational	3.169	0.927	0.9995	0.61	4.74
accelerometer (3Hz)	inclinational	IMU	inclinational	0.352	1.075	0.9993	0.31	1.94
IMU	inclinational	accelerometer (3Hz)	inclinational	2.648	0.933	0.9993	0.63	3.89

[a] The average value of the standard deviations of all velocities around the average curve.

4. Discussion

In this study, 36 conversion models were developed to convert accelerometer-based data of postures (8 models) and velocities (28 models) of the arm and the trunk and generalized velocities (arm) to those from IMUs, and vice versa. The models were based on full-workday measurements of 38 warehouse workers, which included two distinctive different work tasks and included both men and women. The conversion models can facilitate the comparison or merging of measurements collected using different sensor types (i.e., accelerometers only versus IMUs), different low-pass cut-off frequencies for the accelerometer signals (3 and 5 Hz), and using different computational methods (i.e., inclination versus generalized velocity).

4.1. Previous studies of sensor comparison

Previous laboratory-based studies (Chen et al., 2018; Yang et al., 2017) and a recent field-based study (Fan et al., 2021) have shown that measurements of arm velocities from accelerometers only deviate from those using IMUs, especially when velocities are high; e.g., Yang et al. (2017) observed that the 90th percentile of an arm swing velocity of arms swings from accelerometers only was observed to be 1.7 times as high as that from IMUs (Yang et al., 2017). However, none of these studies provided information on conversion models that could be used across a range of angular velocities. Additionally, this study presents conversion models that include the two commonly used velocity "types" for arm movements, i.e., inclination velocity and generalized velocity.

4.2. Methodological considerations

Both the accelerometer data and IMU data were derived from the same instruments, i.e., AX6. Because of this, the sensor ensembles compared were positioned at the same anatomical position and on the same surface, in contrast to previous laboratory-based studies in which the measurements were from different instruments placed on top of each other (Dahlqvist et al., 2016; Korshoj et al., 2014), which is usually not the case in field studies. Having the same placement reduced the potential difference related to soft-tissue artifacts (Leardini et al., 2005; Peters et al., 2010) and to differences in the distance to the shoulder joint, which, because of the centripetal force during arm movements, would induce differences in the accelerometer signals (Bernmark and Wiktorin, 2002). The IMU data measurements did not include magnetometers; therefore, the developed conversion models may not be fully suitable for those data in which magnetometers have been included to derive the angular velocities. However, as shown in Table 1, magnetometers are seldom used in field studies due to magnetic interference in industrial settings (Robert-Lachaine et al., 2017), and hence, any restriction caused by not including magnetometers is limited. Additionally, the use of magnetometers was not seen as a feasible alternative due to the risk of magnetic interference at the study location.

Figs. 7 and 8 show interindividual deviations in the conversion curves. There are differences between the average curves of the two included tasks, which indicate a task dependency on the conversion curves. The task specific average curves were however not statistically different, and the conversion models were based on the full group average curves. Axial rotation of the arm is included in the generalized velocity, and individuals may use various degrees of axial rotations when performing their work tasks. Additionally, as whole-body movements introduce accelerations that are pick-up by the accelerometers, walking may increase the velocity measurements of the accelerometers, more than so for the IMU velocity measurements, so difference in amount of walking may also make a difference in the average curves.

A limitation of the study was that the data used for the developed conversion models were from one job, which mainly included two different work tasks. Since different jobs may also include different typical movement patterns, the conversion models may be somewhat different in other jobs. This may restrict the model's generalizability. Therefore, caution should be applied when using the conversion models on other occupational groups until the models have been tested on more occupations. Also, the conversion models can be improved by including other occupational groups. The difficulties of comparing angular arm velocity data between different occupations despite them using the same instruments (especially if their velocity data is derived from accelerometers without gyroscopes) are not restricted to the developed conversion models, but this applies to most comparisons of merging of data from different occupations, or perhaps even work tasks. Therefore, more attention is warranted to address this issue, to enable more accurate comparisons of the arm velocity exposures.

The number of participants in this study was large enough to obtain a tight confidence range around the average curve, but if the models are used on smaller samples (which they still are recommended to be, again because of the large deviations between the unconverted velocities), it should be understood that the true conversion curves deviate among individuals. The majority of the participants were male (66%), and a balanced sample in terms of sex was not targeted. Additionally, having a larger proportion of men, as in the current study, is in agreement with the general larger proportion of men in this type of job (78%) in Sweden (SCB, 2020). Based on this, we did not aim to build separate conversion models based on sex or to test to what extent this can improve the precision of the models. Hence, more research is needed to test whether future conversion models need to be adjusted for task-related factors such as job type or task and individual factors such as sex or anthropometric parameters.

The developed conversion models were based on wide ranges of angles and angular velocities. Accelerometer-based generalized angular velocities of the arm up to 250°/s were included (the 95th percentiles in this group of workers). These velocities are relatively high compared to a general working population. The 90th and 99th percentiles of the dominant upper arm generalized accelerometer-based velocity for warehouse workers were 204°/s (SD, 57) and 416°/s (SD, 118), respectively (Fan et al., 2021). This can be compared to 79°/s and 217°/s of the right arm among baggage handlers (Wahlström et al., 2016), 108°/s and 287°/s of the right arm among hairdressers (Wahlström et al., 2010) and 35°/s and 142°/s of the right arm among paper mill workers (Heiden et al., 2019). Having such relatively high velocities as well as the relatively large sample size increased the power of the conversion models even at the higher velocities in the model, as shown in Fig. 8.

The time signals of the different sensors and computational methods varied substantially from each other and in complex patterns (Figs. 3 and 4). When comparing two distributions (Figs. 7–9), the average curves are always monotonously increasing. Additionally, in studies of physical workload, distribution-based parameters are commonly used. Therefore, the distributions of each measure were used for the conversion models. In a previous study (Fan et al., 2021), the 10th, 50th and 90th percentiles of different sensors and computational methods were compared. In this study, continuous conversion models were developed and allow conversions of a wide range of angles and velocities, covering the needs of most studies that measure postures and movements of the trunk and arms.

4.3. Practical application and examples of applied use on others' data

The resulting conversion models and the use of such models are important. To illustrate this, in a previous study, the 90th percentile full-shift arm velocity was reported to be approximately 27°/s among nurses (left: 27°/s and right: 27°/s) (Schall et al., 2016). The arm velocities were mentioned as lower when compared to dentists (left: 54°/s and right: 67°/s) (Jonker et al., 2009), automobile disassembly workers (101°/s) (Kazmierczak et al., 2005), hairdressers (left: 108°/s and right: 108°/s) (Wahlström et al., 2010), material pickers (left: 131°/s and right: 164°/s) (Christmansson et al., 2002), and hospital cleaners (traditional organizations: 193°/s) (Unge et al., 2007). Furthermore, the nurses were also stated to have similar 90th percentile arm velocities as air traffic controllers (left: 31°/s and right: 37°/s) (Arvidsson et al., 2006a). Given the nature of nurses' tasks, it may be unexpected that their arm velocities were stated to resemble those in an occupation with a higher degree of sedentary behavior, such as air traffic controllers. These large deviations in arm velocity between nurses and the other occupational groups and the resemblance with air traffic controllers can, to a large extent, be attributed to differences in both sensor type and angular velocity computational method. While the study on nurses used inclination velocities from IMUs, the others used generalized velocities from accelerometers (see Table 1).

When applying the developed conversion formula for the 90th percentile arm velocity from accelerometer-based generalized velocity converted to IMU-based inclination velocity ($y = b*x^m$, second line in Table 4), the values decrease considerably, e.g., from 67°/s to 16°/s for the dentists (i.e., $0.056 * 67^{1.347}$), from 101°/s to 28°/s for the automobile disassembly workers, from 108°/s to 31°/s for the hairdressers and from 193°/s to 67°/s for the hospital cleaners. Hence, the 90th percentile arm velocity among nurses (27°/s) were likely close to that of the automobile disassembly workers and slightly lower than the hairdressers.

This example illustrates the need for conversion of values across studies that have applied different sensor types and angular velocity computational methods. For example, both Kersten and Fethke (2019) and Granzow et al. (2018) performed comparisons with unconverted velocities. It can, however, be assumed that the velocities of the two latter studies as well as in Schall et al. (2016) more accurately display the 'true' arm velocity since these measurements were based on IMUs instead of accelerometers only.

In a recent study, the arm inclination velocities of bakers were recorded using accelerometers (Nourollahi-Darabad et al., 2020). The 90th percentile arm velocity of the bakers of 163°/s was compared with hairdressers' velocity of 108°/s (Wahlström et al., 2010) and car disassembly workers, velocity of 101°/s (Kazmierczak et al., 2005). Since the latter two were based on generalized velocities using accelerometers, the arm velocity of the bakers needs first be converted from 163°/s to 315°/s (the last line in Table 4: Converted velocity = $4.256 * 163^{0.845}$). Hence, the difference in the arm velocities of the bakers to the other occupations increases substantially after applying the conversion. Furthermore, several studies have used time-based parameters (Granzow et al., 2018; Kazmierczak et al., 2005; Schall et al., 2016; Wahlström et al., 2010), for example, the percent time in low (<5°/s) and high (>90°/s) upper arm velocities; these parameters may be computed after conversion of the cutoff limits. In addition, the percent time in a neutral posture for at least 3 s, the percent time at a low velocity for at least 3 s, and the percent time with both neutral posture and low velocity. Of course, when comparing this kind of variable, it is very important that the postures and velocities are comparable. These parameters are derived from the time signals. The conversion formulas may again be used for the cutoff limits, but because of the large difference in the shape of the velocity signals (see Fig. 4), the parameters should likely still not be compared with ditto from measurement with other sensors and/or velocities.

The results of the current study, as well as in a few previous studies (Fan et al., 2021; Yang et al., 2017), illustrate the need to harmonize the metrics for the report of angular velocities for both the arm and the trunk. As shown in the current study and from the examples above, comparisons with measurements obtained using different sensor types and different velocity computational methods can yield large differences in estimated velocities. As Yang et al. (2017) and Chen et al. (2018) showed, IMUs are more accurate than accelerometers in kinematics measurements – so from the point of accuracy, of these two sensor types, IMUs are preferable in both lab-based and field studies. In cases when planned measurements of angular velocities are to be compared with previously collected measurements based on accelerometers – because of the large interindividual deviations related to accelerometers (see Figs. 7–9), it is preferred to use IMUs and apply the conversion models to compute the velocities from accelerometers. Concerning the angular velocity computational methods for the trunk, only the inclination velocity has been used. The inclination velocity may be more intuitive than the generalized velocity since the former is simply the derivation of the inclination angle, while the latter additionally includes axial rotation. Concerning the angular velocity computational methods for the arm, cross-sectional associations between the generalized arm velocity and neck/shoulder complaints and symptoms have been observed (Balogh et al., 2019; Nordander et al., 2016), but there are no corresponding studies including the inclination velocity of the arm. Given the complexity of the shoulder joint and the lack of evidence from longitudinal data that have included comparisons of both measures, there is currently insufficient information to rank their respective strength in associations with work-related MSDs. Hence, more studies are needed to determine one common standard metric for the report of angular arm velocities.

5. Conclusions

Previous research shows that both sensor type (i.e., accelerometers only versus IMUs) and angular velocity computational method (i.e., inclination versus generalized velocity) greatly affect the measurements of arm and trunk movements. To overcome these deviations, 4 angular (posture) and 24 angular velocity (movement) conversion models for the distribution of the data were developed to convert accelerometer-based kinematic results of the arm and the trunk to those from IMUs, and vice versa. The models were based on full-workday measurements of 38 warehouse workers, which included two distinctively different work tasks and included both men and women. A power function with one coefficient and one exponent was used, and it correlated well ($r^2 > 0.999$), in all cases, to the average curves comparing one measurement with another. These conversion models facilitate the comparison or merging of measurements collected using different sensor types (i.e., accelerometers only and IMUs) and using different computational methods (i.e., inclination velocity and generalized velocity). While the detailed conversion models were based on measurements from a relatively high number of workers, future studies are needed to test the transferability of the conversion models in work tasks other than manual handling operations.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

Ahlström, L., Grimby-Ekman, A., Hagberg, M., Dellve, L., 2010. The work ability index and single-item question: associations with sick leave, symptoms, and health - a prospective study of women on long-term sick leave. Scand. J. Work. Environ. Health 36, 404–412.

Åkesson, I., Balogh, I., Hansson, G.Å., 2012. Physical workload in neck, shoulders and wrists/hands in dental hygienists during a work-day. Appl. Ergon. 43, 803–811.

Arvidsson, I., Arvidsson, M., Axmon, A., Hansson, G.Å., Johansson, C.R., Skerfving, S., 2006a. Musculoskeletal disorders among female and male air traffic controllers performing identical and demanding computer work. Ergonomics 49, 1052–1067.

Arvidsson, I., Hansson, G.Å., Mathiassen, S.E., Skerfving, S., 2006b. Changes in physical workload with implementation of mouse-based information technology in air traffic control. Int. J. Ind. Ergon. 36, 613–622.

Arvidsson, I., Balogh, I., Hansson, G., Ohlsson, K., Åkesson, I., Nordander, C., 2012. Rationalization in meat cutting - consequences on physical workload. Appl. Ergon. 43, 1026–1032.

Balogh, I., Ohlsson, K., Hansson, G.Å., Engström, T., Skerfving, S., 2006. Increasing the degree of automation in a production system: consequences for the physical workload. Int. J. Ind. Ergon. 36, 353–365.

Balogh, I., Ohlsson, K., Nordander, C., Björk, J., Hansson, G.Å., 2016. The importance of work organization on workload and musculoskeletal health – grocery store work as a model. Appl. Ergon. 53, 143–151. Pt A.

Balogh, I., Arvidsson, I., Björk, J., Hansson, G.Å., Ohlsson, K., Skerfving, S., Nordander, C., 2019. Work-related neck and upper limb disorders - quantitative exposure-response relationships adjusted for personal characteristics and psychosocial conditions. BMC Muscoskel. Disord. 20.

Bernmark, E., Wiktorin, C., 2002. A triaxial accelerometer for measuring arm movements. Appl. Ergon. 33, 541–547.

Burdorf, A., 2010. The role of assessment of biomechanical exposure at the workplace in the prevention of musculoskeletal disorders. Scand. J. Work. Environ. Health 36, 1–2.

Burdorf, A., Rossignol, M., Fathallah, F.A., Snook, S.H., Herrick, R.F., 1997. Challenges in assessing risk factors in epidemiologic studies on back disorders. Am. J. Ind. Med. 32, 142–152.

Byström, J.U., Hansson, G.A., Rylander, L., Ohlsson, K., Källrot, G., Skerfving, S., 2002. Physical workload on neck and upper limb using two CAD applications. Appl. Ergon. 33, 63–74.

Chen, H., Schall Jr., M.C., Fethke, N., 2018. Accuracy of angular displacements and velocities from inertial-based inclinometers. Appl. Ergon. 67, 151–161.

Chen, H., Schall, M.C., Fethke, N.B., 2020. Measuring upper arm elevation using an inertial measurement unit: an exploration of sensor fusion algorithms and gyroscope models. Appl. Ergon. 89, 103187.

Christmansson, M., Medbo, L., Hansson, G.Å., Ohlsson, K., Unge Byström, J., Möller, T., Forsman, M., 2002. A case study of a principally new way of materials kitting - an evaluation of time consumption and physical workload. Int. J. Ind. Ergon. 30, 49–65.

Coenen, P., Huysmans, M.A., Holtermann, A., Krause, N., van Mechelen, W., Straker, L. M., van der Beek, A.J., 2018. Do highly physically active workers die early? A systematic review with meta-analysis of data from 193 696 participants. Br. J. Sports Med. 52, 1320–1326.

Dahlqvist, C., Hansson, G.T., Forsman, M., 2016. Validity of a small low-cost triaxial accelerometer with integrated logger for uncomplicated measurements of postures and movements of head, upper back and upper arms. Appl. Ergon. 55, 108–116.

Dahlqvist, C., Nordander, C., Forsman, M., Enquist, H., 2018. Self-recordings of upper arm elevation during cleaning - comparison between analyses using a simplified reference posture and a standard reference posture. BMC Muscoskel. Disord. 19, 402.

Douphrate, D.I., Fethke, N.B., Nonnenmann, M.W., Rosecrance, J.C., Reynolds, S.J., 2012. Full shift arm inclinometry among dairy parlor workers: a feasibility study in a challenging work environment. Appl. Ergon. 43, 604–613.

Ettinger, L., Kincl, L., Johnson, P., Carter, C., Garfinkel, S., Karduna, A., 2013. Workday arm elevation exposure: a comparison between two professions. IISE Trans. Occup. Ergon. Hum. Factors 1, 119–127.

Eurofound, 2012. Fifth European Working Conditions Survey. Publications Office of the European Union, Luxembourg, LUX.

Eurofound, 2016. Sixth European Working Conditions Survey. Publications Office of the European Union, Luxembourg, LUX.

Fan, X., Lind, C.M., Rhen, I.-M., Forsman, M., 2021. Effects of sensor types and angular velocity computational methods in field measurements of occupational upper arm and trunk postures and movements. Sensors 5527.

Fethke, N.B., Schall Jr., M.C., Chen, H., Branch, C.A., Merlino, L.A., 2020. Biomechanical factors during common agricultural activities: results of on-farm exposure assessments using direct measurement methods. J. Occup. Environ. Hyg. 17, 85–96.

Fiona, Downie, Robert, Gannon, 2013. OPSITE Flexifix Gentle: preventing breakdown in vulnerable skin. Br. J. Community Nurs. 22, 696–700.

Forsman, M., 2017. The search for practical and reliable observational or technical risk assessment methods to be used in prevention of musculoskeletal disorders. Agron. Res. 15, 680–686.

Godinho, C., Domingos, J., Cunha, G., Santos, A.T., Fernandes, R.M., Abreu, D., Gonçalves, N., Matthews, H., Isaacs, T., Duffen, J., Al-Jawad, A., Larsen, F., Serrano, A., Weber, P., Thoms, A., Sollinger, S., Graessner, H., Maetzler, W., Ferreira, J.J., 2016. A systematic review of the characteristics and validity of monitoring technologies to assess Parkinson's disease. J. NeuroEng. Rehabil. 13, 24.

Granzow, R.F., Schall Jr., M.C., Smidt, M.F., Chen, H., Fethke, N.B., Huangfu, R., 2018. Characterizing exposure to physical risk factors among reforestation hand planters in the Southeastern United States. Appl. Ergon. 66, 1–8.

Hansson, G.A., Asterland, P., Holmer, N.G., Skerfving, S., 2001. Validity and reliability of triaxial accelerometers for inclinometry in posture analysis. Med. Biol. Eng. Comput. 39, 405–413.

Hansson, G.Å., Arvidsson, I., Ohlsson, K., Nordander, C., Mathiassen, S.E., Skerfving, S., Balogh, I., 2006. Precision of measurements of physical workload during standardised manual handling. Part II: inclinometry of head, upper back, neck and upper arms. J. Electromyogr. Kinesiol. 16, 125–136.

Hansson, G.Å., Balogh, I., Ohlsson, K., Granqvist, L., Nordander, C., Arvidsson, I., Åkesson, I., Unge, J., Rittner, R., Strömberg, U., Skerfving, S., 2010. Physical workload in various types of work: Part II. Neck, shoulder and upper arm. Int. J. Ind. Ergon. 40, 267–281.

Heiden, M., Zetterberg, C., Mathiassen, S.E., 2019. Trunk and upper arm postures in paper mill work. Appl. Ergon. 76, 90–96.

Heilskov-Hansen, T., Svendsen, S.W., Thomsen, J.F., Mikkelsen, S., Hansson, G.Å., 2014. Sex differences in task distribution and task exposures among Danish house painters: an observational study combining questionnaire data with biomechanical measurements. PLoS One 9.

Hess, J.A., Kincl, L., Amasay, T., Wolfe, P., 2010. Ergonomic evaluation of masons laying concrete masonry units and autoclaved aerated concrete. Appl. Ergon. 41, 477–483.

ILO, 2015. Global Trends on Occupational Accidents and Diseases. World Day for Safety and Health at Work.

Jonker, D., Rolander, B., Balogh, I., 2009. Relation between perceived and measured workload obtained by long-term inclinometry among dentists. Appl. Ergon. 40, 309–315.

Jonker, D., Rolander, B., Balogh, I., Sandsjö, L., Ekberg, K., Winkel, J., 2011. Mechanical exposure among general practice dentists in Sweden and possible implications of rationalisation. Ergonomics 54, 953–960.

Jonker, D., Rolander, B., Balogh, I., Sandsjö, L., Ekberg, K., Winkel, J., 2013. Rationalisation in public dental care – impact on clinical work tasks and mechanical exposure for dentists – a prospective study. Ergonomics 56, 303–313.

Juul-Kristensen, B., Hansson, G.A., Fallentin, N., Andersen, J.H., Ekdahl, C., 2001. Assessment of work postures and movements using a video-based observation method and direct technical measurements. Appl. Ergon. 32, 517–524.

Kazmierczak, K., Mathiassen, S.E., Forsman, M., Winkel, J., 2005. An integrated analysis of ergonomics and time consumption in Swedish "craft-type' car disassembly. Appl. Ergon. 36, 263–273.

Kersten, J.T., Fethke, N.B., 2019. Radio frequency identification to measure the duration of machine-paced assembly tasks: agreement with self-reported task duration and application in variance components analyses of upper arm postures and movements recorded over multiple days. Appl. Ergon. 75, 74–82.

Koch, M., Lunde, L.-K., Gjulem, T., Knardahl, S., Veiersted, K.B., 2016. Validity of questionnaire and representativeness of objective methods for measurements of mechanical exposures in construction and health care work. PLoS One 11 e0162881-e0162881.

Korshoj, M., Skotte, J.H., Christiansen, C.S., Mortensen, P., Kristiansen, J., Hanisch, C., Ingebrigtsen, J., 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, 247–253.

Leardini, A., Chiari, L., Della Croce, U., Cappozzo, A., 2005. Human movement analysis using stereophotogrammetry. Part 3. Soft tissue artifact assessment and compensation. Gait Posture 21, 212–225.

Lind, C.M., Forsman, M., Rose, L.M., 2019. Development and evaluation of RAMP I – a practitioner's tool for screening of musculoskeletal disorder risk factors in manual handling. Int. J. Occup. Saf. Ergon. 25, 165–180.

Lind, C.M., Forsman, M., Rose, L.M., 2020. Development and evaluation of RAMP II - a practitioner's tool for assessing musculoskeletal disorder risk factors in industrial manual handling. Ergonomics 63, 477–504.

Lötters, F., Burdorf, A., Kuiper, J., Miedema, H., 2003. Model for the work-relatedness of low-back pain. Scand. J. Work. Environ. Health 29, 431–440.

Moriguchi, C.S., Carnaz, L., Alencar, J.F., Miranda Júnior, L.C., Granqvist, L., Hansson, G., Gil Coury, H.J., 2011. Postures and movements in the most common tasks of power line workers. Ind. Health 49, 482–491.

Murray, C., 2018. Global, regional, and national disability-adjusted life-years (DALYs) for 359 diseases and injuries and healthy life expectancy (HALE) for 195 countries and territories, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 392, 1859–1922.

Nordander, C., Ohlsson, K., Balogh, I., Hansson, G.Å., Axmon, A., Persson, R., Skerfving, S., 2008. Gender differences in workers with identical repetitive industrial tasks: exposure and musculoskeletal disorders. Int. Arch. Occup. Environ. Health 81, 939–947.

Nordander, C., Hansson, G.Å., Ohlsson, K., Arvidsson, I., Balogh, I., Strömberg, U., Rittner, R., Skerfving, S., 2016. Exposure–response relationships for work-related neck and shoulder musculoskeletal disorders – analyses of pooled uniform data sets. Appl. Ergon. 55, 70–84.

Nourollahi-Darabad, M., Afshari, D., dianat, I., Jodakinia, L., 2020. Long-duration assessment of upper arm posture and motion and their association with perceived symptoms among bakery workers. Int. J. Ind. Ergon. 80, 103029.

Peppoloni, L., Filippeschi, A., Ruffaldi, E., Avizzano, C.A., 2016. A novel wearable system for the online assessment of risk for biomechanical load in repetitive efforts. Int. J. Ind. Ergon. 52, 1–11.

Peters, A., Galna, B., Sangeux, M., Morris, M., Baker, R., 2010. Quantification of soft tissue artifact in lower limb human motion analysis: a systematic review. Gait Posture 31, 1–8.

Punnett, L., 2014. Musculoskeletal disorders and occupational exposures: how should we judge the evidence concerning the causal association? Scand. J. Publ. Health 42, 49–58.

Rhén, I.-M., Forsman, M., 2020. Inter- and intra-rater reliability of the OCRA checklist method in video-recorded manual work tasks. Appl. Ergon. 84, 103025.
Rislund, C., Hemphälä, H., Hansson, G.-Å., Balogh, I., 2013. Evaluation of three principles for forklift steering: effects on physical workload. Int. J. Ind. Ergon. 43, 249–256.
Robert-Lachaine, X., Mecheri, H., Larue, C., Plamondon, A., 2017. Effect of local magnetic field disturbances on inertial measurement units accuracy. Appl. Ergon. 63, 123–132.
SCB, 2020. The Swedish Occupational Register with Statistics 2018. Statistics Sweden, Örebro, Sweden.
Schall Jr., M.C., Fethke, N.B., Chen, H., 2016. Working postures and physical activity among registered nurses. Appl. Ergon. 54, 243–250.
Schall Jr., M.C., Zhang, X., Chen, H., Gallagher, S., Fethke, N.B., 2021. Comparing upper arm and trunk kinematics between manufacturing workers performing predominantly cyclic and non-cyclic work tasks. Appl. Ergon. 93, 103356.
Schmal, H., Holsgaard-Larsen, A., Izadpanah, K., Brønd, J.C., Madsen, C.F., Lauritsen, J., 2018. Validation of activity tracking procedures in elderly patients after operative treatment of proximal femur fractures. Rehabil. Res. Pract. 2018.
Skotte, J., Korshoj, M., Kristiansen, J., Hanisch, C., Holtermann, A., 2014. Detection of physical activity types using triaxial accelerometers. J. Phys. Activ. Health 11, 76–84.
Sluiter, J.K., Rest, K.M., Frings-Dresen, M.H.W., 2001. Criteria document for evaluating the work-relatedness of upper-extremity musculoskeletal disorders. Scand. J. Work. Environ. Health 7, 1–102.
Takala, E.P., Pehkonen, I., Forsman, M., Hansson, G.A., Mathiassen, S.E., Neumann, W. P., Sjogaard, G., Veiersted, K.B., Westgaard, R.H., Winkel, J., 2010. Systematic evaluation of observational methods assessing biomechanical exposures at work. Scand. J. Work. Environ. Health 36, 3–24.
Trask, C., Mathiassen, S.E., Wahlström, J., Forsman, M., 2014. Cost-efficient assessment of biomechanical exposure in occupational groups, exemplified by posture observation and inclinometry. Scand. J. Work. Environ. Health 40, 252–265.
Unge, J., Ohlsson, K., Nordander, C., Hansson, G.Å., Skerfving, S., Balogh, I., 2007. Differences in physical workload, psychosocial factors and musculoskeletal disorders between two groups of female hospital cleaners with two diverse organizational models. Int. Arch. Occup. Environ. Health 81, 209–220.
van Rijn, R.M., Huisstede, B.M., Koes, B.W., Burdorf, A., 2010. Associations between work-related factors and specific disorders of the shoulder – a systematic review of the literature. Scand. J. Work. Environ. Health 36, 189–201.
Veiersted, K.B., Gould, K.S., Osteras, N., Hansson, G.A., 2008. Effect of an intervention addressing working technique on the biomechanical load of the neck and shoulders among hairdressers. Appl. Ergon. 39, 183–190.
Violante, F.S., Farioli, A., Graziosi, F., Marinelli, F., Curti, S., Armstrong, T.J., Mattioli, S., Bonfiglioli, R., 2016. Carpal tunnel syndrome and manual work: the OCTOPUS cohort, results of a ten-year longitudinal study. Scand. J. Work. Environ. Health 42, 280–290.
Wahlström, J., Mathiassen, S.E., Liv, P., Hedlund, P., Ahlgren, C., Forsman, M., 2010. Upper arm postures and movements in female hairdressers across four full working days. Ann. Occup. Hyg. 54, 584–594.
Wahlström, J., Bergsten, E., Trask, C., Mathiassen, S.E., Jackson, J., Forsman, M., 2016. Full-shift trunk and upper arm postures and movements among aircraft baggage handlers. Ann. Occup. Hyg. 60, 977–990.
Wærsted, M., Enquist, H., Veiersted, K.B., 2019. Hairdressers' shoulder load when blow-drying – studying the effect of a new blow dryer design on arm inclination angle and muscle pain. Int. J. Ind. Ergon. 74, 102839.
Yang, L., Grooten, W.J.A., Forsman, M., 2017. An iPhone application for upper arm posture and movement measurements. Appl. Ergon. 65, 492–500.
Yung, M., Dale, A.M., Kapellusch, J., Bao, S., Harris-Adamson, C., Meyers, A.R., Hegmann, K.T., Rempel, D., Evanoff, B.A., 2019. Modeling the effect of the 2018 revised ACGIH hand activity threshold limit value (TLV) at reducing risk for carpal tunnel syndrome. J. Occup. Environ. Hyg. 16, 628–633.