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ORIGINAL RESEARCH

Dynamic Joint Motions in Occupational Environments as Indicators of Potential Musculoskeletal Injury Risk

Jonathan S. Dufour, Alexander M. Aurand, Eric B. Weston, Christopher N. Haritos, Reid A. Souchereau, and William S. Marras
The Ohio State University

The objective of this study was to test the feasibility of using a pair of wearable inertial measurement unit (IMU) sensors to accurately capture dynamic joint motion data during simulated occupational conditions. Eleven subjects (5 males and 6 females) performed repetitive neck, low-back, and shoulder motions simulating low- and high-difficulty occupational tasks in a laboratory setting. Kinematics for each of the 3 joints were measured via IMU sensors in addition to a "gold standard" passive marker optical motion capture system. The IMU accuracy was benchmarked relative to the optical motion capture system, and IMU sensitivity to low- and high-difficulty tasks was evaluated. The accuracy of the IMU sensors was found to be very good on average, but significant positional drift was observed in some trials. In addition, IMU measurements were shown to be sensitive to differences in task difficulty in all 3 joints ($P < .05$). These results demonstrate the feasibility for using wearable IMU sensors to capture kinematic exposures as potential indicators of occupational injury risk. Velocities and accelerations demonstrate the most potential for developing risk metrics since they are sensitive to task difficulty and less sensitive to drift than rotational position measurements.

Keywords*:* inertial measurement unit, motion capture, kinematics, motion analysis

Work-related musculoskeletal disorders (MSDs) are prevalent in private industry. In 2018 in the United States, MSDs resulting from overexertion and bodily reaction occurred at a rate of 27.1 per 10,000 full-time workers, leading to a median of 12 days away from work per incident.[1] The treatment of work-related MSDs such as low-back, neck, and shoulder pain also constitutes an immense economic burden. The United States spends $88 billion per year in direct costs treating patients with neck and low-back pain (more than was spent treating any other conditions besides diabetes and heart disease),[2] and indirect costs associated with these spine disorders are estimated to be $625 billion.[3,4] Likewise, expenditures on shoulder injuries may exceed $7 billion.[5]

During the early part of this century, a comprehensive literature review by the National Research Council and the Institute for Medicine concluded that MSDs are, indeed, linked to work exposures.[6] One widely accepted risk factor includes working in an awkward or extreme posture. However, there is substantial scientific evidence suggesting that to appropriately estimate injury risk, higher order kinematics need to be monitored in addition to static posture alone.[7,8] That is, to understand MSD injury risk, ergonomics practitioners must be able to capture accurate joint kinematics (position, velocity, and acceleration) for exposures of interest in an occupational environment.

Over the past 10–15 years, significant advancements in sensing technologies, cloud computing, and machine learning have synergized to create new opportunities to use data to improve occupational safety and health. Technologies that sense how workers move are of increasing interest due to well-known connections between dynamic joint motions and injury risk.[8–12] Broadly, technologies that have emerged to capture and assess human motion include (1) markered optical motion capture, (2) markerless optical motion capture, and (3) inertial measurement unit (IMU) sensors. Each technology has significant advantages and disadvantages.

Often considered the "gold standard," markered optical motion capture (optoelectronic) systems are well established as the most accurate way to capture complex human motions and boast errors as low as 100 μm.[13] Despite having outstanding accuracy, markered optical motion capture applications are limited to use under controlled laboratory environments due to their significant cost, sensitivity to light and vibration, line-of-sight requirements, and reliance on dozens of markers that need to be placed on the person of interest.

Markerless motion capture systems have been growing in popularity due to their ability to capture motion without the need to place markers on the person of interest. The emergence of affordable commercial systems like the Microsoft Kinect have resulted in a flurry of new applications aimed at increasing worker safety. Some markerless motion capture systems have demonstrated good accuracy for simple applications such as measuring lower-extremity angles during gait.[14,15] However, significant limitations in accuracy have also been reported,[16] and most studies demonstrating good performance are limited to lower-extremity joint motions performed in unrealistically clean and controlled environments with spandex suits or exposed skin. Real-world occupational environments are likely to challenge the performance and applicability of markerless motion capture systems as these environments often include loose-fitting clothing, background noise, and more complex (multiplanar) tasks. Though postural measurement errors introduced from these artifacts may not be biomechanically significant if they are less than a few degrees, the

Dufour, Aurand, Weston, Haritos, Souchereau, and Marras are with the Spine Research Institute, The Ohio State University, Columbus, OH, USA. Dufour, Aurand, Weston, Souchereau, and Marras are also with the Department of Integrated Systems Engineering, The Ohio State University, Columbus, OH, USA. Marras (marras.1@osu.edu) is corresponding author.

resulting noise is magnified in joint velocities and accelerations, making dynamic measurements less useful.

Finally, many emerging occupational human motion sensing solutions have begun to utilize IMU sensors, which leverage a series of gyroscopes, accelerometers, and (generally) magnetometers. These sensors are attractive due to their low cost, small size, immunity to occlusion, and relatively high accuracy. A multitude of studies have previously validated IMU-measured kinematics against a "gold standard" system for various experimental tasks, including simple functional motions,[17–23] gait/locomotion,[24–27] sports applications,[28,29] and simulated occupational exposures.[30–37] The results of these prior studies suggest that IMU fusion algorithms can generally produce root mean square orientation errors of 5° or less, representing a level of error that is generally acceptable for biomechanics applications,[35] though higher peak orientation errors are still likely. Moreover, the potential usefulness of IMU motion capture has been further demonstrated by studies that have utilized IMUs alongside kinetic information to predict joint moments[38,39] or have utilized IMUs alongside machine learning and artificial neural network approaches to predict ground reaction forces or joint loading[40,41] or to describe "correct" versus "incorrect" lifting postures.[42]

This being said, the primary limitation of IMUs exists in the form of a well-known artifact called yaw drift during which a sensor incurs error in its prediction of its orientation relative to Earth's gravity vector over time.[43] The magnetometers onboard IMU sensors are often used to try to correct this drift issue, but this solution is not fool-proof and can be prone to error in practice, especially in environments that have an abundance of ferrous metals. One prior study has noted that the root mean square error (RMSE) between IMUs and an optoelectronic system could reach peaks of 50° near a large metal object compared with 2.6° with no disturbance,[44] and Robert-Lachaine et al[34] recently noted that up to 30 seconds may be necessary to restore accuracy in IMU motion capture systems after experiencing magnetic disturbance. The IMU motion capture accuracy may also be limited by factors including soft tissue artifact, movement of the sensors on the body, and inaccuracies in the transformation between the local coordinate systems of onboard IMU sensors and the anatomical coordinate system for a particular joint.[20,24,26,27]

To address the problem of yaw drift, it has been suggested that increasing the number of IMUs may improve the overall accuracy of predicted joint angles and moments.[45] The increased data input allows software solutions to keep drift in check by leveraging reasonable assumptions about the relationships between sensors given their known anatomical location on the body. Because this utilization of additional "a priori" information shows promise, some companies, such as Xsens, have attempted to improve data precision by leveraging as many as 17 IMUs placed all over the body. However, there is also significant cost and operational burden associated with reliably configuring each worker with 17 sensors. Moreover, there are many instances in which ergonomics practitioners are interested in performing a risk assessment for only one joint of interest. Therefore, the objective of this study was to test the feasibility of using only 2 wearable IMU sensors to accurately capture dynamic joint motion data during simulated occupational conditions. This objective was achieved by comparing joint angle data (position, velocity, and acceleration) collected from IMU sensors with data derived from a "gold standard" optoelectronic system upon implementing custom algorithms to minimize yaw drift during dynamic activities. In addition, to test whether IMUs are sensitive to changes in work design, complex multiplanar low-back, neck, and shoulder motions were performed at 2 task difficulty levels, and differences in IMU kinematic variables were assessed.

Methods

Approach

Repetitive occupational tasks of relative low and high difficulty were performed in a laboratory setting. Low-back, neck, and shoulder motions were monitored via IMU sensors as well as a "gold standard" markered optical motion capture system. IMU accuracy was benchmarked relative to the optical motion capture system, and IMU sensitivity to low- and high-difficulty tasks was evaluated.

Subjects

Eleven subjects (5 males and 6 females) were recruited for this study (age 21.3 [1.5] y, mass 69.3 [13.0] kg, and stature 175.55 [6.1] cm) from a university population. To capture a wide range of motion patterns, we made a special effort to recruit subjects with a relatively wide range of anthropometric characteristics for this study. Subjects did not have significant experience related to the occupational tasks simulated in a laboratory environment. The study was approved by The Ohio State University's Institutional Review Board, and all subjects provided informed consent prior to study participation.

Design

Three mini studies were performed, one for each of 3 targeted joints (low back, neck, and shoulder). Within each mini study, a repeated-measures study design was used to measure the main effect of a single independent variable, task difficulty (low or high). The low- and high-difficulty tasks performed therein represented automotive assembly jobs deemed to pose low and high risk for injury, respectively, to each of the joints (low back, neck, and shoulder) via a previous field data collection. Note that because the relation to injury risk was not explicitly validated, the variable was named "difficulty" instead of "injury risk" or something of the sort. Low- and high-difficulty tasks took 60 seconds to complete and were each performed for 5 repetitions. Experimental conditions were randomized for each subject with all repetitions being performed consecutively over a 5-minute period. The primary dependent variables of interest in this study were IMU measurement error and measurement accuracy relative to a "gold standard" optical motion tracking system. Minimum, maximum, and range of rotational position, velocity, and acceleration values from the IMU data were also calculated for each joint.

Instrumentation and Apparatus

Subjects were monitored simultaneously with 2 separate motion capture systems (Figure 1). The first system consisted of 5 wearable Xsens MTw2 IMU sensors (Xsens North America Inc, El Segundo, CA) that were captured at a rate of 100 Hz in custom laboratory software. The IMU sensors were mounted securely to custom harnesses made by a local product design and development company (Priority Designs, Inc, Whitehall, OH) via an Afinia H800 (Afinia 3D, Chanhassen, MN) 3D-printed snap-fit mounting platform designed specifically for this study. Though 5 sensors were used in total, motion from each joint of interest was derived from just 2 IMU sensors (ie, chest and hip sensors tracked low-back motion, head and chest sensors tracked neck motion, and chest and upper arm sensors tracked shoulder motion).

Each 3D-printed mounting platform also included a series of 3 (left upper arm and right upper arm) or 4 (head, chest, and hips) rigidly attached 14-mm retroreflective markers. Markers were located relative to IMU sensors with an accuracy of 100 µm, as determined by the resolution of the 3D printer. These markers were tracked by a "gold standard" 42-camera OptiTrack (Natural Point, Corvallis, OR) optical motion tracking system with demonstrated error of <100 µm.[6] Camera system data were recorded at a rate of 120 Hz via OptiTrack's Motive software. All simulated occupational tasks were mocked up via custom 80/20 T-slotted aluminum framing (80/20 Inc, Columbia City, IN) as shown in Figure 2. Apparatus dimensions were determined based on the average 50th percentile US male and female anthropometry measurements.[46]

Figure 1 — Sensor configuration showing Xsens inertial measurement units (rectangular sensors on harnesses) and optical motion capture system (markers on harnesses, cameras around the room).

Procedure

Subjects were given an overview of the study and were asked to sign an informed consent document per The Ohio State University Institutional Review Board requirements. Subject age, stature, and mass were then recorded into custom laboratory software. Five harnesses (head, upper back, hips, right upper arm, and left upper arm) were placed on the subject, and IMU sensors were snapped into place on each harness. After setup, experimental conditions were performed. Each exertion was performed 12 times during a 60-second repetition. Pace was maintained via an audible metronome that sounded every 5 seconds.

Tasks that targeted the low back required subjects to repeatedly lift a box from its origin and place it at its destination without moving their feet. The box mass was 5.1 kg and had a width, depth, and height of 0.27, 0.25, and 0.27 m, respectively. Holes in the side of the box served as handles. For low-difficulty lifts, the origin of the box was located directly in front of the subject at a vertical location of 0.59 m from the ground. For high-difficulty lifts, the origin of the box was located asymmetrically 90° to the left of the subject at 0.27 m from the ground. The destination of the box was located directly in front of the subject at a vertical location of 0.95 m from the ground for all conditions.

Tasks that targeted the neck required subjects to visually locate targets in 8 different locations with the subject located .61 m away from the center target. Upon locating each target, subjects were asked to verbally call out a unique 4-digit number to confirm visual location. Low-difficulty targets were positioned in the central-near peripheral field-of-view (≤30°). High-difficulty targets were positioned in the near-mid peripheral field-of-view (30°–60°). Subjects returned their vision to a neutral target directly in front of them after calling out each experimental target and were required to keep their feet in the same position throughout all exertions.

Tasks that targeted the shoulder required subjects to repeatedly place a small machine screw in a small bin 0.56 m in front of them using their right hand. Subjects were asked to keep their feet in the same position as they performed these tasks. For low-difficulty placements, the target bin was located at a height of 1.39 m directly in front of the subject. For high-difficulty placements, the target bin was located at a height of 1.68 m and offset laterally to the right of the subject by 0.56 m. Note that only values for the right shoulder will be reported herein as this is the shoulder that was the primary target of the experimental task.

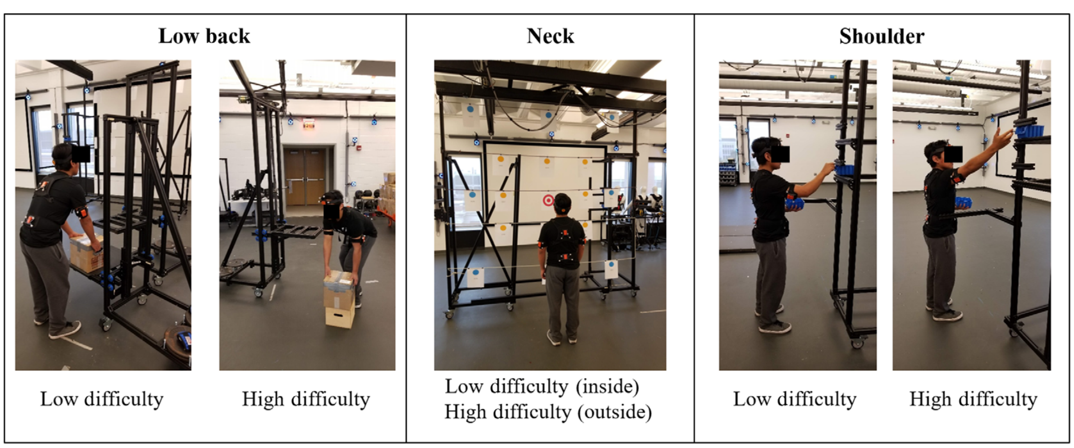

Figure 2 — Experimental tasks.

Data Processing and Statistical Analysis

Positional data from optical motion capture markers were transformed into local coordinate system orientations for each body segment. The IMU sensor data were also transformed into the same local coordinate systems and adjusted to account for the effect of sensor drift at the start of each trial by aligning the sensors about the yaw axis when the subject was standing in a neutral posture. Positional data from the optical motion capture system were resampled and interpolated to match the frequency of the IMU data. Signals were also time synchronized by calculating a time delay that minimized the RMSE between the 2 signals and shifting the IMU sensor data by that time delay to ensure that the signals overlapped. All additional calculations were identical for both systems. First, local coordinate system orientations were low-pass filtered with a cutoff frequency of 4 Hz. Then, joint orientations were calculated as the distal segment orientation relative to the proximal segment orientation for each joint. Only 2 sensors were used to measure motions for each joint so that results could be replicated if only a single joint was of interest. All orientation transformations were performed using quaternion mathematics and then converted to Euler rotation sequences that were optimized for each joint to prevent gimbal lock and Euler Singularities. Euler angles were then differentiated twice to obtain rotational velocities and accelerations.

The IMU measurement error was calculated as the RMSE relative to the optical motion capture system across each 1-minute trial for a given position, velocity, or acceleration signal. Percent error was calculated by normalizing RMSE to the range of each signal, and accuracy was calculated as one minus percent error. The minimum, maximum, and range of rotational position, velocity, and acceleration values were also extracted from the IMU data as additional dependent variables of interest for each joint. In the low back and neck, values were presented for each anatomical plane (axial, lateral, and sagittal). However, in the shoulder joint, values were presented as minimum and maximum elevation where appropriate. Elevation was defined as the angle in any plane above hanging directly downwards. For example, when standing upright with the arms by the sides of the body, elevation is 0°. Likewise, when the arm is level with the ground (in any direction), this represents an elevation of 90°, and when the arm is straight overhead, this represents an elevation of 180°.

All statistical tests were performed in in JMP PRO software (version 14.0; SAS Institute Inc, Cary, NC). A 1-way ANOVA with $\alpha = .05$ was used to determine significant differences in each of the dependent measures attributable to task difficulty (low and high) for each joint. The effect of subject and the interaction effect between subject and task difficulty were included in the model and treated as random variables.

Results

Mean IMU error (RMSE) and accuracy measurements for each joint after processing are shown in Table 1. Across the 3 joints and 2 task difficulty levels, average RMS errors in position, velocity, and acceleration were found to be 1.37°, 3.07°/s, and 44.9°/s^2, respectively. Although mean accuracy was similar across all joints, average error magnitudes were highest in the right shoulder (mean RMS error 2.18°). Task difficulty significantly influenced RMSE and accuracy measures for low-back velocity ($P = .009$) and neck velocity ($P = .030$) signals wherein the high-difficulty task yielded larger RMSE values and reduced accuracy values than the low-difficulty task.

Though IMU accuracy was generally very good, significant drift was observed over the course of some of the 60-second trials. An example of one of the worst cases of drift is shown in Figure 3. Trials that were recorded while sensors were drifting experienced relatively large errors in position measurements (maximum RMSE for the position signal was 8.01° in the low back, 2.58° in the neck, and 9.09° in the right shoulder). However, drift affected velocity and acceleration measurements to a lesser extent.

High-difficulty tasks produced higher joint position, velocity, and acceleration measurements than low-difficulty tasks (Figure 4). Differences between low and high task difficulties were found to be statistically significant for all measures (P value for maximum shoulder elevation in the acceleration signal was .042, all other P values were <.001.)

Discussion

On average, the IMU sensors used in this study were found to have relatively low errors and high accuracies after applying custom processing algorithms to mitigate yaw drift at the beginning of each trial. Average RMS error in position data was found to be 1.37°, which is well below the acceptable position threshold of 5° presented by Robert-Lachaine et al[35] for manual materials handling tasks. Errors were comparable in the low back and neck but were

Table 1 Mean (SD) RMSE and Accuracy of IMU Measurements Relative to the Optical Motion Capture System Separated by Task Difficulty

Joint	Low back		Neck		Right shoulder	
Task difficulty	Low	High	Low	High	Low	High
RMSE						
Position, deg	1.32 (1.25)	1.39 (1.46)	0.76 (0.32)	0.80 (0.37)	2.18 (0.85)	2.06 (1.23)
Velocity, deg/s	1.32 (0.50)	1.64 (0.83)*	1.25 (0.53)	1.42 (0.59)*	6.98 (7.95)	7.26 (8.11)
Acceleration, deg/s^2	19.0 (4.53)	21.5 (6.75)	20.7 (9.63)	22.9 (10.2)	96.9 (141.1)	108.4 (148.8)
Accuracy						
Position, deg	98.1% (1.9%)	97.9% (2.2%)	99.3% (0.3%)	99.3% (0.3%)	98.7% (0.5%)	98.7% (0.7%)
Velocity, deg/s	99.5% (0.2%)	99.4% (0.3%)*	99.7% (0.1%)	99.7% (0.1%)*	99.4% (0.7%)	99.3% (0.7%)
Acceleration, deg/s^2	99.0% (0.2%)	98.9% (0.3%)	99.4% (0.3%)	99.4% (0.3%)	99.3% (1.1%)	99.2% (1.1%)

Abbreviations: ANOVA, analysis of variance; IMU, inertial measurement unit; RMSE, root mean square error. Note: *Statistically significant effect of task difficulty from the 1-way ANOVA at an alpha level of .05.

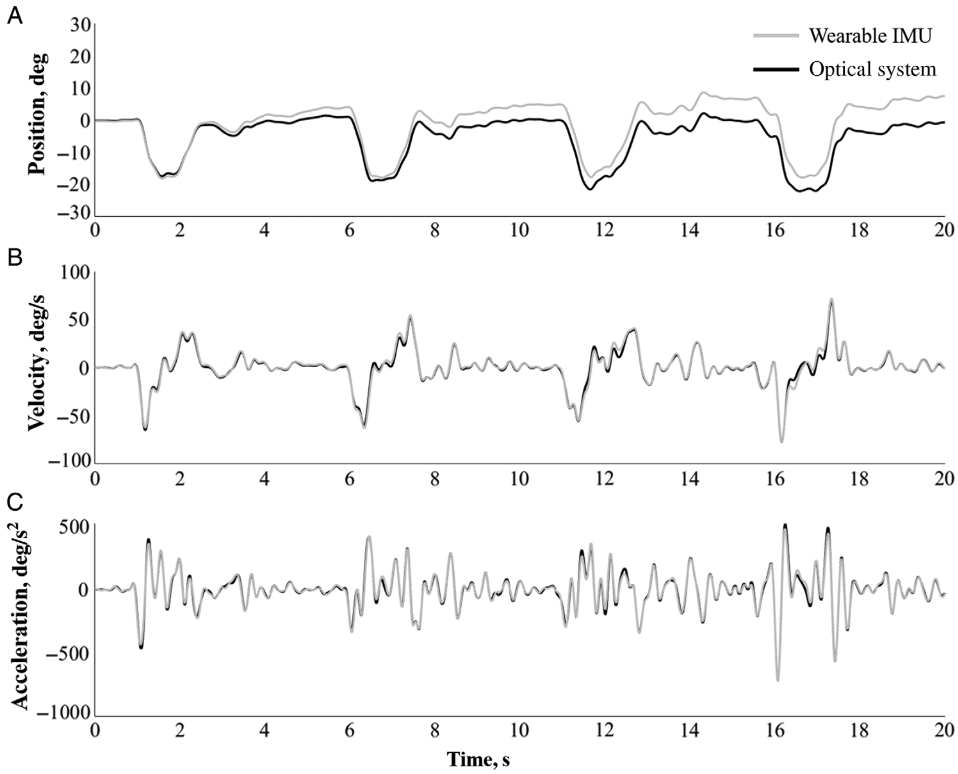

Figure 3 — An example of one of the worst cases of drift in (A) position, (B) velocity, and (C) acceleration for the IMU sensor (gray) relative to optical motion capture system (black). IMU indicates inertial measurement unit.

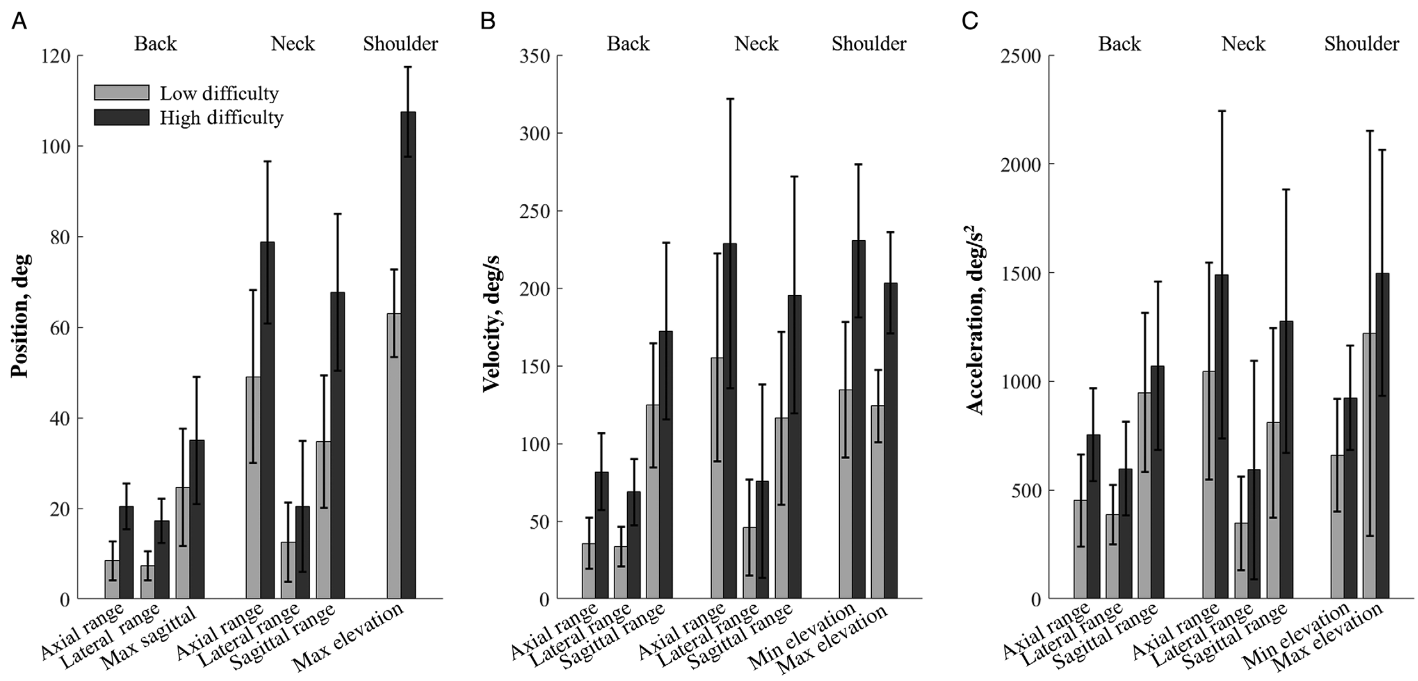

Figure 4 — Effect of task difficulty across the various inertial measurement unit sensor measurements describing (A) position, (B) velocity, or (C) acceleration. The effect of task difficulty was statistically significant for all dependent measures shown.

highest in the right shoulder. Task difficulty did not affect error or accuracy measures except for increased errors and reduced accuracy in rotational velocity in the low back and neck for the high-difficulty task relative to the low-difficulty task. Though these differences were found to be statistically significant, differences in error magnitude and accuracy were small and are not expected to bear any biomechanical significance. It should be noted that large errors in rotational position measurements did occur in a subset of trials over time, yielding maximum RMSE up to 9.1°. In contrast, velocities and accelerations were not generally affected by sensor drift as the artifact occurred slowly over time.

Though a multitude of studies have previously validated IMU-measured kinematics against a "gold standard" system, many of these prior studies were limited by a lack of complexity in the movements examined or joints analyzed. Moreover, relatively few studies have examined IMU accuracy for simulated or actual occupational exposures[30–37] and, instead, have assessed IMU accuracy for simple planar motion or simple gait/locomotion such as walking or sit-to-stand. These simpler motions restrict the range of motion, degrees of freedom, motion coupling, and motion dynamics associated with the experimental task and may subsequently underestimate the true error associated with IMUs, especially because increases in task complexity have previously been shown to increase orientation errors in IMU sensors.[20] Regardless, the RMS errors in position data approximate those observed by Robert-Lachaine et al,[33] who observed a mean RMSE of approximately 2.8° across the full body for an extended (32 min) lifting task. This is a promising result given that the present study utilized just 2 IMU sensors per joint and the study by Robert-Lachaine et al leveraged data from 17 sensors across the whole body to make joint angle predictions. Likewise, the RMSE values reported herein also represent an improvement over values reported by Godwin et al[20] and Plamondon et al[32] for lifting tasks (mean RMSE range 4.9°–23.6° and 2.5°–5.1°, respectively), suggesting improvements attributable to improvements in the IMU fusion algorithm with time and/or our custom algorithms utilizing knowledge of neutral postures to minimize yaw drift.

The optical motion capture system used in this study as the ground truth has demonstrated excellent accuracy in previous studies with errors as low as 100 μm.[6] Even so, it is possible that some of the errors we associated with the IMU sensors may have been errors in measurements produced by the optical motion capture system. This is especially true for velocities and accelerations, which may include errors accrued during derivation of marker position data. Errors in optical motion capture shoulder measurements were also likely artificially high in this study as only 3 markers were used on upper arm segments compared with the 4 used on the rest of the segments. This lack of redundancy for the upper arm segments may explain why RMSE values for the right shoulder were generally observed to be larger than in the neck and low back.

The long-term goal of these efforts is to eventually identify which kinematic measurements are associated with real occupational injuries, which could provide for updated risk models. Alternatively, collection of reliable full-body kinematic data from IMUs could be utilized alongside kinetic information collected from force shoes or pressure insoles to predict joint moments as an additional indicator of potential injury risk.[38,39] However, making connections to injury risk can often prove to be difficult as prospective studies and intimate access to occupational injury records are often required. Regardless, in this first study, we wanted to investigate whether IMU measurements were sensitive to differences in relative task difficulty since it is much easier to control in a laboratory environment and can be used as a surrogate for injury risk to establish feasibility.

The IMU position, velocity, and acceleration measurements were all found to be sensitive to differences in task difficulty for all 3 joints observed. Increases in position (posture) measurements during high-difficulty tasks is not overly interesting given that the study was designed to elicit these changes. However, it is interesting to note that increases in posture were generally accompanied by increases in joint velocities and accelerations. This makes sense intuitively as subjects were required to perform the same number of exertions over a 60-second period for both low- and high-difficulty tasks but were required to move further. As the results of this study show promise, the natural next step would be to design larger studies that aim to identify which IMU measurements may be useful for classifying potential MSD injury risk. Given that joint velocities and accelerations are less sensitive to IMU drift, they demonstrate increased predictive power for assessing occupational injury risk and should be the focus of future study. This is especially the case given that drift correction algorithms perform modestly or poorly at this time.[34] Moreover, though not observed in this study, it is important to note that positional drift can, indeed, cause error in anatomical joint velocity and acceleration component measurements by modifying the relative coordinate systems used to calculate these higher order signals. Velocity and acceleration magnitudes, however, should remain completely impervious to sensor drift, in theory.

It is important to interpret the findings of this study in context with its limitations. First, the study was performed in a controlled laboratory environment free of magnetic field interference from ferrous metals and some electronics. In addition, as IMU sensors rely on fusion algorithms that use historical data to adjust for perceived estimate errors, the relatively short 60-second trials observed in this study may have affected the results. This effect could have been positive or negative as longer warm-ups and collection periods can make the sensors more stable but can also provide more time for drift to occur. Moreover, we only evaluated a single IMU manufacturer and model. Xsens sensors have been shown to be among the most accurate IMU sensors on the market, especially compared with lower cost alternatives.[35] Results from other IMUs may vary depending on the accelerometer, gyroscope, and magnetometer sensors they use and the fusion algorithms they deploy. The results of the study may be further limited by the subject population and experimental task. Though we recruited a larger number of subjects (11) compared with prior validation studies that have relied on as few as 3 or 4,[19,23,24] a larger subject pool could have allowed for the potential to capture an even wider range of motion patterns. Finally, low- and high-difficulty tasks were determined based on automotive assembly jobs previously deemed to pose low and high risk for injury (respectively) to each of the joints examined. As a result, multiple aspects of the experimental task (eg, vertical height, twisting) were manipulated between low- and high-difficulty tasks. It remains unclear if the kinematic measurements reported on herein would be sensitive enough to differentiate between more subtle differences in task difficulty.

In conclusion, the IMU sensors examined in this study were shown to have low mean errors and excellent mean accuracy relative to a "gold standard" optical motion capture system. Though average errors were good, significant positional drift was still observed in a subset of trials. This positional drift could impact posture interpretation, especially over a longer duration of time, as is typical in actual work context and ergonomic assessments. Moreover, ergonomics assessments utilizing posture alone may be affected more so than those that use velocity or acceleration as inputs. In contrast, drift did not significantly impact joint velocity and acceleration measurements. Thus, higher order joint velocity and accelerations that are less sensitive to drift should be the primary focus of future studies that aim to reliably use IMU sensors in the field. Finally, all kinematic measurements, including joint positions, velocities, and accelerations, were shown to be good differentiators of task difficulty in this study, suggesting that IMU sensors have the potential to classify MSD injury risk in future studies.

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