

**Development and Evaluation of Methods to Assess Physical Exposures in the Workplace
using Wearable Technologies**

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ABSTRACT

Work-related musculoskeletal disorders (WSMDs) are an important health concern in the workplace. Accurately quantifying the level of physical exposures (i.e., kinematics and kinetics) is essential for risk assessments, developing and/or testing interventions, and improving estimates of exposure-response relationships. Such exposures ideally should be quantified *in situ*, while workers interact with the actual work environment to complete their tasks. However, in practice, relatively crude and/or time-consuming methods are often used, including self-reports, observational methods, and simple instrumentation, since directly assessing physical exposures is challenging in the workplace, and typically resource prohibitive.

Inertial motion capture (IMC) and in-shoe pressure measurement (IPM) systems are emerging wearable technologies, and they can, respectively, facilitate monitoring of body kinematics and external forces on the body in the workplace. Thus, this research examined the potential of such technologies in exposure assessments, and evaluated them in comparison to mature laboratory systems (i.e., optical motion capture system and force platform) or direct observation.

Performance of an IMC system was evaluated during several manual material handling (MMH) tasks, in terms of estimated body kinematics and kinetics at selected body parts. A practical issue, regarding calibrating the IPM system in the field, was addressed by defining an *ad hoc* global coordinate system using a force platform. Several regression models were developed for estimating center-of-pressure location and ground reaction forces. Given that outputs from the IMC and the IPM systems are numerically fine-grained, but generally lack contextual information about a given job, task classification approaches were explored to automatically identify task types and their time proportions in a job.

Overall, the outcomes from these studies demonstrated the potential of the IMC and the IPM systems for measuring physical exposures in the workplace. However, estimation of physical exposures using these systems requires further improvements in some cases. This research provided groundwork for future rapid and direct assessments of physical exposures in the workplace, and which needs to be expanded and validated in future efforts.

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Chapter 1: Introduction

A multitude of epidemiological and occupational health studies have demonstrated that diverse individual, psychosocial, and physical factors interact in the development of work-related musculoskeletal disorders (WMSDs). Yet, controlling and/or preventing exposures to such risk factors in the workplace continue to be challenging problems, and WMSDs remain prevalent in and associated costs are substantial. WMSDs account for ~30% of all lost workday cases reported in recent years (BLS, 2010; 2011) and involve a median of ~9 days away from work. In 2009, direct workers compensation costs for occupational injuries and illnesses were estimated to be \$50.1 billion (Liberty Mutual, 2012), and more specifically the combined direct and indirect costs of nonfatal cases with lost workday ≥ 1 were estimated to be \$60.1 billion (Waehrer *et al.*, 2004). These data, however, likely underrepresent the true scope of the problem of WMSDs due to the considerable underreporting of WMSDs (Boden & Ozonoff, 2008; Morse *et al.*, 2005).

One challenge in controlling/preventing WMSDs is quantifying exposures to physical risk factors (e.g., non-neutral postures, high forces/moments) in the actual workplace, which is needed to describe relationships between exposures and health outcomes (Burdorf *et al.*, 1997; Lötters & Burdorf, 2002; Marras *et al.*, 2010; Westgaard & Winkel, 1997). These authors suggested that detailed information on how changes in the level of physical exposures affect health outcomes is needed to understand dose-response relationships, and also to effectively design and/or evaluate ergonomic interventions. In addition, recent systematic reviews on low back pain (Roffey *et al.*, 2010; Wai *et al.*, 2010a; 2010b) found limited evidence for causal relationships between physical exposures and low back pain, yet noted as a limitation that many of the reviewed epidemiological studies reported only crude exposure measures (e.g., yes/no), making it impossible to assess a dose-response relationship. As such, there is a growing and justified emphasis on improving direct quantification of physical exposures in the workplace (Garg & Kapellusch, 2009; Marras *et al.*, 2009; Waters *et al.*, 2007).

Quantification of physical exposures often involves some combinations of body kinematics and external kinetics applied to the body, at times substituted or supplemented with physiological (e.g., muscle activity, heart rate, etc.) and subjective (e.g., discomfort, exertion, etc.) measures. Less commonly, internal loads (i.e., forces acting on specific body tissues such as intervertebral

joint) are estimated using biomechanical models. Mature measurement technology exists to capture body kinematics (e.g., optical motion capture systems, OMC) and external kinetics (e.g., force platforms), though these are rather non-portable and could be restrictive of an individual's behavior in occupational settings. In fact, a current lack of instrumentation that is reliable, unobtrusive, and readily applicable in the workplace is viewed as a major impediment to capturing external loads and/or body motion data in the field (Garg & Kapellusch, 2009; Marras *et al.*, 2010; Straker *et al.*, 2010). This lack appears to explain why relatively few studies (Faber *et al.*, 2008; Morlock *et al.*, 2000; Norman *et al.*, 1998) have estimated detailed physical exposures *in situ*.

Therefore, there is a general agreement on the need for better field-based measurement systems. Of note, working postures and motions can be directly assessed, using self-reports, observational methods (e.g., checklists), and traditional technologies. The two formers are easy and practical to be used in various occupational settings, but such methods are rather crude and labor intensive (e.g., Li & Buckle, 1999; Spielholz *et al.*, 2001; Teschke *et al.*, 2009). The latter includes electrogoniometers (Hansson *et al.*, 2004; Juul-Kristensen *et al.*, 2001; Marras *et al.*, 1992), inclinometers (Hansson *et al.*, 2001; Teschke *et al.*, 2009), and the CUELA (computer assisted recordings and long-term analysis of musculoskeletal loads) system comprised of a set of gyroscope, inclinometers, and potentiometers (Ellegast & Kupfer, 2000; Freitag *et al.*, 2007). Most of the studies listed above have reported a reasonable accuracy of their systems in the main axis of motion, yet this accuracy was typically examined over a short time period, and outputs of these systems are usually less comprehensive than those of an OMC system (e.g., 3D location and/or orientation information of a body segment). Some research groups have developed wearable systems to facilitate better field-based exposure measurements, for example a moment exposure tracking system with instrumented handles (Marras *et al.*, 2010) or a hybrid system for the 3D measurement of trunk motion (Plamondon *et al.*, 2007). Yet, these still are prototypes, and may interfere with or alter natural behaviors.

Advancements in wearable (portable) measurement systems have the potential to enable detailed exposure assessments in actual work settings. In particular, ground reaction forces (GRFs; external kinetics), typically captured using force platforms, can be obtained in the field using an

in-sole pressure measurement (IPM) system or instrumented shoes. Such systems have demonstrated the potential to estimate GRFs (Chesnin *et al.*, 2000; Fong *et al.*, 2008; Rouhani *et al.*, 2010; Savelberg & de Lange, 1999) and whole-body center of mass (COM) during walking (Schepers *et al.*, 2009), and to detect gait events (Bamberg *et al.*, 2008; Catalfamo *et al.*, 2008). In the case of body kinematics, an inertial motion capture (IMC) system can provide kinematic information such as the orientation and position of multiple body segments. An IMC system includes small, light-weight inertial measurement units (IMU; for example, width $\times$ length $\times$ depth = $3.5 \times 5.3 \times 2.1$ cm, and weight = 30 g for XSensTM) that are comprised of an accelerometer, gyroscope, and magnetometer. Reported applications of IMUs have focused mainly on basic, clinical, and sports-related research. IMUs have been used to assess kinematics of the upper extremity (Cutti *et al.*, 2007; de Vries *et al.*, 2010), the lower extremity (Favre *et al.*, 2008; Ferrari *et al.*, 2009), the spine (Giansanti *et al.*, 2007; Goodvin *et al.*, 2006), and the whole body (Brodie *et al.*, 2008). In these studies, good measurement accuracy was generally reported. Further, Schiefer *et al.* (2011) updated the sensors in the CUELA system with IMUs to improve their system performance, and suggested the potential of the IMU-based CUELA system in long-term tracking of human motion at the workplace. Thus, overall, portable measurement systems (specifically, IPM and IMU) appear to be viable for use in field-based exposure assessments.

Two potential methodological challenges may need to be overcome to facilitate the use of IPM and IMC systems in field-based exposure assessments. First, outputs of the IPM system [i.e., GRFs and/or center of pressure (COP) positions] need to be transformed to match corresponding outputs from a force platform (Chesnin *et al.*, 2000; Forner-Cordero *et al.*, 2004; Savelberg & de Lange, 1999). More importantly, the IPM system is a standalone system (i.e., distinct coordinate system); thus, it should be spatially synchronized with a motion capture system to quantify joint kinetics. Existing studies have addressed this issue while considering the coordinate system of an OMC system as the global coordinate system (Forner-Cordero *et al.*, 2004; Fradet *et al.*, 2008). However, such an approach is challenging in the field with an IMC system, since defining a global coordinate system is not easy or straightforward with the IMC versus an OMC system.

Second, though using the IPM and IMU systems will provide a finer granularity in exposure data than self-reports and observational methods, these portable measurement systems will typically lack practically-important descriptive information such as what tasks are performed, when, how frequently, and/or how long, if/how exposures change over time for a repeated task, etc.

Extracting descriptive information (e.g., task types, duration) from the outputs of portable measurement systems can be viewed as task classification – automatically recognizing tasks that a person performs. Largely in the fields of healthcare-related research and pervasive computing, different types of wearable sensors (e.g., accelerometer, gyroscope, IMU) have been used to classify daily activities (Allen *et al.*, 2006; Ermes *et al.*, 2008; Pärkkä *et al.*, 2006; Qian *et al.*, 2010). Such activities have included high-level behaviors such as ascending/descending stairs, brushing teeth, driving a car, and folding laundry, to list a few. Similarly, manual material handling (MMH) tasks are high-level behaviors, so classification algorithms could be used to automatically recognize MMH tasks performed by a worker, using outputs of portable measurement systems. Whether MMH task classification is feasible, and the level of accuracy involved, remains to be determined.

Specific aims

Portable measurement systems (i.e., IPM and IMU) have clear potential to provide both detailed and descriptive information on physical exposures that a worker undergoes in the workplace. This research was performed to help realize such potential, with an overall objective to develop and evaluate new approaches for quantifying physical exposures in the workplace using portable measurement systems. Four specific aims were addressed in support of this:

SA #1: Assess the ability of a commercially-available IMC system to quantify physical exposures for several MMH tasks over a relatively prolonged period of time. Specific measures of interest included joint angles and angular velocities, and joint moments.

SA #2: Develop a simple transformation method between a commercially-available IPM system and a “laboratory” motion capture system (i.e., OMC). Assess the performance of the transformation method, by comparing joint moments during several MMH tasks, estimated using the IPM system vs. force platforms.

SA #3: Automatically classify MMH task types using several combinations of outputs from the IPM and IMU systems. Explore three selected classification algorithms (i.e., k-nearest neighbor, multilayer feedforward neural network, and linear discriminant analysis) for each combination.

SA #4: Apply selected MMH-task classifiers, developed above, to estimate time proportions of tasks in a job (that are required to calculate task-based physical job exposures). Use the results to evaluate the application potential of the portable measurement system in exposure assessment and interventions.

In summary, this research was intended to facilitate direct assessments of physical exposures among workers in real work environments. The main focus was on developing MMH-task classifiers, based on commercially-available IPM and IMU systems, that automatically classify MMH task types, and demonstrating the potential of these classifiers in estimating task-based physical job exposure. Specifically, two laboratory-based studies were designed to achieve the four Specific Aims. Outcomes of this work are considered an important step toward more efficient and effective assessments of physical exposures *in situ*, and more targeted interventions, while future research will need to expand and validate these outcomes. The remainder of the dissertation is organized as follows. Chapter 2 describes the performance of the IMC system in quantifying physical exposures (SA #1). Chapter 3 reports on the development and assessment of a simple transformation method between the IPM and the laboratory motion capture system (SA #2). Chapter 4 describes the development of MMH-task classifiers using the IPM and IMU systems (SA #3), and evaluates task-based physical job exposures using selected MMH-task classifiers (SA #4). Lastly, Chapter 5 summarizes the major findings, discusses their practical implications, and provides suggestions for future research.

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Chapter 2: Performance evaluation of a wearable inertial motion capture system for capturing physical exposures during manual material handling tasks

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Abstract

With a long-term goal of improving quantification of physical exposures in the workplace, this study examined the ability of a commercially-available inertial motion capture (IMC) system in quantifying exposures during five different simulated manual material handling tasks. Fourteen participants repeated all these tasks in three 20 min. sequential time blocks. Performance of the IMC system was compared against an optical motion capture (OMC) system (“gold standard”) in terms of joint angles, angular velocities, and moments at selected body parts. Though several significant changes in performance over time were found, the magnitude of these were relatively small and may have limited practical relevance. The IMC system yielded peak kinematic values that differed by up to 28% from the OMC system. The IMC system, in some cases, incorrectly reflected the actual extremity positions of a participant, and which can cause relatively large errors in joint moment estimation. Given the potential limitations, practical recommendations are offered and discussed.

Practitioner Summary: Use of an inertial motion capture system can advance the quantification of physical exposures in situ. Results indicate a good potential capacity for capturing physical exposure data in the field for an extended period, while highlighting potential limitations. Future system application can help provide better understandings of dose-exposure relationships.

Keywords: *inertial motion capture, optical motion capture, physical exposures, manual material handling*

Introduction

Enhancing the quantification of physical exposures (e.g., joint kinematics and kinetics) in the workplace has been argued as a growing need (Garg & Kapellusch 2009; Marras *et al.* 2009; Waters *et al.* 2007). Ideally, such quantification should be *in situ*, since the work environment (e.g., physical constraints, workplace culture, etc.) can influence the specific work strategies adopted, and which in turn can affect the level of estimated physical exposures (Cutti *et al.* 2007; Garg & Kapellusch 2009; Marras *et al.* 2009; Waters *et al.* 2007; Wells *et al.* 2004). This potential influence, along with evidence that the temporal variation of physical exposures is likely related to injury risk (Wells *et al.* 2007; Westgaard & Winkel 1996), argues for the importance of being able to quantify physical exposures in the workplace.

Occupational physical exposures have been quantified in numerous existing studies. Such quantification typically involves some combination of kinematics and kinetics, often supplemented or substituted by physiological (e.g., muscle activity or heart rate) and subjective (e.g., discomfort or exertion) measures. Less commonly, loads acting internally (i.e., to specific body tissues such as intervertebral joint) are estimated using biomechanical models. Mature technology exists to capture body kinematics (e.g., optoelectronic motion capture systems, OMC) and external kinetics (e.g., force platforms), though these are somewhat non-portable and could be restrictive of worker behaviors. Such limitations likely explain why relatively few studies (Faber *et al.* 2008; Marras *et al.* 1993; Morlock *et al.* 2000; Norman *et al.* 1998) have obtained detailed kinematics and/or kinetics *in situ*.

Recent advances in wearable measurement systems, such as inertial motion capture (IMC) systems, may facilitate monitoring of body kinematics in diverse work environments. The potential application of an IMC system, or more specifically its primary component — an inertial measurement unit (IMU) — has been widely explored in recent years, primarily in more basic, clinical, and sports-related research. For example, IMUs have demonstrated potential as an alternative tool for clinical evaluation to assess joint kinematics of the upper extremity (Cutti *et al.* 2007; de Vries *et al.* 2010; Luinge *et al.* 2007), the lower extremity (Cloete & Scheffer 2008; Favre *et al.* 2008; Picerno *et al.* 2008), and the spine/trunk (Giansanti *et al.* 2007; Goodvin *et al.* 2006). In such studies, however, IMUs exhibited measurement errors in orientation that

depended on motion characteristics (e.g., direction and speed of motions), and were generally tested over short time periods. This raises concerns regarding application to occupational physical exposure assessment, particularly since occupational tasks involve varying motion directions, ranges, and speeds. Further, many occupational tasks (in distribution centers, hospitals, and construction sites, as examples) are often non-routinized, so that a prolonged observation can be required to describe exposure variability (Gold *et al.* 2006; Paquet *et al.* 2005). Though there are other prototype wearable systems [e.g., a hybrid system for the 3D measurement of trunk motion using IMUs (Plamondon *et al.*, 2007)], our current interest is in the application of an IMC to occupational manual materials handling (MMH) tasks, which are a well-documented risk factor for work-related musculoskeletal disorders (NRC & the Institute of Medicine 2001). To the authors' knowledge, however, use of an IMC for such tasks has yet to be evaluated.

This study thus aimed to assess the ability of an IMC system to quantify physical exposures for several MMH tasks over a relatively prolonged period of time. To achieve this, MMH tasks were simulated in a laboratory environment. Such an environment was required so that IMC measures had a basis of comparison. Here, an OMC was used, which is generally viewed as the “gold” standard for kinematic measurement (in a laboratory). Comparisons were hence made of physical exposure measures (joint angles, angular velocities, and moments of selected body parts) obtained using an OMC vs. a commercially available IMC system. Results of this study were intended thereby to contribute to the development of future investigations of MMH tasks using an IMC system.

Methods

A convenience sample of 14 participants (11 males and 3 females) was recruited from the local community; means (SD: Range) of age, stature, and body mass were 22.9 (4.9: 19 - 38) yrs, 172.4 (8.9: 157 - 185) cm, and 72.8 (9.5: 54 - 86) kg, respectively. All participants reported being physically active and with no musculoskeletal disorders within the past year. Informed consent was provided using procedures approved by the Virginia Tech Institutional Review Board (Appendix A).

Experimental design

For the purpose of assessment, five simulated MMH tasks were completed by participants in a laboratory setting, and these tasks were intended to represent a range of occupational demands. All tasks were performed using an 18 kg box (width x length x depth = 33 x 48.3 x 24 cm). This mass is near the median of values handled by the U.S. workforce (Ciriello *et al.* 1999). The specific MMH Tasks were (Figure 1):

- 1) Symmetric lifting and lowering, to/from ground height (LL_{GROUND}). Participants lifted the box from the ground to individual elbow height, paused briefly (~2 sec), and lowered the box back to the ground.
- 2) Symmetric lifting and lowering, to/from knuckle height (LL_{KNUCKLE}). As above, but beginning and ending the task at individual knuckle height.
- 3) Asymmetrical lifting and lowering (LL_{ASYM}). Participants transferred the box from one table to another. The tables were located at each side of the participant at a horizontal distance of about 65 cm from the centerline of a body.
- 4) Carrying (Carrying). Participants carried the box for 2 m, roughly the median value in the US workplace (Ciriello *et al.* 1999).
- 5) Pushing/Pulling (PushPull). Participants symmetrically pushed (pulled) the box away from (toward) the body a distance of 70 cm, with the table adjusted to individual knuckle height and the box located in front of the participant.

Three trials of each MMH task were completed, and each began with participants standing with each foot on a separate force platform, in an upright stance, with the arms hanging relaxed, and the feet hip-width apart. All tasks were performed in a freestyle manner that was self-selected as comfortable for a given task, and which was considered a more realistic representation of actual workplace behaviors. To determine if the performance of the IMC system (see below) changes over time (e.g., due to “drift”), all tasks were completed in three 20 min. *Time Blocks*. Each block consisted of 15 trials (3 repetitions x 5 MMH tasks), and 10 min of rest was provided between each block. During the intervals between trials and during 10-min rest periods, participants were asked to relax and behave naturally but to stay on the 5.2 × 5.5 m wooden platform (the experimental area, in which there were no significant ferromagnetic influences).

The presentation order of *Task* was partially counterbalanced, and the order was held constant for a given participant in each time block.

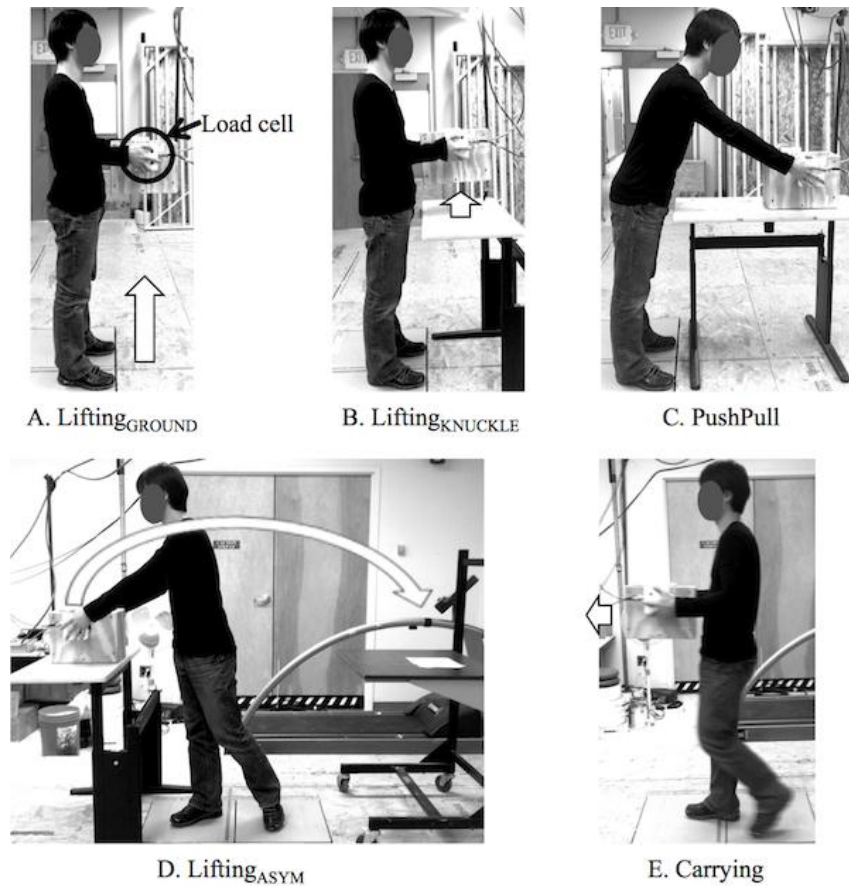


Figure 1. Illustration of experimental tasks.

Instrumentation

Bilateral ground reaction forces and moments were collected using the two force platforms (AMTI OR6-7-1000; AMTI, Watertown, MA, USA), and tri-axial hand forces were collected using two load cells (AMTI MC3A-6) that were attached at the lateral faces of the box as handles (Figure 1). Force platform and load cell signals were sampled at 960 Hz, then low-pass filtered (15 Hz cut-off; second order Butterworth; bidirectional) and down-sampled to 60 Hz offline. Whole-body kinematics were captured simultaneously using two systems: 1) a 7-camera OMC system (Vicon MX, Vicon Motion Systems Inc., Denver, CO, US); and 2) a commercially-available IMC system (MVN, Xsens technologies B.V., Enschede, the Netherlands). Both were sampled at 60 Hz and low-pass filtered offline (10 Hz cutoff; 4th order Butterworth;

bidirectional). For the OMC, passive reflective markers were placed bilaterally or in the mid-sagittal plane over several anatomical landmarks: calcaneus, first and fifth metatarsal heads, lateral and medial malleoli, lateral and medial tibial epicondyles, acromial processes, lateral and medial humeral epicondyles, radialis and ulnar styloid processes, the spinous processes of the seventh cervical (C7) and eighth thoracic (T8) vertebrae, incisura jugularis; xiphoid process, anterior and posterior iliac superior spines. In addition, clusters of 3-4 markers were placed midway between C7 and T8, and over or adjacent to IMUs at the pelvis, the lower legs, upper arms, lower arms and heels. The MVN includes 17 miniature IMUs, positioned on the head, sternum and pelvis; and bilaterally on the scapulae, the upper and lower arms, hands, thighs, shanks, and feet (Figure 2), and provides a built-in anatomical model of the human body (Roetenberg & Luinge 2009). Note that the MVN does not include an IMU over the thorax, but the system provides thoracic kinematics estimated from IMUs on the scapulae; we used thoracic kinematics from the MVN as a “virtual” IMU, and scapular IMUs were not used directly here. Data capture was done via a graphical interface (MVN Studio 3.0, Xsens technologies B.V., Ensched), and the included kinematic coupling algorithm (KiCTM) was enabled to address problems with magnetic disturbances.

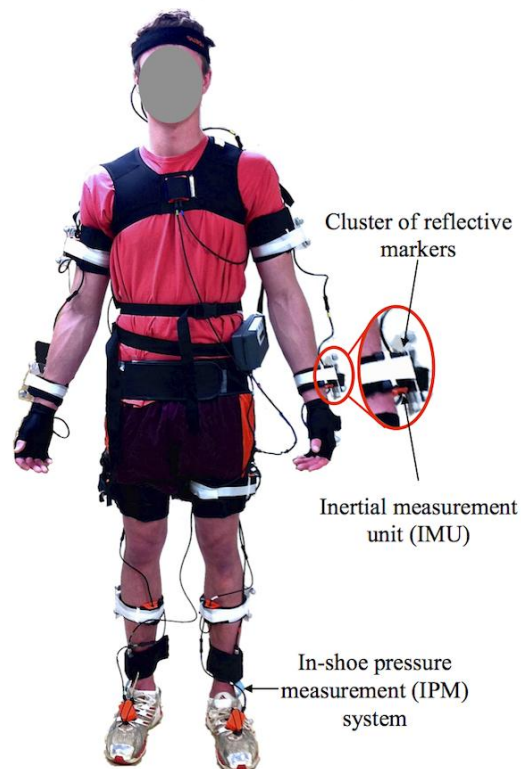


Figure 2. The MVN system setup, along with clusters of reflective markers.

Experimental Procedures

Initially, participants donned the MVN motion capture suit, and reflective markers and marker clusters were attached. The MVN system was then turned on (and was left on for the entire session), followed by two calibration stages (~ 30 min). The first stage involved completing four predefined calibration steps to align IMUs to the segments of a participant (see Roetenberg & Luinge 2009). These steps, as indicated in the system manual, include standing straight (N pose), standing straight with arms stretched horizontally (T pose), squatting, and moving the hands together in all directions (Hand touch). The software reports calibration quality in one of four levels (good, acceptable, fair and poor), and a minimum of Acceptable quality was ensured for each step as recommended in the system manual. The second stage was a calibration procedure (moving body segments in all directions) used to find a transformation matrix between the laboratory and MVN coordinate systems (Tsai & Lenz 1989); this was required because the OMC and the MVN system have different global coordinate systems.

Prior to the MMH trials, anatomical markers were removed after being referenced separately to clusters and IMUs on the corresponding body segments. For the latter, the markers were first transformed to the MVN coordinate system using data from the calibration trials, so that the same anatomical landmarks were shared between the OMC and the MVN systems. In addition, and to synchronize the OMC and MVN systems, participants were instructed to perform an easily identifiable movement at the start of each trial (i.e., quickly raising a foot). All off-line data processing was completed using Matlab 7 (MathworksTM Inc., Natick, MA, USA).

Physical exposure measures and dependent variables

Pertinent to physical exposure assessment, kinematic measures were 3-D included joint angles (i.e., between distal and proximal segments) and angular velocities of the knees, hips, trunk and shoulders. Kinetic measures included 3-D external moments at the knees, hips, L5/S1, and shoulders. Note that only sagittal plane kinematic and kinetic measures were considered for the knees.

A direct comparison of the MVN system against the OMC system in terms of quantifying physical exposures is difficult, largely due to differences in anatomical landmark locations

between the systems (i.e., misalignment of the corresponding segment coordinate systems). To address such misalignment, an anatomical model was introduced, similar to the approach of Cutti *et al.* (2007), such that the IMC system shared the same anatomical landmarks as the OMC system. Specifically, all physical exposure measures were obtained using three separate *anatomical models*: 1) defined by anatomical landmarks reconstructed using the clusters (Model #0; “gold standard”); 2) defined by the IMUs of the MVN system (Model #1; intermediary model); and 3) the noted MVN built-in anatomical model (Model #2).

For each anatomical model, and based generally on International Society of Biomechanics recommendations (Wu *et al.* 2002; 2005), segmental coordinate systems were defined, and joint angles were calculated following the Z-X-Y sequence of Euler angles (respective rotations in the sagittal, frontal, and transverse planes). Joint angular velocities and moments were calculated using a homogeneous matrix approach (Doriot & Chéze 2004) that did not require an Euler sequence. Both joint angular velocities and moments were expressed in the proximal segments’ coordinate systems and segmental inertial properties were estimated for each model, based on previous segment definitions (Dumas *et al.* 2007). Only the vertical force component at the ground or hand was incorporated to compute joint moments, and was applied at the ankle and elbow joint centers to enforce the same point of application of force platform measures and hand forces across the models. Note that the elbow (not the wrist) joint centers were selected here because, for some participants, clusters on the forearms were too poorly captured by the OMC system. Shoulder moments were estimated for all tasks using hand forces and a “top-down” modeling approach. L5/S1 and lower extremity joint moments were estimated “bottom-up”, for all tasks except Carrying. We did not require participants to walk on the force platforms during Carrying tasks, to elicit more naturalistic carrying behaviors. Thus, during Carrying the L5/S1 moments were estimated top-down with assumed rigid body motion of the thorax. Since participants were not required to walk on the force platforms during Carrying tasks, lower-extremity moments were not calculated or analyzed during these tasks. A representative example of the exposure measures derived using each model is presented in Figure 3.

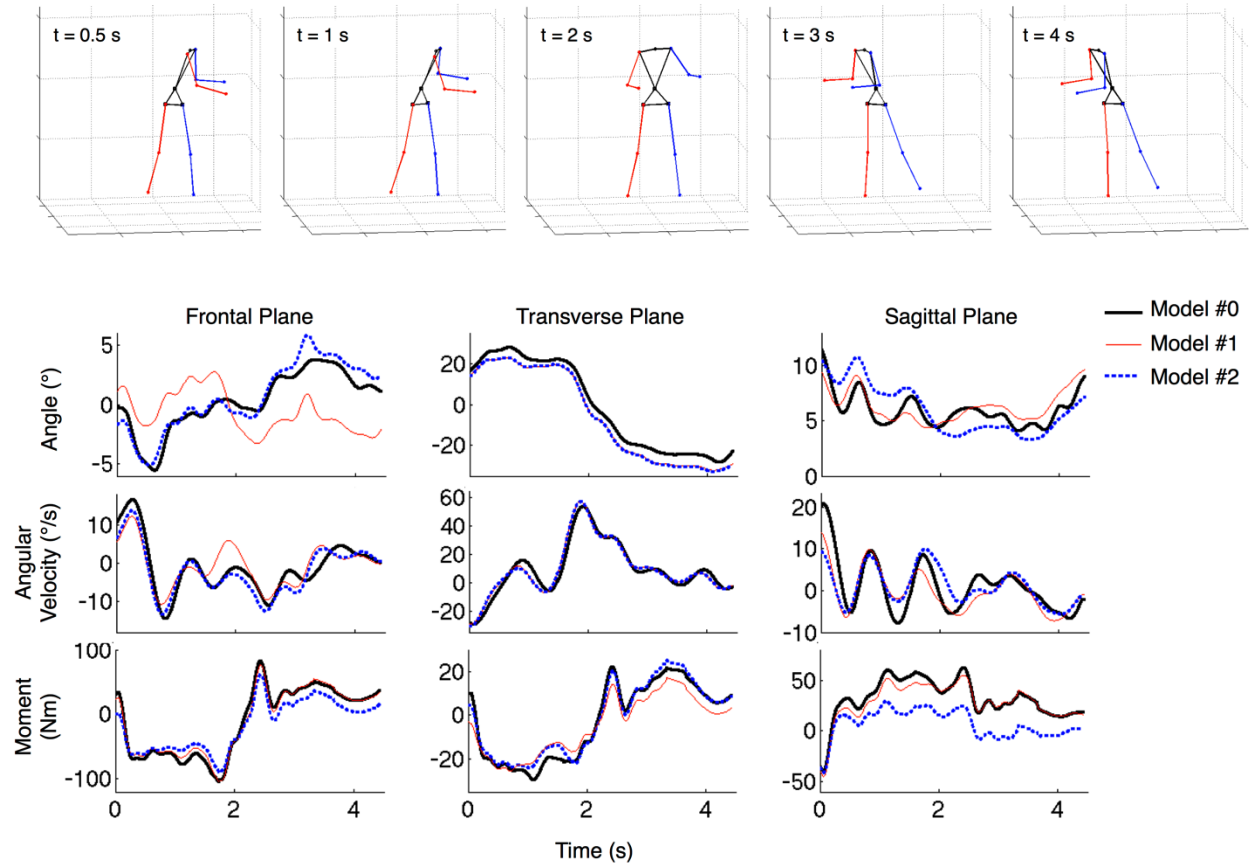


Figure 3. Example of whole body kinematics (Top) and trunk kinematics and kinetics (Bottom) obtained during an asymmetric lifting trial using three Models. Model #0 is the anatomical model defined using the optical motion capture (OMC) system, Model #1 is the anatomical model defined using the inertial motion capture (IMC), and Model #2 is the MVN built-in anatomical model of the IMC system.

To assess the correspondence between measures obtained from Models #1 and #2 versus those from Model #0 (the gold standard), two comparative measures were determined:

- Mean Absolute Error (MAE): $\sum |\mathbf{B} - \mathbf{A}| / L$ where $\mathbf{A}$ and $\mathbf{B}$ are time series of exposures respectively from Model #0 and Model #1 (or #2), and L is the time series length.
- Peak Absolute Error (PAE): The larger of the differences between the positive or negative 95th percentiles of $\mathbf{B}$ and $\mathbf{A}$.

These measures were obtained separately for each trial and for all joint angle, angular velocity, and moment time series. Note that all joint angles were calculated relative to those in a neutral standing pose (N pose above) during upright stance (i.e., all joint angles were zero in this pose).

Statistical analyses

Comparative measures were obtained using three separate anatomical models (*Model*), at multiple joints (*Joint*), during five *Task*, and over three *Time Blocks*. Correspondingly, four-way, repeated-measures analysis of variance (RANOVA) was performed separately on each comparative measure. Since lower-extremity joint moments were not obtained for Carrying tasks, separate RANOVAs were performed on comparative measures of joint moments with tasks excluding Carrying and only with Carrying. In all analyses, bilateral measures were pooled, and all comparative measures were log-transformed prior to statistical analyses to achieve normally distributed residuals. Significant effects were examined using LSmean post-hoc contrasts. All statistical analyses were complete using JMP 9.0 (SAS Institute Inc., Cary, NC, USA) with statistical significance determined when $p \leq .01$. All summary data are presented as means (95% Confidence Intervals).

Results

Joint angles

Significant main and interactive effects of *Time Block* were observed on many MAE and PAE values of joint angles. Specifically, *Time Block* and its interactions with *Joint*, *Task*, and *Joint* $\times$ *Task* affected all MAE ($p \leq 0.01$) and PAE values ($p \leq 0.0051$), except that *Time Block* $\times$ *Joint* interactions had no significant effects on MAE_X. Post-hoc contrasts for these *Time Block*-related effects showed that such effects were varied across task and joint conditions, but typically caused larger MAE and PAE values for Time Blocks 2 and 3 vs. Time Block 1. Across all combinations of joint and task, the magnitude of differences between time blocks was $\leq 0.8^\circ$, 3.63° , and 0.6° for MAE_X, MAE_Y, and MAE_Z, respectively; and $\leq 0.44^\circ$, 2.72° , and 0.85° for PAE_X, PAE_Y, and PAE_Z, respectively.

Joint, *Task*, and/or *Model* had significant main and interaction effects on all MAE and PAE values. In particular, *Joint* $\times$ *Task* ($p < 0.0001$) and *Joint* $\times$ *Task* $\times$ *Model* ($p \leq 0.0021$)

interactions significantly influenced all the measures, except that the latter had no significant effects on PAE_Y . A summary of all measures is thus presented for each joint, task and model (Table 1), which reveals that the performance of Models #1 and #2 was comparable, and that this performance appeared to be associated with the specific kinematic characteristics required for a given task (e.g., whole body, predominantly shoulder movements, etc.).

Table 1. Summary statistics [LSmean (95% CI)] of comparative measures (MAE and PAE) for joint angles. Note that Model #0 is the anatomical model defined using the optical motion capture (OMC) system; Model #1 is the anatomical model defined using the inertial motion capture (IMC) system while sharing the same anatomical landmarks with the OMC system; and Model #2 is the MVN built-in anatomical model of the IMC system.

	Axis	Task	Model #1 vs. Model #0				Model #2 vs. Model #0			
			L5/S1	Shoulder	Hip	Knee	L5/S1	Shoulder	Hip	Knee
MAE (deg)	X	LL _{GROUND}	1.51 (1.32, 1.72)	3.68 (3.28, 4.11)	2.39 (2.14, 2.68)		1.89 (1.66, 2.16)	5.13 (4.58, 5.74)	3.34 (2.98, 3.74)	
		LL _{KNUCKLE}	1.42 (1.25, 1.62)	2.24 (2.00, 2.51)	1.63 (1.46, 1.83)		1.11 (0.97, 1.27)	2.82 (2.52, 3.16)	1.05 (0.93, 1.17)	
		LL _{ASYM}	2.50 (2.19, 2.86)	4.04 (3.61, 4.52)	2.64 (2.36, 2.96)		2.00 (1.75, 2.29)	4.34 (3.88, 4.86)	1.91 (1.71, 2.14)	
		Carrying	1.54 (1.34, 1.75)	1.40 (1.25, 1.57)	2.22 (1.98, 2.48)		1.48 (1.30, 1.69)	1.44 (1.29, 1.61)	2.13 (1.91, 2.39)	
		PushPull	0.89 (0.78, 1.01)	3.15 (2.81, 3.52)	0.99 (0.88, 1.10)		0.76 (0.66, 0.86)	4.19 (3.74, 4.69)	0.68 (0.60, 0.76)	
	Y	LL _{GROUND}	2.51 (2.24, 2.83)	2.52 (2.30, 2.75)	3.17 (2.90, 3.46)		2.50 (2.22, 2.81)	2.55 (2.34, 2.79)	4.83 (4.42, 5.28)	
		LL _{KNUCKLE}	2.86 (2.54, 3.21)	2.77 (2.54, 3.03)	4.73 (4.33, 5.17)		2.88 (2.56, 3.24)	2.89 (2.64, 3.16)	4.46 (4.08, 4.88)	
		LL _{ASYM}	3.09 (2.75, 3.48)	2.68 (2.45, 2.93)	3.24 (2.97, 3.55)		3.11 (2.77, 3.50)	3.02 (2.76, 3.30)	3.37 (3.08, 3.68)	
		Carrying	1.54 (1.37, 1.73)	1.13 (1.04, 1.24)	2.81 (2.57, 3.07)		1.60 (1.42, 1.80)	1.13 (1.04, 1.24)	3.56 (3.25, 3.89)	
		PushPull	2.40 (2.13, 2.70)	2.53 (2.32, 2.77)	2.26 (2.07, 2.47)		2.41 (2.14, 2.71)	2.62 (2.40, 2.86)	2.36 (2.16, 2.58)	
	Z	LL _{GROUND}	4.84 (4.28, 5.47)	5.97 (5.39, 6.62)	2.88 (2.60, 3.19)	2.89 (2.61, 3.20)	4.56 (4.04, 5.15)	4.96 (4.48, 5.50)	2.42 (2.19, 2.69)	3.07 (2.77, 3.40)
		LL _{KNUCKLE}	1.63 (1.44, 1.84)	2.59 (2.34, 2.87)	1.69 (1.53, 1.88)	1.20 (1.08, 1.33)	1.49 (1.32, 1.68)	2.88 (2.60, 3.19)	0.93 (0.84, 1.03)	1.55 (1.40, 1.72)
		LL _{ASYM}	2.27 (2.01, 2.57)	3.99 (3.60, 4.42)	2.32 (2.09, 2.57)	2.48 (2.24, 2.75)	1.53 (1.35, 1.73)	3.17 (2.86, 3.51)	1.37 (1.24, 1.52)	1.78 (1.61, 1.98)
		Carrying	1.31 (1.16, 1.48)	1.36 (1.23, 1.51)	2.00 (1.81, 2.22)	3.40 (3.07, 3.77)	1.16 (1.03, 1.31)	1.41 (1.27, 1.56)	2.30 (2.07, 2.54)	3.69 (3.33, 4.09)
		PushPull	1.66 (1.47, 1.88)	4.17 (3.76, 4.62)	1.10 (1.00, 1.22)	1.21 (1.09, 1.34)	1.50 (1.33, 1.69)	3.69 (3.33, 4.08)	0.88 (0.79, 0.98)	1.30 (1.17, 1.44)
	PAE (deg)	LL _{GROUND}	0.85 (0.68, 1.06)	2.24 (1.89, 2.65)	1.67 (1.41, 1.97)		1.21 (0.96, 1.51)	3.12 (2.64, 3.70)	2.19 (1.85, 2.59)	
		LL _{KNUCKLE}	0.73 (0.59, 0.92)	1.74 (1.47, 2.07)	0.98 (0.82, 1.16)		0.59 (0.47, 0.74)	2.41 (2.03, 2.85)	0.74 (0.63, 0.88)	
		LL _{ASYM}	1.55 (1.24, 1.94)	1.83 (1.54, 2.17)	1.28 (1.08, 1.52)		1.17 (0.93, 1.46)	2.90 (2.45, 3.44)	0.96 (0.81, 1.14)	
		Carrying	0.83 (0.66, 1.04)	0.87 (0.74, 1.03)	1.36 (1.15, 1.61)		1.12 (0.89, 1.40)	0.9 (0.76, 1.07)	1.08 (0.91, 1.28)	
		PushPull	0.60 (0.48, 0.75)	1.88 (1.59, 2.22)	0.64 (0.54, 0.75)		0.41 (0.33, 0.51)	1.66 (1.40, 1.97)	0.42 (0.36, 0.50)	
		LL _{GROUND}	1.46 (1.20, 1.79)	1.78 (1.54, 2.06)	2.07 (1.78, 2.40)		1.48 (1.21, 1.81)	1.88 (1.62, 2.18)	3.09 (2.67, 3.58)	
		LL _{KNUCKLE}	1.85 (1.51, 2.26)	2.19 (1.89, 2.54)	3.38 (2.92, 3.91)		1.93 (1.58, 2.36)	1.59 (1.38, 1.85)	3.27 (2.82, 3.79)	
		LL _{ASYM}	2.03 (1.66, 2.49)	1.75 (1.51, 2.03)	2.99 (2.58, 3.46)		1.93 (1.57, 2.36)	2.08 (1.79, 2.41)	3.26 (2.82, 3.78)	
		Carrying	0.96 (0.79, 1.18)	0.87 (0.75, 1.00)	2.05 (1.77, 2.38)		1.09 (0.89, 1.34)	0.76 (0.66, 0.89)	2.32 (2.00, 2.69)	
		PushPull	1.40 (1.15, 1.72)	1.91 (1.65, 2.22)	1.53 (1.32, 1.78)		1.40 (1.14, 1.72)	1.85 (1.59, 2.14)	1.55 (1.34, 1.80)	
		LL _{GROUND}	7.20 (5.85, 8.85)	4.82 (4.12, 5.62)	2.22 (1.90, 2.59)	1.44 (1.23, 1.68)	7.33 (5.97, 9.02)	5.35 (4.58, 6.25)	1.64 (1.40, 1.91)	1.94 (1.66, 2.26)
		LL _{KNUCKLE}	1.67 (1.36, 2.05)	1.68 (1.44, 1.96)	1.33 (1.14, 1.55)	1.00 (0.86, 1.17)	1.56 (1.27, 1.91)	2.00 (1.71, 2.34)	0.83 (0.71, 0.97)	0.82 (0.70, 0.96)
		LL _{ASYM}	1.33 (1.08, 1.64)	2.80 (2.40, 3.27)	2.04 (1.75, 2.39)	1.17 (1.00, 1.36)	0.93 (0.75, 1.14)	2.62 (2.24, 3.06)	1.19 (1.02, 1.39)	0.79 (0.68, 0.93)
		Carrying	0.93 (0.76, 1.14)	0.94 (0.80, 1.09)	1.27 (1.09, 1.49)	0.91 (0.78, 1.07)	0.81 (0.66, 0.99)	1.01 (0.87, 1.18)	1.31 (1.13, 1.53)	0.87 (0.74, 1.02)
		PushPull	1.29 (1.05, 1.59)	4.86 (4.17, 5.68)	0.85 (0.73, 1.00)	0.64 (0.55, 0.75)	1.39 (1.13, 1.71)	5.45 (4.67, 6.36)	0.76 (0.65, 0.88)	0.48 (0.41, 0.57)

• X, Y, and Z indicate values in the frontal, transverse and sagittal planes, respectively. • For a given task, largest values across joints are highlighted in bold.

Joint angular velocities

All MAE values were significantly affected by *Time Block* and/or *Time Block* $\times$ *Task* interactions ($p \leq 0.0057$), such that values were larger for Time Block 3 vs. Time Blocks 1 and 2. For a given task, the magnitude of differences between time blocks was $\leq 0.61^\circ/\text{s}$, $0.53^\circ/\text{s}$, and $1.03^\circ/\text{s}$ for MAE_x, MAE_y, and MAE_z, respectively. *Time Block* had no significant effects on PAE values ($p \geq 0.047$), and no obvious trends associated with *Time Block* were observed for any given joint and/or task.

All MAE and PAE values were influenced by *Joint*, *Task*, and/or *Model*. Significant interactions of *Joint* $\times$ *Task* ($p < 0.0001$) and *Joint* $\times$ *Task* $\times$ *Model* ($p \leq 0.0024$) especially affected all the measures, except that the latter had no effects on PAE_y. For each joint, task, and model, all measures are summarized in Table 2, which permitted similar observations on performance as noted above for joint angles.

Table 2. Summary statistics [LSmean (95% CI)] of comparative measures (MAE and PAE) for joint angular velocities. See text or Table 1 caption for model descriptions.

	Axis	Task	Model #1 vs. Model #0				Model #2 vs. Model #0			
			L5/S1	Shoulder	Hip	Knee	L5/S1	Shoulder	Hip	Knee
MAE (deg/s)	X	LL _{GROUND}	3.27 (2.95, 3.62)	5.88 (5.38, 6.42)	5.33 (4.88, 5.83)		3.70 (3.34, 4.10)	7.09 (6.49, 7.75)	8.15 (7.46, 8.91)	
		LL _{KNUCKLE}	1.38 (1.25, 1.53)	2.90 (2.66, 3.17)	1.09 (0.99, 1.19)		1.36 (1.23, 1.51)	2.98 (2.73, 3.26)	0.97 (0.89, 1.06)	
		LL _{ASYM}	4.27 (3.85, 4.73)	5.27 (4.83, 5.76)	3.58 (3.28, 3.91)		3.94 (3.56, 4.37)	5.05 (4.62, 5.52)	3.80 (3.47, 4.15)	
		Carrying	5.33 (4.81, 5.91)	4.52 (4.14, 4.94)	8.42 (7.71, 9.21)		6.08 (5.48, 6.74)	4.11 (3.76, 4.49)	7.67 (7.02, 8.38)	
		PushPull	1.99 (1.79, 2.20)	6.43 (5.88, 7.02)	1.68 (1.54, 1.84)		1.90 (1.71, 2.10)	8.51 (7.79, 9.30)	1.26 (1.15, 1.38)	
	Y	LL _{GROUND}	3.91 (3.59, 4.26)	5.77 (5.36, 6.21)	3.95 (3.67, 4.25)		4.06 (3.73, 4.43)	4.69 (4.36, 5.04)	5.86 (5.45, 6.31)	
		LL _{KNUCKLE}	1.93 (1.77, 2.10)	3.06 (2.84, 3.29)	1.10 (1.02, 1.18)		1.90 (1.75, 2.07)	2.91 (2.70, 3.13)	1.21 (1.12, 1.30)	
		LL _{ASYM}	4.45 (4.08, 4.84)	4.90 (4.55, 5.27)	3.11 (2.89, 3.34)		4.73 (4.35, 5.16)	4.45 (4.13, 4.78)	3.40 (3.16, 3.66)	
		Carrying	3.59 (3.29, 3.91)	1.87 (1.74, 2.02)	6.41 (5.96, 6.90)		3.94 (3.61, 4.29)	1.80 (1.67, 1.94)	11.70 (10.94, 12.67)	
		PushPull	3.48 (3.20, 3.79)	6.20 (5.76, 6.68)	1.34 (1.24, 1.44)		3.48 (3.19, 3.79)	5.52 (5.13, 5.96)	1.47 (1.37, 1.59)	
	Z	LL _{GROUND}	9.54 (8.59, 10.60)	10.87 (9.87, 11.97)	6.21 (5.64, 6.83)	5.70 (5.17, 6.27)	9.46 (8.51, 10.51)	9.51 (8.64, 10.48)	5.69 (5.16, 6.26)	5.87 (5.33, 6.47)
		LL _{KNUCKLE}	2.38 (2.14, 2.64)	3.44 (3.13, 3.79)	1.32 (1.19, 1.45)	0.91 (0.83, 1.00)	2.33 (2.10, 2.59)	3.44 (3.13, 3.79)	1.24 (1.13, 1.37)	0.86 (0.78, 0.95)
		LL _{ASYM}	4.25 (3.82, 4.72)	6.14 (5.58, 6.76)	3.82 (3.47, 4.21)	3.27 (2.97, 3.60)	3.47 (3.13, 3.86)	4.78 (4.34, 5.26)	3.05 (2.77, 3.36)	2.31 (2.10, 2.54)
		Carrying	3.59 (3.23, 3.99)	3.23 (2.93, 3.55)	7.86 (7.14, 8.65)	10.60 (9.62, 11.67)	2.62 (2.36, 2.91)	2.67 (2.42, 2.94)	10.72 (9.73, 11.80)	11.63 (10.56, 12.81)
		PushPull	3.97 (3.57, 4.41)	7.76 (7.05, 8.54)	1.80 (1.63, 1.98)	1.30 (1.18, 1.43)	3.69 (3.32, 4.10)	7.83 (7.11, 8.62)	1.57 (1.43, 1.73)	1.08 (0.98, 1.18)
PAE (deg/s)	X	LL _{GROUND}	2.30 (1.85, 2.86)	6.13 (5.18, 7.26)	4.04 (3.41, 4.78)		2.46 (1.98, 3.07)	8.65 (7.31, 10.25)	6.06 (5.12, 7.18)	
		LL _{KNUCKLE}	1.18 (0.95, 1.48)	3.57 (3.01, 4.23)	0.77 (0.65, 0.92)		0.84 (0.68, 1.05)	2.90 (2.45, 3.43)	0.68 (0.57, 0.80)	
		LL _{ASYM}	3.19 (2.56, 3.97)	4.31 (3.64, 5.10)	2.39 (2.02, 2.83)		3.22 (2.59, 4.02)	4.10 (3.46, 4.85)	3.13 (2.65, 3.71)	
		Carrying	2.84 (2.28, 3.54)	2.44 (2.06, 2.89)	4.75 (4.01, 5.63)		3.46 (2.78, 4.31)	2.31 (1.95, 2.74)	5.13 (4.33, 6.08)	
		PushPull	1.24 (0.99, 1.54)	6.03 (5.09, 7.14)	1.10 (0.93, 1.30)		1.26 (1.01, 1.58)	10.03 (8.47, 11.87)	0.93 (0.79, 1.10)	
	Y	LL _{GROUND}	2.93 (2.36, 3.63)	5.54 (4.71, 6.51)	3.33 (2.83, 3.91)		3.24 (2.61, 4.02)	4.49 (3.82, 5.28)	5.40 (4.59, 6.35)	
		LL _{KNUCKLE}	1.80 (1.46, 2.24)	2.47 (2.10, 2.91)	0.72 (0.61, 0.85)		1.69 (1.36, 2.10)	2.45 (2.09, 2.89)	0.86 (0.73, 1.01)	
		LL _{ASYM}	3.80 (3.06, 4.71)	3.76 (3.20, 4.42)	2.31 (1.97, 2.71)		4.59 (3.70, 5.69)	3.71 (3.16, 4.36)	2.64 (2.25, 3.10)	
		Carrying	3.57 (2.88, 4.43)	1.32 (1.13, 1.56)	3.48 (2.96, 4.09)		2.71 (2.18, 3.36)	1.36 (1.16, 1.60)	4.02 (3.42, 4.72)	
		PushPull	2.29 (1.85, 2.84)	5.51 (4.69, 6.48)	0.97 (0.82, 1.13)		2.26 (1.83, 2.81)	5.06 (4.31, 5.95)	1.18 (1.00, 1.38)	
	Z	LL _{GROUND}	19.17 (15.52, 23.66)	12.73 (10.82, 14.99)	5.27 (4.48, 6.20)	5.48 (4.65, 6.45)	19.16 (15.52, 23.66)	15.30 (13.00, 18.01)	5.81 (4.93, 6.83)	6.46 (5.49, 7.61)
		LL _{KNUCKLE}	2.55 (2.07, 3.15)	3.11 (2.64, 3.66)	1.40 (1.19, 1.65)	0.77 (0.65, 0.91)	2.60 (2.11, 3.21)	4.10 (3.48, 4.82)	1.18 (1.00, 1.39)	0.75 (0.64, 0.89)
		LL _{ASYM}	3.19 (2.58, 3.93)	4.80 (4.08, 5.65)	2.70 (2.29, 3.18)	2.51 (2.14, 2.96)	3.25 (2.63, 4.01)	4.86 (4.13, 5.72)	1.84 (1.56, 2.17)	2.05 (1.74, 2.41)
		Carrying	2.34 (1.90, 2.89)	3.19 (2.71, 3.76)	3.57 (3.04, 4.21)	6.03 (5.13, 7.10)	1.36 (1.10, 1.68)	2.68 (2.28, 3.16)	2.67 (2.26, 3.14)	7.21 (6.12, 8.48)
		PushPull	5.53 (4.48, 6.83)	5.91 (5.02, 6.96)	2.18 (1.86, 2.57)	1.03 (0.88, 1.22)	4.10 (3.32, 5.06)	6.26 (5.32, 7.36)	1.31 (1.11, 1.54)	0.83 (0.70, 0.98)

Joint moments

Relatively few *Time Block*-related effects were observed on the comparative measures for joint moments, except that *Time Block* interacted significantly with *Model* on MAE_x ($p < 0.0001$), and had a significant main effect on MAE_z ($p = 0.0025$). Also, *Time Block* $\times$ *Model* interactions were marginally significant on PAE_x ($p = 0.021$). A difference in MAE_x and PAE_x values between time blocks of ≤ 0.30 Nm and 0.27 Nm were found, respectively, for Model #1; and ≤ 0.32 Nm and 0.44 Nm for Model #2.

The main and all interactive effects of *Joint*, *Task*, and *Model* significantly affected all MAE and PAE values ($p < 0.0001$), except that there were no significant three-way interaction effects on PAE_z ($p = 0.048$). In the case of Carrying, *Joint* and *Model* had significant main effects on all MAE values ($p \leq 0.002$), and interaction effects were found on MAE_y ($p = 0.0021$). *Joint* significantly affected all PAE values ($p < 0.0001$), and *Model* effects on PAE_y approached significance ($p = 0.012$) and significantly affected PAE_z ($p < 0.0001$). Accordingly, all the comparative measures were summarized in Table 3 for each joint, task, and model. Therein, it was observed that, similar to joint angles and angular velocities, the performance differed in relation to characteristics of the different tasks. Of note, Model #1 generally outperformed Model #2 for joint moments, in contrast to kinematics as summarized above.

Table 3. Summary statistics [LSmean (95% CI)] of comparative measures (MAE and PAE) for joint moments. See text or Table 1 caption for model descriptions.

			Model #1 vs. Model #0				Model #2 vs. Model #0			
Axis	Task		L5/S1	Shoulder	Hip	Knee	L5/S1	Shoulder	Hip	Knee
MAE (Nm)	X	LL _{GROUND}	6.74 (5.77, 7.87)	1.11 (0.96, 1.27)	4.86 (4.23, 5.58)		13.89 (11.89, 16.22)	1.28 (1.12, 1.47)	10.64 (9.26, 12.22)	
		LL _{KNUCKLE}	4.92 (4.21, 5.75)	0.50 (0.44, 0.57)	2.64 (2.30, 3.04)		7.66 (6.56, 8.95)	1.30 (1.13, 1.49)	12.34 (10.74, 14.17)	
		LL _{ASYM}	12.67 (10.85, 14.80)	0.72 (0.63, 0.83)	6.73 (5.86, 7.73)		34.22 (29.3, 39.96)	1.43 (1.25, 1.64)	14.4 (12.54, 16.54)	
		Carrying	5.21 (4.43, 6.11)	0.77 (0.67, 0.89)			5.75 (4.90, 6.75)	0.99 (0.86, 1.14)		
		PushPull	4.44 (3.80, 5.18)	0.11 (0.10, 0.13)	2.47 (2.15, 2.84)		8.05 (6.90, 9.41)	1.50 (1.30, 1.72)	10.70 (9.32, 12.29)	
	Y	LL _{GROUND}	3.77 (3.12, 4.55)	0.68 (0.57, 0.81)	2.43 (2.04, 2.89)		6.90 (5.72, 8.33)	1.00 (0.84, 1.19)	6.14 (5.16, 7.31)	
		LL _{KNUCKLE}	1.00 (0.83, 1.20)	0.25 (0.21, 0.30)	0.62 (0.52, 0.74)		2.14 (1.77, 2.58)	0.48 (0.40, 0.57)	2.92 (2.46, 3.48)	
		LL _{ASYM}	3.87 (3.21, 4.67)	0.37 (0.31, 0.44)	2.01 (1.69, 2.39)		10.26 (8.51, 12.39)	0.64 (0.54, 0.76)	4.30 (3.61, 5.12)	
		Carrying	0.99 (0.74, 1.32)	0.37 (0.28, 0.49)			1.18 (0.89, 1.57)	0.57 (0.43, 0.75)		
		PushPull	1.07 (0.89, 1.29)	0.05 (0.04, 0.06)	0.71 (0.60, 0.84)		2.61 (2.16, 3.15)	0.24 (0.20, 0.28)	3.17 (2.66, 3.77)	
	Z	LL _{GROUND}	14.34 (11.75, 17.52)	1.43 (1.19, 1.71)	7.55 (6.29, 9.06)	2.38 (1.98, 2.85)	16.50 (13.52, 20.15)	2.20 (1.83, 2.64)	8.23 (6.86, 9.88)	6.59 (5.50, 7.91)
		LL _{KNUCKLE}	7.95 (6.51, 9.71)	0.75 (0.63, 0.91)	4.20 (3.50, 5.04)	1.55 (1.29, 1.85)	11.40 (9.33, 13.92)	1.38 (1.15, 1.65)	6.19 (5.16, 7.43)	5.60 (4.67, 6.71)
		LL _{ASYM}	13.61 (11.14, 16.62)	0.84 (0.70, 1.01)	7.19 (5.99, 8.62)	2.54 (2.11, 3.04)	20.02 (16.39, 24.45)	1.27 (1.06, 1.53)	9.91 (8.26, 11.89)	6.50 (5.42, 7.79)
		Carrying	4.39 (3.67, 5.23)	0.99 (0.85, 1.16)			8.23 (6.90, 9.83)	1.94 (1.66, 2.26)		
		PushPull	5.55 (4.55, 6.78)	0.16 (0.13, 0.19)	3.70 (3.08, 4.43)	1.34 (1.12, 1.61)	9.82 (8.04, 12.00)	0.55 (0.45, 0.65)	5.77 (4.81, 6.92)	4.67 (3.89, 5.60)
PAE (Nm)	X	LL _{GROUND}	4.06 (3.17, 5.20)	0.48 (0.39, 0.58)	3.16 (2.58, 3.87)		9.08 (7.09, 11.62)	0.88 (0.72, 1.07)	5.56 (4.54, 6.82)	
		LL _{KNUCKLE}	3.06 (2.39, 3.92)	0.17 (0.14, 0.20)	1.92 (1.56, 2.35)		4.30 (3.36, 5.50)	1.17 (0.96, 1.44)	7.54 (6.16, 9.24)	
		LL _{ASYM}	7.77 (6.06, 9.94)	0.24 (0.20, 0.30)	3.32 (2.71, 4.07)		26.25 (20.50, 33.61)	1.23 (1.01, 1.51)	8.57 (6.99, 10.50)	
		Carrying	2.12 (1.69, 2.66)	0.68 (0.57, 0.82)			2.33 (1.86, 2.93)	0.87 (0.72, 1.04)		
		PushPull	2.86 (2.24, 3.67)	0.12 (0.10, 0.15)	1.65 (1.34, 2.02)		3.47 (2.71, 4.44)	1.15 (0.94, 1.41)	6.79 (5.54, 8.32)	
	Y	LL _{GROUND}	3.32 (2.54, 4.35)	0.38 (0.30, 0.47)	1.68 (1.35, 2.09)		6.06 (4.63, 7.92)	0.57 (0.46, 0.71)	3.54 (2.85, 4.41)	
		LL _{KNUCKLE}	0.69 (0.53, 0.90)	0.16 (0.13, 0.20)	0.37 (0.30, 0.46)		1.37 (1.05, 1.79)	0.29 (0.24, 0.37)	1.78 (1.43, 2.21)	
		LL _{ASYM}	2.77 (2.12, 3.62)	0.16 (0.13, 0.20)	1.33 (1.07, 1.66)		7.87 (6.01, 10.30)	0.27 (0.22, 0.34)	3.68 (2.96, 4.58)	
		Carrying	0.62 (0.44, 0.88)	0.27 (0.20, 0.38)			0.78 (0.55, 1.10)	0.34 (0.24, 0.47)		
		PushPull	0.61 (0.46, 0.80)	0.05 (0.04, 0.06)	0.53 (0.43, 0.67)		1.33 (1.01, 1.73)	0.23 (0.19, 0.29)	2.00 (1.61, 2.49)	
	Z	LL _{GROUND}	14.42 (10.69, 19.44)	1.85 (1.43, 2.40)	9.27 (7.17, 11.99)	1.35 (1.05, 1.75)	15.21 (11.28, 20.51)	2.76 (2.14, 3.58)	8.19 (6.33, 10.59)	3.29 (2.54, 4.25)
		LL _{KNUCKLE}	5.43 (4.03, 7.33)	0.28 (0.22, 0.36)	3.09 (2.39, 4.00)	1.25 (0.96, 1.61)	6.12 (4.54, 8.26)	0.60 (0.46, 0.77)	3.85 (2.98, 4.98)	4.07 (3.14, 5.26)
		LL _{ASYM}	10.31 (7.65, 13.90)	0.53 (0.41, 0.69)	11.18 (8.64, 14.45)	0.65 (0.50, 0.83)	15.64 (11.60, 21.09)	0.89 (0.69, 1.15)	13.38 (10.35, 17.31)	1.37 (1.06, 1.77)
		Carrying	2.18 (1.71, 2.77)	0.77 (0.63, 0.94)			4.19 (3.29, 5.33)	1.67 (1.37, 2.03)		
		PushPull	4.12 (3.06, 5.56)	0.12 (0.09, 0.15)	2.63 (2.04, 3.41)	0.92 (0.71, 1.20)	7.18 (5.32, 9.68)	0.39 (0.30, 0.50)	3.73 (2.89, 4.83)	2.82 (2.18, 3.65)

Discussion

The study examined the performance of a commercially-available IMC system to quantify physical exposures over time – specifically, angles, angular velocities, and moments at selected body parts. Many comparative measures of physical exposures indicated a statistically significant change in performance over time. Yet, these change seemed to be relatively minor and suggest relatively limited practical implications (e.g., the magnitude of MAE differences between time blocks for joint angles was $\leq 3.63^\circ$). This suggests that the performance of the MVN system is rather stable over the time period examined. Moreover, and consistent with existing studies, the accuracy of kinematics captured by the IMC system varied more substantially across different MMH tasks, and generally consistent with the movement characteristics involved for tasks (cf. Tables 1 and 2).

For joint angles, mean MAE and PAE values, in several cases, exceeded the root-mean-square accuracy of an individual IMU in orientation, as noted by the manufacturer ($\leq 3^\circ$ in a dynamic condition), and in particular the upper bounds of 95% CIs for MAE and PAE values were about two and three times (5.74° and 9.02° , respectively) the noted accuracy. Those errors were apparent both with the intermediary model (Model #1, IMC with reflective markers) and the MVN built-in anatomical model (Model #2), which suggests that the observed errors are not simply due to misalignments between segment coordinate systems defined separately using the OMC and the IMC system. Although not directly comparable, existing studies have reported similar findings, in that a typical orientation error was 8.3° in an upright posture, $3^\circ - 21.7^\circ$ during level walking (Picerno *et al.*, 2008), $\sim 5^\circ - \sim 20^\circ$ for arm motions during daily tasks (Luinger *et al.*, 2007), and $0.6^\circ - 25.6^\circ$ during dynamic whole-body tasks (Godwin, *et al.*, 2009). Yet, for controlled single-joint-movements of the shoulder or the elbow, smaller errors ($< 3.6^\circ$) were found (Cutti *et al.*, 2007). In general, these noted studies with dynamic task conditions found larger mean errors versus the current results, which may be explained by the MVN built-in anatomical model of the IMC system. The built-in model estimates segment orientations by facilitating joint kinematic constraints and aiding IMUs (Roetenberg & Luinger 2009), so that the built-in model likely yields a smaller estimation error in segmental orientation than an individual IMU.

In addition, the magnitude of MAE and PAE values for joint angles and angular velocities varied with joint axes of rotation, joints, and tasks (Tables 1 and 2), which agrees collectively with the findings from existing studies (Brodie *et al.* 2008; Godwin *et al.* 2009; Picerno *et al.* 2008). Authors of these studies argued that the vendor's algorithm for orientation estimation is not optimal in all situations; and, in particular, Godwin *et al.* (2009) noted that estimation errors were larger in non-dominant axes of motion than in a predominant axis. Thus, caution may need to be exercised in using the system for exposure assessment in practice. For example, if the nature of different tasks involves differing predominant joint movements (e.g., shoulders in a push/pull task versus hips and knees for a carrying task), kinematics captured by the IMC system may have substantially different error magnitudes. Relative to peak joint kinematics obtained using the OMC system, the MVN built-in model yielded values different by up to ~ 20, 14, and 13%, respectively, in the frontal, the transverse, and the sagittal planes for joint angles; and ~27, 24, and 28% for joint angular velocities. In addition, a qualitative assessment indicated that peak joint kinematics from the MVN built-in model tend to be underestimated compared to those from the OMC system in the sagittal plane and overestimated in other planes.

While the intermediary model and the MVN built-in model performed similarly in capturing joint kinematics, the latter exhibited poorer performance in joint moment estimations (Table 3). A follow-up observation on trial recordings with the MVN Studio 3.0 indicated that the MVN model, to some degree, incorrectly reflected the actual extremity positions of the participant. Relative to peak joint moments from Model #0, the MVN built-in anatomical model resulted in errors up to ~ 57, 63, and 39%, respectively, in the frontal, the transverse and the sagittal planes, whereas corresponding errors with the intermediary model were 24, 38, and 14%. One could view the intermediary model as the MVN built-in anatomical model if the MVN calibration could ensure the MVN built-in model to reflect relative positions of each body segments of a wearer in an absolute sense. That is, if the MVN built-in model can reflect relative positions of body segments of a wearer more correctly, the performance of the MVN built-in model ideally can be the same as the intermediary model. The performance of the former can be expected to improve further with improved estimates of joint kinematics. For example, Faber *et al.* (2010) estimated joint moment during lifting using orientation sensors (defined with clusters of optoelectronic markers), and reported errors in moment estimations of less than ~15%. These

orientation sensors were defined using an OMC system, and thus their measurement performance was likely unaffected by the direction and speed of motions as occurs with an IMU.

Several limitations in the present work should be acknowledged. First, the performance of the MVN system may be affected by ferromagnetic disturbances that can distort orientations registered by an IMU. However, we visually checked, using the MVN Studio 3.0, that there were no strong ferromagnetic disturbances in the vicinity of the area for the experiment (equipped with force platforms and the tables). Thus, no substantial performance degradation was expected with the MVN system, though some such degradation may have existed. Second, the sampling frequency (60 Hz) that we used for the OMC and IMC systems can lead to signal misalignments up to half the sampling interval (~ 8 ms), and such misalignments may yield errors in MAE values. However, we visually evaluated the quality of signal synchronization for all trials, and no peculiar degradation in such quality was observed. Third, only vertical forces were considered in the calculation of joint moments. Since the OMC and the MVN systems have distinct global coordinate systems, it is challenging to ensure the same alignment of shear forces relative to the anatomical models, and thus shear forces were excluded to control for a potential error source. Though the magnitude of shear vs. vertical forces is generally small except for the push/pull task, the exclusion of shear forces in joint moment estimation likely affected the magnitude of errors, and which could have systematically affected errors in the push/pull task.

This study examined the performance of the IMC system in quantifying physical exposures for several MMH tasks over a relatively prolonged period of time. Overall, our results showed that the system is reasonably stable in estimating physical exposures over time, and appears to perform better than using individual IMUs. However, and as has been found in existing studies using individual IMUs, the performance of the IMC system depended on kinematic characteristics of a task (e.g., dominant joint, speed of motion, etc.). Specifically, if a task involved relatively large movements about a given axis and joint, kinematic and kinetic errors for this axis/joint were typically relatively large. Caution should thus be taken with: 1) direct numerical comparisons of physical exposure measures obtained using the OMC vs. the IMC system, 2) direct numerical comparisons of such measures obtained using the IMC system

between different tasks (e.g., larger errors observed typically with whole body dynamic tasks such as lifting from the ground and asymmetrical lifting); and 3) extracting time-dependent measures (e.g., cumulative measure) of physical exposures, since mean absolute errors were often larger than peak absolute errors. Despite these potential limitations, the IMC system demonstrated a reasonable capacity for capturing physical exposure data in the field for an extended period; the primary utility may be in assessing physical exposure differences between tasks or work conditions. Such an application would help accumulate realistic exposure data with incorporation of wearable/portable kinetic measurement systems [e.g., instrumented handles (Marras *et al.*, 2010) and/or shoes (Faber *et al.*, 2012), pressure insoles (Forner-Cordero *et al.*, 2006)], and can thereby facilitate better understandings of dose-exposure relationships and designing laboratory studies with higher ecological validity. To further advance the use of an IMC system in physical exposure assessments, future studies need to focus on improving the performance of an IMU system under dynamic conditions, and documenting performance limits of an IMC system in quantifying physical exposures under actual work environments (e.g., detectable difference in physical exposures in various occupational settings).

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Chapter 3: Application of an in-shoe pressure measurement system to quantify ground reaction forces, center of pressure, and lumbosacral joint kinetics during manual material handling tasks

Sunwook Kim

Abstract

An in-shoe pressure measurement (IPM) system can facilitate the *in-situ* measurement of three-dimensional (3D) ground reaction forces (GRFs), often required to quantify physical exposures in the workplace. This study examined three simple regression methods that used IPM outputs to estimate 3D GRFs and center of pressure (COP) locations. Ten participants performed several manual material handling (MMH) tasks. For each task, performance of the IPM system was compared when using data from a force platform (“gold standard”), using three comparative measures of errors obtained in 3D GRFs, COP locations, and resulting 3D lumbosacral (L5/S1) joint moments obtained using estimated GRFs and COP locations. Errors varied significantly with the regression method and MMH task. Only the vertical component of GRFs and the sagittal L5/S1 moment showed relatively small errors – for example the vertical GRF estimated using a least squares method yielded < ~4% errors in peak values – while other components showed relatively larger errors. To promote the use of an IPM system for exposure assessment in the field, these results suggest the need for improving the quality of COP and shear GRFs estimates using IPM outputs during MMH tasks.

Keywords: *in-shoe pressure measurement, manual material handling, ergonomic exposure assessment*

Introduction

Measurements of ground reaction forces (GRFs), typically in combination with body segment kinematics, are often obtained when quantifying physical exposures (i.e., lower-extremity and low-back joint kinetics) during occupational tasks. Force platforms are a typical measuring instrument to capture GRFs, and which are commonly fixed in the floor or other structures (e.g., walkways, stairs). Accordingly, and as highlighted in several studies (e.g., Savelberg & de Lange, 1999; Veltink *et al.*, 2005), force platforms are stationary, and their size, placement, and/or available quantities can restrict the foot placement of an individual. More generally, capturing GRFs is challenging in real-world (or work) environments. To overcome such limitations, several wearable GRF measurement systems have been introduced, such as in-shoe pressure measurement (IPM; Chesnin *et al.*, 2000; Forner-Cordero *et al.*, 2004; Savelberg & de Lange, 1999) and instrumented shoe (IS) systems (e.g., Liedtke *et al.*, 2007; Spolek *et al.*, 2005).

An IPM system typically uses a matrix of pressure-sensitive sensors that can be placed inside the shoe, and which measures the plantar pressure distribution below the foot sole (i.e., only vertical loading is registered). That is, pressure outputs only provide an estimate of the vertical component of GRF and center of pressure (COP) locations below the foot sole. Note that the latter is different from COP locations obtained between the shoe and the ground using a force platform. Subsequently, these are often processed to estimate three-dimensional (3D) GRFs (Forner-Cordero *et al.*, 2004; Rouhani *et al.*, 2010; Savelberg & de Lange, 1999) and COP locations (Forner-Cordero *et al.*, 2004; Fradet *et al.*, 2008) captured by the force platform under the shoe. The IS system, however, uses two triaxial force/moment transducers attached externally to the shoe sole (Liedtke *et al.*, 2007; Schepers, Koopman, & Veltink, 2007; Veltink *et al.*, 2005), enabling more direct measurements of GRFs and COPs than the IPM system. Though measurements of the IS can be more direct, those studies reported that attaching the transducers externally increases both shoe height and sole rigidity. Further, to the authors' knowledge, no study has formally examined how the IS system interacts with different floor surfaces and terrains in terms of slip resistance. Using an IPM system, therefore, appears to be more practical and valid in various work settings, since the system can be used with one's own shoes.

Pressure sensitive sensor matrices (i.e., insoles) of the IPM system have distinct coordinate systems. Thus, to calculate joint kinetics, COP positions from the IPM system need to be expressed in the same global coordinate system as a motion capture system. Existing studies (Forner-Cordero *et al.*, 2004; Forner-Cordero *et al.*, 2006; Fradet *et al.*, 2008) defined a transformation matrix between the coordinate systems of the IPM and that of an optical motion capture system, while considering the latter as the global coordinate system with additional information (e.g., reflective markers on the shoe and a pointer with reflective markers). This approach, however, may be infeasible outside of a laboratory environment. For example, if using other motion capture systems [e.g., an inertial motion capture (IMC) system], obtaining necessary information with the IMC system is not as simple or rapid as using additional reflective markers. Therefore, a need exists for a simple approach to relate IPM outputs to the coordinate system of the IMC system. Further, and from a practical perspective, it is of interest to determine how using an IPM system (i.e., estimated GRFs and COP locations) affects the accuracy of joint kinetic estimations during occupationally-relevant tasks such as manual material handling (MMH).

Therefore, this study explored a potential field-based approach to relate the coordinate systems of an IPM and an IMC system in the field, and to estimate GRFs and COP positions. In this work, it was assumed that a portable force platform and a built-in anatomical model for the IMC system are available. Note that commercial IMC systems (e.g., functional assessment of biomechanicsTM system from Biosyn systems Inc., MVN from Xsens Technologies B. V.) typically have an anatomical model implemented in data collection software. Here, however, an anatomical model was defined using an optical motion capture system, to prevent introducing errors while aligning coordinate systems of the force platform and the IMC system. To assess the potential of the IPM system in quantifying physical exposures, comparisons were made between estimated GRFs and COP locations using IPM outputs versus using direct outputs from a force platform during several MMH tasks (e.g., lifting, pushing/pulling, etc.). Comparisons were also made for the resulting 3D lumbosacral (L5/S1) joint moments, given that these are common assessment metrics during MMH tasks.

Methods

Ten healthy, young participants (19-29 years old, 5 males and 5 females) from the university and local community completed the study. Their mean (SD: range) stature, body mass, and foot length were 171.5 (6.9: 164-183) cm, 76.1 (13.2: 62.5-104.6) kg, and 26.8 (1.5: 24.5-29) cm, respectively. All participants were physically active and had no self-reported musculoskeletal injuries limiting normal daily activities. Prior to any data collection, participants completed an informed consent procedure approved by the Virginia Tech Institutional Review Board.

Experimental design

Participants completed each four simulated MMH tasks that were intended to represent a range of occupational demands. All tasks were performed with a box (width $\times$ length $\times$ depth = 33 $\times$ 48.3 $\times$ 24 cm) with mass set equal to 20/15% of individual body mass for male/female participants. The specific MMH tasks were: a) symmetric lifting and lowering from the ground to individual elbow height, and vice versa (LL_{Ground}); b) symmetric lifting and lowering from individual knuckle height to individual elbow height, and vice versa (LL_{KNUCKLE}); c) asymmetric lifting and lowering from/to tables located at each side of a participant (LL_{ASYM}); and d) pushing and pulling away from/toward the body (PushPull). More detailed descriptions are provided in Chapter 2. The presentation order of tasks was randomized, and two trials of each task were completed. While performing the tasks, participants kept each foot on a separate force platform, were allowed to move each foot freely over force platform surface, and performed all tasks in self-selected comfortable styles and speeds.

Instrumentation and data collection

External foot kinetics were collected using two force platforms (AMTI OR6-7-1000; AMTI, Watertown, MA, US) and a commercially-available IPM system (PedarTM, Novel GmbH, Munich, Germany) with 99 pressure sensors in each insole. The former sampled 3D GRFs and moments at 960 Hz, while the latter sampled plantar pressures under both feet at 60 Hz. Force platform outputs were low-pass filtered (15 Hz cut-off; 2nd order Butterworth; bidirectional), and then down-sampled to 60 Hz. The IPM system was synchronized with other systems via a TTL pulse (PedarTM Sync Box).

Whole-body kinematics were sampled at 60 Hz, using a 7-camera optical system (Vicon MX, Vicon Motion Systems Inc., Denver, CO, US). Passive reflective markers were placed bilaterally or in the mid-sagittal plane over several anatomical landmarks: calcaneus, 1st and 5th metatarsal heads, lateral and medial malleoli, lateral and medial tibial epicondyles, acromial processes, lateral and medial humeral epicondyles, radialis and ulnar styloid processes, the spinous processes of the seventh cervical (C7) and eighth thoracic (T8) vertebrae, incisura jugularis, xiphoid process, and anterior and posterior iliac superior spines. Clusters of 3-4 markers were also placed midway between C7 and T8, and over the pelvis, lower legs, upper arms, lower arms, and heels. Prior to the MMH tasks, selected anatomical markers were removed after being referenced to a corresponding cluster; removed markers were then reconstructed using clusters on the corresponding body segments (Veldpaus & Woltring, 1988). All off-line data processing was completed using Matlab 7 (MathworkTM Inc., Natick, MA, US).

Ad hoc global coordinate system for the IPM and the motion capture system

While participants stood upright and still, with each foot on a separate force platform, positions of selected reflective markers on the foot were captured by the motion capture system and also marked on the force platform (Figure 4). Given that COP is in the plane of the force platform, the coordinate system of each foot segment can be expressed with the z coordinate being zero:

$$\vec{Y} = \frac{0.5(MT1+MT5)-HEEL}{||0.5(MT1+MT5)-HEEL||}; \quad \vec{X} = \vec{Y} \times \vec{Z}; \quad \vec{Z} = [0 \ 0 \ 1]^T \quad (1)$$

The origin ($\vec{O}_{Foot}$) was set to be the midpoint between the lateral (ANKL) and the medial malleolus (ANKM). Thus, a transformation matrix from the foot segment to the coordinate system of the motion capture system (or the force platform) was obtained as:

$$\mathbf{T}_{O_{Foot}}^{Motion}(\text{or } \mathbf{T}_{O_{Foot}}^{FP}) = \begin{bmatrix} \vec{X} & \vec{Y} & \vec{Z} & \vec{O}_{Foot} \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R}_O^{Motion}(\text{or } \mathbf{R}_O^{FP}) & \vec{O}_{Foot} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

where $\vec{X}$, $\vec{Y}$, $\vec{Z}$ and $\vec{O}_{Foot}$ were defined using position data from the corresponding coordinate system, and $\mathbf{R}$ is a 3×3 matrix. For all subsequent data analyses, motion and force platform data were pre-multiplied with $(\mathbf{T}_{O_{Foot}}^{Motion})^{-1}$ and $(\mathbf{T}_{O_{Foot}}^{FP})^{-1}$, respectively; thus, both systems were expressed in the same coordinate system.

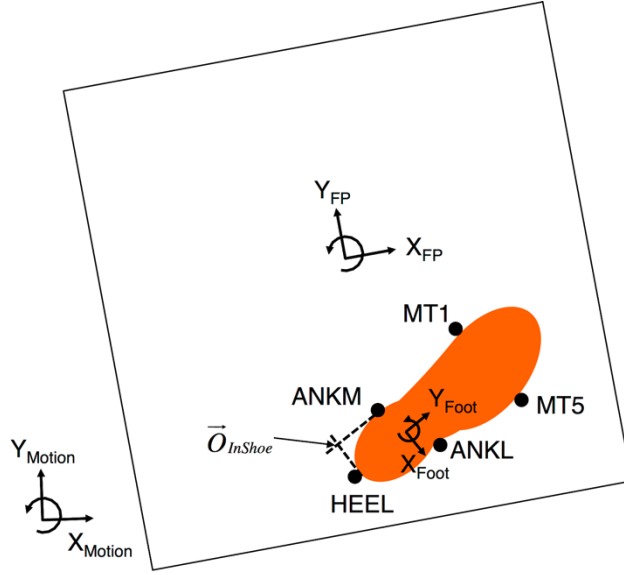


Figure 4. Illustration of the different coordinate systems and anatomical landmarks. The subscripts Motion, FP, and Foot refer to the coordinate system of a motion capture system, a force platform, and a foot segment, respectively. MT1, MT5, ANL, ANKM, and HEEL respectively refer to markers at the 1st and the 5th metatarsals, the lateral and the medial malleoli, and the heel. Last, $\vec{O}_{InShoe}$ was used as an estimate of the origin of the insole.

Fitting IPM outputs to COPs and GRFs

No simple mathematical relationship exists between IPM and force platform outputs, so three simple regression approaches were explored in this study. To use force platform outputs as response variables, 3D GRFs (F_X , F_Y and F_Z) and frictional (or “free”) moment (T , or M_Z , due to shear forces) were normalized respectively to half the body mass and the product of body mass and stature, similar to the approach by Rouhani *et al.* (2010). Then, 3D GRFs were pre-multiplied with $(\mathbf{R}_{k_{Foot}}^{Motion})^{-1}$, defined using motion data at the k^{th} frame, and COP positions were pre-multiplied with $(\mathbf{T}_{k_{Foot}}^{Motion})^{-1}$. Then, 18 variables were use as predictors in a multiple regression model to predict 3D GRFs and T . These predictors included the means and SDs of forces in nine regions of the insole, after normalizing to half of body mass. These nine regions were the lateral and medial part of the heel, two areas in the mid-foot, three areas in the fore-foot, one area the big toe, and final area for the remaining four toes. Such a regional grouping was defined based on work by Savelberg & de Lange (1999), and was used to reduce the number

of model predictors. For COP estimation, 21 predictor variables were used that included the same normalized means and SDs of forces in the nine insole regions, along with all combinations of COP outputs from the IPM system (i.e., $\widehat{COP}_X$, $\widehat{COP}_Y$, and $\widehat{COP}_X \times \widehat{COP}_Y$).

Three regression models were constructed for each response measure (i.e., each 3D GRF component, T, and COP locations). First, each force and COP output from the IPM system were used directly as the corresponding response measure (i.e., no shear GRFs and T), without using predictor variables (referred to as f_{NONE}). In other words, raw outputs were used from the IPM system, or a regression model with unit slope and zero intercept. The origin ($\vec{O}_{InShoe}$) for COP from the IPM system was roughly estimated as in Figure 4. Second, input variables were fitted (as predictors) using a simple least-squares (LSQ) multiple regression model (f_{LSQ}). Third, input variables were fitted using a multilayer feed-forward neural network (MFNN) with one hidden layer (size = 15) and sigmoid transfer function (see Bishop, 1995; Haykin, 1999 for more details), and which is referred to as f_{MFNN} .

Since the first regression model (f_{NONE}) needed no training, the model was applied directly to each MMH trial. In contrast, f_{LSQ} and f_{MFNN} were trained and tested using 2-fold cross-validation (CV) at the participant level. In this, for each participant, the training and the testing were performed twice using one replication of all MMH tasks for training and the other replication for testing. To assess the performance of the regression models, comparisons were made on estimated GRFs, T, COP, and 3D external moments at L5/S1 obtained from the model versus those obtained using the force platform (the latter assumed as “true” values). Note that L5/S1 moments were estimated using a “bottom-up” approach, with segmental inertial properties and joint centers estimated based on previous segment definitions (Dumas *et al.*, 2007), and these moments were expressed in the pelvis coordinate system. For each trial, three comparative measures were obtained from time series of GRFs, T, COP and 3D L5/S1 moments:

- Mean absolute error (MAE): mean of the absolute errors (i.e., differences between time series of estimated and “true” values of a response measure).
- Absolute error at the peak value (AEP): the absolute value of error at the time of the peak of the “true” response variable, similar the approach of Faber *et al.* (2010). In the case of COP, AEP values were obtained at the time of the peak resultant GRF.

- Refined index of agreement (IOA): a measure of the overall magnitude of errors relative to the sum of mean-centered “true” values (Willmott, Robeson, & Matsuura, 2011). This index ranges from -1 to 1, and a value closer to 1 represents a better model performance. For example, an IOA value of 0.5 (or -0.5) indicates that the sum of errors is half (or twice) of the sum of mean-centered “true” values. When IOA = 0, it means that the sum of errors and the sum of centered “true” values are equivalent.

A representative example of time series of GRFs, COP and L5/S1 moments estimated using the regression models is provided in Figure 5.

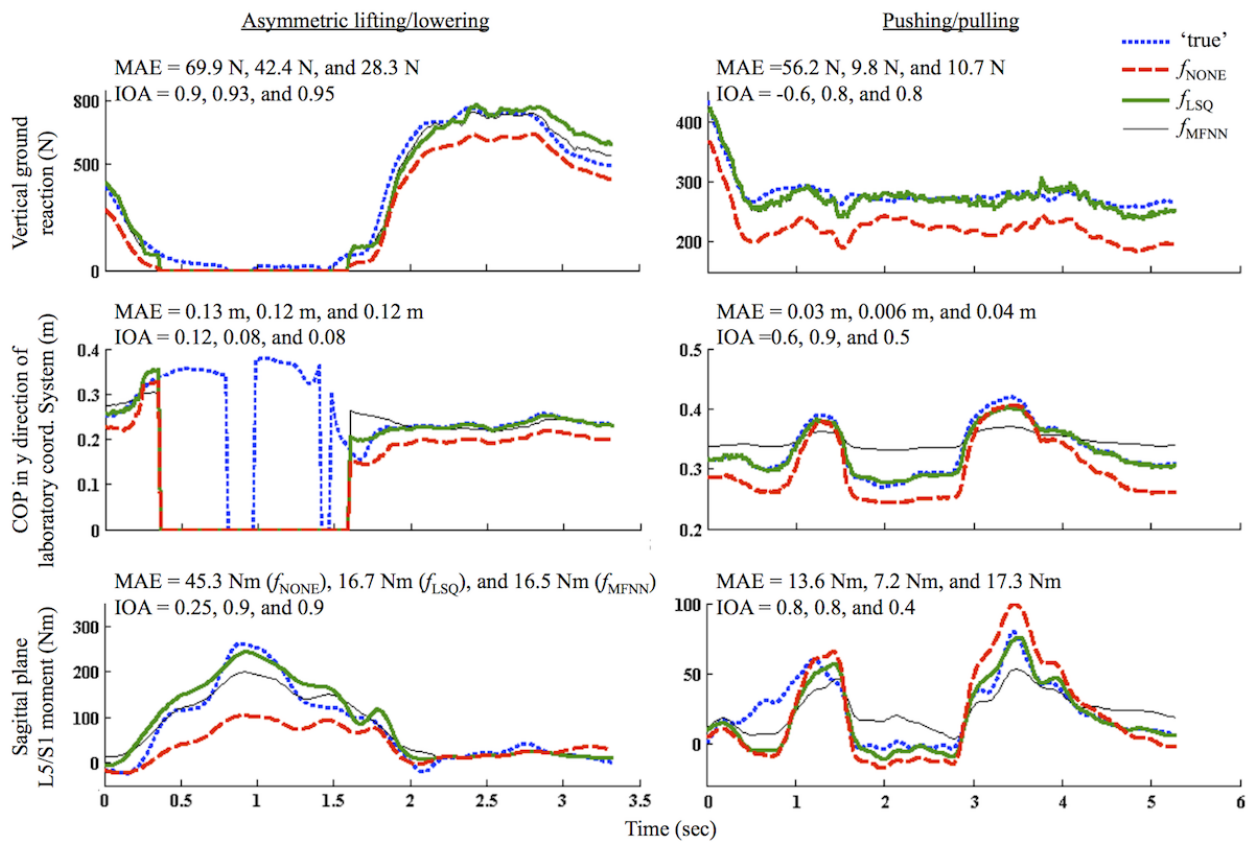


Figure 5. Example of time series of GRF, COP, and L5/S1 moments estimated using the regression models and obtained using the force platform (denoted as "true"). Note that, for each trial, participants initially stood along x- and y-axis, while facing in the positive y direction of the laboratory coordinate system.

Statistical analyses

To test if performance, in terms of estimating GRFs (and T), COP, and 3D L5/S1 moments, differed between the three regression methods (*Method*) and four MMH task types (*Task*), two-way repeated-measures analyses of variance (RANOVA) were performed separately on each comparative measure for each outcome measure. Significant effects were explored using Tukey's HSD post-hoc tests. Of note, comparative measures for GRFs and COP were obtained bilaterally, yet statistical tests were performed with the measures from the right leg only and were considered. All statistical analyses were complete using JMP 9.0 (SAS Institute Inc., Cary, NC, USA) with statistical significance determined when $p \leq .05$, and interpretations of statistical results focused primarily on general patterns than on the behavior of an individual measure across conditions. All summary data are presented as means (SD).

Results

Center of pressure locations

Both the main and interaction effects of *Model* and *Task* were significant on AEP_X and AEP_Y ($p < 0.0001$), while only the main effects were significant for the remaining comparative measures, ($p \leq 0.0004$). A summary of all measures is presented for each model and task (Table 4), and which shows that, in many cases, f_{LSQ} performed better than either f_{MFNN} or f_{NONE} . In addition, LL_{ASYM} appeared to have relatively larger errors than other tasks, and $LL_{KNUCKLE}$ had relatively smaller IOA_X values.

Table 4. Summary statistics [mean (SD)] of comparative measures for COP. Note, the subscripts X and Y indicate the direction of the laboratory coordinate system: positive x-axis rightward and y-axis forward. For each trial, participants initially stood along the x- and y-axis, while facing in the positive y direction. The units for the mean absolute error (MAE) and the absolute error at the peak (AEP) are mm, whereas the index of agreement (IOA) ranges from -1 to 1.

	LL _{GROUND}			LL _{KNUCKLE}			LL _{ASYM}			PushPull		
	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}
MAE _X	19.1 (9.1)	9.4 (2.5)	10.6 (3.6)	7.7 (4.1)	5.8 (2.0)	5.5 (3.6)	50.2 (26.3)	39.6 (27.0)	38.7 (28.0)	8.5 (4.7)	7.9 (1.5)	5.4 (3.2)
MAE _Y	19.3 (6.1)	7.8 (2.6)	15.8 (3.9)	15.3 (7.8)	5.4 (1.8)	14.9 (3.7)	67.4 (33.6)	54.9 (32.1)	59.3 (31.0)	23.6 (8.6)	6.7 (2.0)	24.7 (5.2)
AEP _X	26.2 (13.7)	11.6 (6.6)	13.5 (7.7)	8.5 (5.5)	5.3 (3.2)	5.8 (4.7)	28.3 (19.2)	8.8 (5.2)	6.3 (4.4)	7.9 (6.3)	9.0 (3.6)	8.1 (5.7)
AEP _Y	18.9 (7.8)	7.5 (4.1)	15.4 (12.2)	17.3 (13.6)	4.5 (3.3)	15.9 (10.7)	28.0 (7.3)	9.6 (9.0)	8.5 (7.4)	20.7 (8.3)	11.1 (15.9)	32.1 (12.2)
IOA _X	-0.2 (0.4)	0.2 (0.3)	0.2 (0.4)	-0.3 (0.4)	-0.2 (0.4)	-0.03 (0.6)	-0.3 (0.5)	-0.1 (0.6)	-0.1 (0.6)	0.1 (0.5)	0.02 (0.5)	0.3 (0.4)
IOA _Y	0.7 (0.2)	0.9 (0.1)	0.8 (0.1)	0.6 (0.2)	0.9 (0.1)	0.6 (0.2)	0.2 (0.5)	0.4 (0.4)	0.3 (0.4)	0.7 (0.1)	0.9 (0.02)	0.7 (0.1)

Ground reaction forces and frictional moment

The main and interaction effects of *Model* and *Task* were significant on all measures ($p < 0.037$) except AEP_X and AEP_Z. The latter were affected only by the two main effects ($p \leq 0.002$).

Table 5 presents a summary of all measures for each model and task. Overall, f_{NONE} consistently performed worse than f_{LQR} and f_{MFNN} , which both appeared to perform comparably. Further, and similar to COP, errors were relatively larger during LL_{ASYM} vs. other tasks, and IOA values were relatively smaller for LL_{KNUCKLE}.

Table 5. Summary statistics [mean (SD)] of comparative measures for GRFs. Note, the subscripts X, Y, and Z indicate the direction of the laboratory coordinate system: positive x-axis rightward, y-axis forward and z-axis upward. The subscript T indicates the frictional moment. The units for $MAE_{X,Y,Z}$ and $AEP_{X,Y,Z}$ are Newton, and the units for MAE_T and AEP_T are Nm. Note that f_{NONE} did not yield shear GRFs or T.

	LL _{GROUND}			LL _{KNUCKLE}			LL _{ASYM}			PushPull		
	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}
MAE_X	.	14.0 (7.6)	15.6 (7.7)	.	6.3 (2.5)	6.6 (4.0)	.	13.8 (4.5)	14.4 (4.5)	.	6.5 (2.7)	5.4 (3.1)
MAE_Y	.	8.9 (2.8)	8.1 (2.0)	.	6.6 (2.8)	4.8 (2.6)	.	8.7 (2.9)	7.9 (2.2)	.	9.6 (4.3)	12.0 (4.2)
MAE_Z	69.8 (53.5)	23.4 (12.4)	20.4 (8.7)	81.8 (70.03)	15.8 (8.6)	15.3 (8.6)	77.7 (42.5)	40.6 (10.5)	42.2 (14.0)	82.1 (50.4)	15.9 (6.6)	15.0 (5.9)
MAE_T	.	2.8 (1.1)	3.0 (1.3)	.	2.3 (1.3)	1.8 (0.9)	.	2.5 (0.7)	3.6 (1.4)	.	2.3 (0.7)	3.3 (1.5)
AEP_X	.	27.0 (13.8)	34.4 (15.02)	.	8.7 (4.1)	10.8 (6.3)	.	27.04 (17.6)	35.3 (15.3)	.	8.2 (4.7)	8.0 (6.9)
AEP_Y	.	21.04 (10.1)	24.7 (10.4)	.	15.0 (9.2)	14.2 (7.4)	.	11.5 (6.8)	16.4 (7.0)	.	26.3 (8.8)	34.9 (11.9)
AEP_Z	90.8 (73.3)	22.2 (16.1)	26.8 (26.5)	95.3 (80.8)	15.5 (14.0)	17.5 (17.6)	132.63 (84.7)	28.5 (27.3)	42.7 (50.2)	83.2 (37.9)	18.7 (16.4)	14.6 (13.1)
AEP_T	.	6.7 (3.5)	6.1 (4.7)	.	4.0 (2.3)	2.1 (1.6)	.	4.2 (3.4)	8.8 (3.6)	.	5.4 (1.8)	4.32 (3.4)
IOA_X	.	0.5 (0.2)	0.5 (0.1)	.	-0.1 (0.4)	0.0 (0.4)	.	0.6 (0.1)	0.6 (0.1)	.	-0.09 (0.3)	0.1 (0.4)
IOA_Y	.	0.4 (0.1)	0.4 (0.1)	.	0.1 (0.3)	0.4 (0.2)	.	0.4 (0.2)	0.5 (0.1)	.	0.6 (0.07)	0.5 (0.04)
IOA_Z	0.3 (0.3)	0.7 (0.1)	0.8 (0.1)	-0.1 (0.5)	0.7 (0.2)	0.7 (0.2)	0.9 (0.1)	0.9 (0.02)	0.9 (0.04)	-0.4 (0.4)	0.6 (0.1)	0.6 (0.1)
IOA_T	.	0.4 (0.2)	0.3 (0.2)	.	-0.1 (0.4)	0.06 (0.4)	.	0.6 (0.1)	0.5 (0.1)	.	0.3 (0.3)	0.05 (0.4)

3D L5/S1 moments

Model and *Task* had significant main and interaction effects on all measures ($p \leq 0.0076$) with a few exceptions. MAE_X was affected significantly by *Task* and *Model* $\times$ *Task* interactions ($p = 0.0016$), and AEP_X was affected by only *Model* and *Task* ($p \leq 0.0106$). In addition, MAE_Y and AEP_Y were affected significantly by *Task* ($p < 0.0001$). Table 6 summarizes values of all measures for each model and task, and which shows that, in many cases, f_{LSQ} performed better than f_{NONE} and f_{MFNN} . Further, f_{NONE} and f_{MFNN} often showed comparable performance in the estimation of GRF, COP, and L5/S1 moments.

Table 6. Summary statistics [mean (SD)] of comparative measures for L5/S1 moments. Note, here the subscripts X, Y, and Z indicate, respectively, the sagittal, frontal, and transverse planes of the pelvis. The units for MAE and AEP are Nm.

	LL _{GROUND}			LL _{KNUCKLE}			LL _{ASYM}			PushPull		
	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}	f_{NONE}	f_{LSQ}	f_{MFNN}
MAE _X	21.4 (13.5)	15.1 (7.0)	16.1 (5.6)	11.8 (6.6)	11.9 (5.3)	16.6 (7.9)	28.1 (9.1)	24.6 (8.6)	21.3 (4.8)	20.2 (7.5)	20.5 (7.7)	19.5 (6.2)
MAE _Y	24.0 (14.5)	17.6 (10.4)	18.4 (9.6)	10.7 (8.5)	10.4 (6.8)	12.4 (8.2)	29.3 (7.7)	26.0 (11.3)	26.8 (11.0)	16.1 (24.9)	14.5 (13.9)	12.4 (6.2)
MAE _Z	21.1 (9.5)	12.2 (6.03)	12.9 (6.0)	9.7 (4.4)	4.1 (2.1)	5.3 (2.2)	9.4 (3.6)	11.1 (4.5)	12.5 (5.6)	8.3 (11.7)	6.5 (7.1)	8.5 (4.4)
AEP _X	36.4 (38.7)	18.8 (10.8)	23.8 (11.5)	24.6 (21.0)	24.1 (14.4)	38.2 (15.7)	48.8 (47.7)	28.6 (36.4)	30.7 (26.4)	20.5 (14.2)	14.7 (12.7)	17.5 (15.0)
AEP _Y	41.8 (22.4)	36.7 (29.5)	38.4 (21.2)	11.8 (14.9)	11.1 (8.9)	19.8 (17.7)	39.9 (31.2)	31.7 (15.6)	36.1 (25.6)	16.4 (25.7)	16.5 (16.2)	14.6 (16.2)
AEP _Z	39.3 (22.6)	22.3 (13.6)	22.2 (13.9)	16.0 (7.4)	5.8 (4.3)	6.4 (4.8)	14.8 (8.9)	12.3 (10.2)	15.7 (7.7)	14.3 (8.2)	12.1 (12.1)	6.9 (5.9)
IOA _X	0.7 (0.2)	0.8 (0.1)	0.8 (0.1)	0.6 (0.2)	0.5 (0.2)	0.3 (0.4)	0.5 (0.2)	0.6 (0.1)	0.6 (0.2)	0.7 (0.1)	0.7 (0.2)	0.6 (0.1)
IOA _Y	0.04 (0.3)	0.4 (0.2)	0.3 (0.3)	0.2 (0.4)	0.3 (0.3)	-0.06 (0.6)	0.7 (0.1)	0.6 (0.3)	0.5 (0.2)	0.3 (0.4)	0.3 (0.4)	0.1 (0.4)
IOA _Z	0.05 (0.4)	0.6 (0.2)	0.4 (0.3)	-0.6 (0.1)	0.4 (0.3)	-0.4 (0.4)	0.7 (0.1)	0.7 (0.1)	0.2 (0.3)	0.07 (0.4)	0.5 (0.3)	0.1 (0.4)

Discussion

The study assessed the potential application of an IPM system to quantify physical exposures in the field, specifically GRFs and COP locations, along with L5/S1 moments (presumably with the additional use of an inertial motion capture system). To use outputs of the IPM system to estimate GRFs and COP positions (“true” values captured by a force platform), *ad hoc* global coordinate systems for the IPM and the motion capture system were first defined using anatomical landmarks of a foot. Subsequently, three different regression methods were explored to estimate GRFs and COP locations during several MMH tasks. Depending on the regression method and the task type, the magnitude of errors and IOA values varied considerably; e.g. GRF in the vertical direction: $15.3 \text{ N} \leq \text{MAE}_Z \leq 69.8 \text{ N}$; COP: $5.4 \text{ mm} \leq \text{MAE} \leq 67.4 \text{ mm}$. Such a range of errors in GRF and COP during the MMH tasks led to mean absolute errors of estimated

L5/S1 moments that ranged from 11.8 Nm to 28.1 Nm in the sagittal plane, 10.4 Nm to 29.3 Nm in the frontal plane, and 5.1 Nm to 2.1 Nm in the transverse plane.

Compared to other GRF components and L5/S1 moments about other axes, the vertical GRF component and the sagittal L5/S1 moment showed relatively small errors and good agreement in the time series (see Tables 5 and 6). Specifically, and relative to peak values from the force platform, estimates of vertical GRF had errors of up to ~19% with f_{NONE} , ~4% with f_{LSQ} and ~5% with f_{MFNN} . These two regression methods (LSQ and MFNN), however, led to larger relative errors (~20-85%) in shear GRF estimates. Existing studies (Fong *et al.*, 2008; Rouhani *et al.*, 2010) have similarly found comparatively better performance when estimating vertical vs. shear GRFs during walking; yet, they reported errors of < ~5% in vertical GRF estimates and < ~24% in shear GRF estimates. The relatively poorer performance for shear GRF estimation in our study is likely due to the rather more complex body movements involved (i.e., MMH tasks vs. walking). Further, the selection of nine contact regions of the insole as predictors to the regression models, compared to predictor selection methods such as a principal component analysis (Rouhani *et al.*, 2010) and stepwise linear regression (Fong *et al.*, 2008), may have been less effective.

In the case of L5/S1 moments, and relative to peak values obtained using the force platform, estimates of sagittal moments had errors of up to ~41% with f_{NONE} , ~26% with f_{LSQ} , and ~36% with f_{MFNN} , and larger errors (~25-94%) were found when estimating transverse and frontal moment. Though not directly comparable, Faber *et al.* (2010), using instrumented shoes, reported much smaller errors for L5/S1 moment estimates (< 7%) during different types of lifting, pushing, and walking. In their study, the instrumented shoes also resulted in errors in COP location and GRFs at the time of peak GRF that were < 10 mm and < 3% of body mass, respectively. This clearly outperformed our findings (Table 4 and 5), and is not surprising since the instrument shoes vs. the IPM system more directly captures COP and GRFs by using triaxial force/moment transducers attached to the shoe sole (Liedtke *et al.*, 2007; Veltink *et al.*, 2005). Thus, our results appear to emphasize the need for a method that can better estimate COP location and shear GRFs during different MMH tasks, which would also improve the performance of the IPM system in estimating L5/S1 moments. Additionally, given that the fit of

the regression methods used here (LSQ and MFNN) was not particularly better with training data (Appendix B) vs. validation data (i.e., Tables 4 – 6), it would appear that the models were not effective in capturing the variability of COP locations and GRFs during various MMH tasks using IPM outputs. Note that improving the performance of a model is discussed in Chapter 5. However, it should be noted that the regression methods were trained and validated following only a single 2-fold CV, and also that the training dataset size was rather small (1 trial x 4 tasks). These two limitations likely account for, at least in part, the relatively large errors found here compared to other studies (Molinaro *et al.*, 2005).

In conclusion, we explored a potential field-based approach for using an IPM system to estimate 3D GRFs and COP locations, and to quantify joint kinetics during MMH tasks. Assuming the availability of a portable force platform and an IMC system, IPM outputs were fitted for each individual to estimate 3D GRFs and COP locations during MMH tasks. The least-squares multiple regression generally performed better than other methods (i.e., raw IPM outputs and MFNN), and the asymmetric lifting/lowering task yielded larger errors than other tasks. Yet, regardless of the method and the task type, large errors were observed in all response measures except the vertical component of GRFs. Further, using estimated 3D GRFs and COP locations led to relatively large errors in the frontal and transverse plane L5/S1 moments than in the sagittal plane. Therefore, our results suggest the need for a future focus on more effective methods to estimate COP and shear GRFs during various MMH tasks. To further promote a wide adoption of the IPM system for exposure assessment in the field, future work should explore population-based methods to estimate COP and GRFs, which eliminates or minimizes the use of a portable force platform.

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Chapter 4: Exposure assessments in manual materials handling: evaluation of task-classification methods using wearable technologies

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Abstract

Wearable technologies such as inertial measurement units (IMUs) and in-shoe pressure measurement (IPM) sensors, respectively facilitate ambulatory (field) monitoring of whole body motions and external forces applied to the body. The study explored different algorithms for automatically classifying manual material handling (MMH) tasks performed by 10 participants during a simulated job. Five different MMH-task classifiers were developed using three different conventional classification algorithms (i.e., k -nearest neighbor, multilayer feedforward neural network, and linear discriminant analysis), while considering each seven different combinations of IMU and/or IPM outputs as inputs to the classifiers. The results showed, depending on an MMH-task classifier, that precision and recall values achieved can be $\geq \sim 87\%$ and $\sim 79\%$ across the MMH tasks and that the percentage difference in an estimated time proportion for an MMH task can be $\leq \sim 14\%$. The latter suggested that using the portable measurement systems with MMH-task classifiers could be viable in a task-based exposure assessment. Several suggestions to improve MMH-task classifiers were discussed.

Keywords: *task classification, manual material handling, ergonomic exposure assessment, portable measurement*

Introduction

Work-related musculoskeletal disorders (WMSDs) are an important health concern in the workplace, which account for ~30% of all lost work days (BLS, 2010; 2011) and involve substantial associated costs (Liberty Mutual, 2012). Quantifying exposures to WMSD physical risk factors (e.g., non-neutral postures, high forces/moments) is frequently needed for both research and practice. For example, accurately quantifying physical exposures can help clarify relationships between exposures and health outcomes, and aid in the design and evaluation of ergonomic interventions (Burdorf *et al.*, 1997; Lötters & Burdorf, 2002; Westgaard & Winkel, 1997). In the workplace, both tasks and work conditions (e.g., work processes/cycles, workspace constraints) can change over time, and such changes can affect the level of physical exposures that an individual or group of workers experience even in the same job. As such, field-based exposures are ideally preferred over alternatives such as lab-based simulations. Quantifying detailed physical exposures in diverse work environments, though, has been considered to be challenging, and to require additional investigation and development (Garg & Kapellusch, 2009; Marras *et al.*, 2009; Waters *et al.*, 2007).

Body motions and external forces applied to the body can be captured *in situ*, using recent wearable technologies. For example, detailed body segment kinematics can be potentially monitored in the workplace, using inertial measurement units (Findlow *et al.*, 2008; Godwin *et al.*, 2009; Plamondon *et al.*, 2007). Ground reaction forces can be estimated using in-shoe pressure measurement (IPM) systems (Forner-Cordero *et al.*, 2004; Savelberg & de Lange, 1999) and instrumented shoes (Faber *et al.*, 2010; Veltink *et al.*, 2005). Information yielded by portable measurement systems appears to be numerically detailed and precise in many cases (Chapters 2-3). Lacking from these systems, however, is contextual information of a given job; specifically, what tasks are performed, when, how frequently and/or how long, etc. To address this, some previous authors have suggested using both an observational method and a direct measurement system as an improved approach for comprehensive assessments of physical exposures (Juul-Kristensen *et al.*, 2001; Teschke *et al.*, 2009; Wells *et al.*, 1994). Yet, using both systems is more costly, time consuming, and resource demanding than using either alone. Continuous observation of postures, in particular, is quite labor intensive (Rezaghali *et al.*, 2012).

Extracting exposure contexts (e.g., task types, duration) can be viewed as a form of task classification, involving (ideally) automatic recognition of the different tasks that an individual performs. Though largely in the fields of healthcare-related research and pervasive computing, different types of wearable sensors (e.g., accelerometers, IMUs, IPMs) have been employed to classify daily tasks (Altun & Barshan, 2010; Blanke & Schiele, 2009; Pärkkä *et al.*, 2006; Yüksek & Barshan, 2011) and manufacturing tasks (Ogris *et al.*, 2011; Stiefmeier *et al.*, 2006). Existing studies have often focused on the classification of high-level behaviors (i.e., semantically meaningful), such as ascending/descending stairs, lying, opening/closing a hood, running, and sitting, to list a few. Similarly, manual material handling (MMH) tasks are high-level behaviors, so task classification could be employed to monitor MMH tasks performed by a worker. Note, our focus here is only on MMH tasks, since these are a well-documented risk factor for WMSDs (NRC, 2001).

Continuously monitoring MMH tasks in a job could provide a better identification of task durations than self-reports or observational methods, and if so would likely improve task-based exposure assessment when used in estimating job exposures. The task-based approach is a common exposure assessment method, which combines information on how long a worker performs each of the tasks in a given job together with expected task exposures from either a database or as estimated from direct measurements (Mathiassen *et al.*, 2005; Winkel & Mathiassen, 1994). Accordingly, the contribution of a task to an overall job exposure can be assessed (Mathiassen *et al.*, 2005). However, this approach is labor intensive due to the need for information on task proportions (van der Beek & Frings-Dresen, 1998), and resulting accuracy can be substantially compromised by inaccurate estimates of the task proportions (Mathiassen *et al.*, 2005).

The goal of the current study was thus to examine the potential of using two commercially-available portable measurement systems (IMU and IPM) to classify MMH tasks during a simulated job. In the case of the IMU system, IMUs can be placed on multiple body parts, depending on the number of available units, the number of workers to monitor, etc. To address this, we explored different combinations of IMU and/or IPM output time series as inputs to three

different conventional classification algorithms (linear discriminant analysis, *k*-nearest neighbor, and multi-layer feedforward neural network). Three distinct algorithms were tested, since, as noted in recent reviews on classification methods (Jain *et al.*, 2000; Preece *et al.*, 2009b), no single optimal solution exists for all classification problems. The performance of these, in terms of MMH-task classification ability (i.e., precision and recall), was compared for the different sensor output combinations, classification algorithms, and task type, in terms of classification performance. Additionally, and to explore the potential of MMH-task classification in a task-based exposure assessment, the time proportions of tasks estimated from selected MMH-task classifiers were compared to “ground truth” available from direct observations. As this study was more exploratory and data-driven in nature, no *a priori* hypotheses were formulated.

Methods

Ten healthy, young participants (19-29 years old, 5 males and 5 females) from the university and local community completed the study. Their mean (SD: range) stature, body mass, and foot length were 171.5 (6.9: 164-183) cm, 76.1 (13.2: 62.5-104.6) kg, and 26.8 (1.5: 24.5-29) cm, respectively. All participants reported being moderately physically active and having no musculoskeletal injuries limiting normal daily activities. Prior to any data collection, participants completed an informed consent procedure approved by the Virginia Tech Institutional Review Board.

Experimental procedures and instrumentation

Participants completed three replications, each involving four cycles of the simulated job. A single cycle of the simulated job consisted of a set of six MMH activities that were designed to include all major types of MMH tasks (lifting/lowering, pushing/pulling, and carrying). The specific MMH activities (see the illustration and relevant dimensions in Figure 1) were:

- Activity 1: carry the box to a table (i.e., symmetric lifting, carrying, and lowering to knuckle height).
- Activity 2: transfer the box from one table to another (i.e., asymmetric lifting).
- Activity 3: carry the box from one table to another (i.e., lifting from knuckle height, carrying and lowering to the knuckle height).
- Activity 4: push the box away from the body over a distance of 70 cm.

- Activity 5: pull the box toward the body over a distance of 70 cm.
- Activity 6: place the box from a table to the ground (i.e., lifting from knuckle height, carrying, and lowering to the ground).

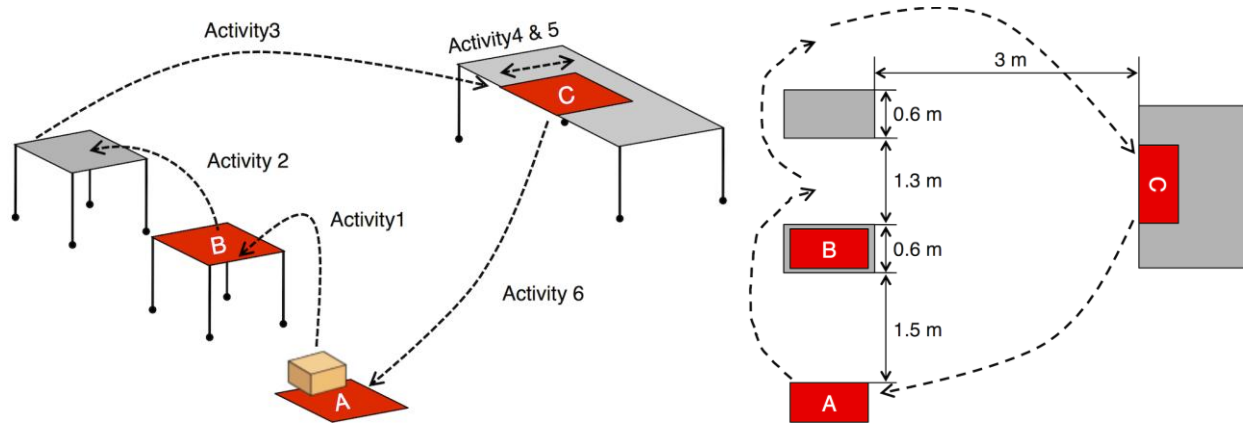


Figure 6. Illustration of the simulated job (Left), involving six MMH activities, and the relevant dimensions (Right). Dotted lines indicate the clockwise movement paths. The red rectangular zones (A, B, and C) indicate three different starting locations for a job cycle.

Participants began a job cycle from each of three starting locations (see Figure 6). The presentation order of starting location was first randomized, and within each starting location the work direction (i.e., clockwise vs. counterclockwise) was randomized. Participants were asked to complete each activity using self-selected comfortable styles and speeds, but within 15 sec. The beginning of a cycle was paced with computer-generated auditory tones, and 30 sec. of rest was given between cycles. Each replication of four job cycles lasted 7 min, and 3 min. of rest was given after each cycle. Note that participants were allowed to move freely during these rest periods.

Whole-body kinematics were monitored using an IMU system (MOVEN inertial motion capture system, Xsens technologies B.V., Enschede, the Netherlands) with 17 IMUs. Ground reaction forces were obtained using with an IPM system (PedarTM, Novel GmbH, Munich, Germany) with 99 pressure sensors in each of two insoles. Both systems were sampled at 60 Hz. To synchronize the systems, one reflective marker was placed on the heel of one foot, monitored using a 7-camera optical motion capture system (Vicon MX, Vicon Motion Systems Inc.,

Denver, CO, US). Participants were asked to perform an easily identifiable movement at the start of each round (i.e., quickly raising a foot), which was to synchronize the two motion capture systems. The IPM system was synchronized with the other systems via a TTL pulse (PedarTM Sync Box). All off-line data processing was completed using Matlab 7 (MathworkTM Inc., Natick, MA, US).

MMH task classification

Given the large number of possibilities for different measurement unit configurations, seven different input data sets were defined, and intended to represent a range of possible applications. These input sets consisted of different combinations of IMC and/or IPM output time series:

- Whole body joint angles (WB_{ANG}): flexion/extension and lateral bending angles of the pelvis (respectively determined relative to the gravitational vector and the ground), 3-D trunk angles relative to the pelvis, bilateral 3-D direct cosine angles of the upper arm relative to the trunk, bilateral 1-D elbow joint included angles (i.e., flexion-extension), bilateral 3-D direct cosine angles of the upper leg relative to the pelvis, and bilateral 1-D included knee joint angles (i.e., flexion-extension). Thus, each frame of data was a 21-dimensional vector.
- Whole body joint angles and angular velocities (WB_{ANG+VEL}): whole body joint angles and their time derivatives were included. Each frame of data was a 42-dimensional vector.
- Whole body joint angles with IPM outputs (WB+IPM): whole body joint angles and two pressure outputs (i.e., 99 pressure sensors from each foot) were included. Pressure outputs were normalized to half the product of body mass and foot area (see Chapter 3). Each frame of data was a 219-dimensional vector.
- Upper body joint angles with IPM outputs (UB+IPM): upper body joint angles were the flexion/extension and lateral bending angles of the pelvis, 3-D trunk angles, bilateral 3-D direct cosine angles of the upper arm, and bilateral 1-D elbow joint included angles. Each frame of data was a 211-dimensional vector, including normalized pressure sensor outputs.
- Lower body joint angles with IPM outputs (LB+IPM): lower body joint angles were the flexion/extension and lateral bending angles of the pelvis, bilateral 3-D direct cosine

angles of the upper leg, and bilateral 1-D knee joint included angles. Each frame of data was a 208-dimensional vector, including normalized pressure sensor outputs

- Pelvis angles with IPM outputs (PELV+IPM): pelvis angles were the flexion/extension and lateral bending angles. Each frame of data was a 200-dimensional vector, including normalized pressure sensor outputs.
- IPM outputs (IPM_{ONLY}): two sets of normalized pressure sensor outputs (99 each) were only included, so that each frame of data was a 198-dimensional vector.

Task classification was performed for each participant, using each of the seven input data sets above. In this study, eight MMH tasks involved in the activities were of main interest in terms of classification: 1) lifting from the ground (Lifting_{GROUND}), 2) lifting from knuckle height (Lifting_{KNUCKLE}), 3) lowering to the ground (Lowering_{GROUND}), 4) lowering to knuckle height (Lowering_{KNUCKLE}), 5) pushing, 6) pulling, 7) carrying, and 8) walking (only as required to perform the activities). Figure 7 provides an overview of the processes involved in MMH task classification for each participant.

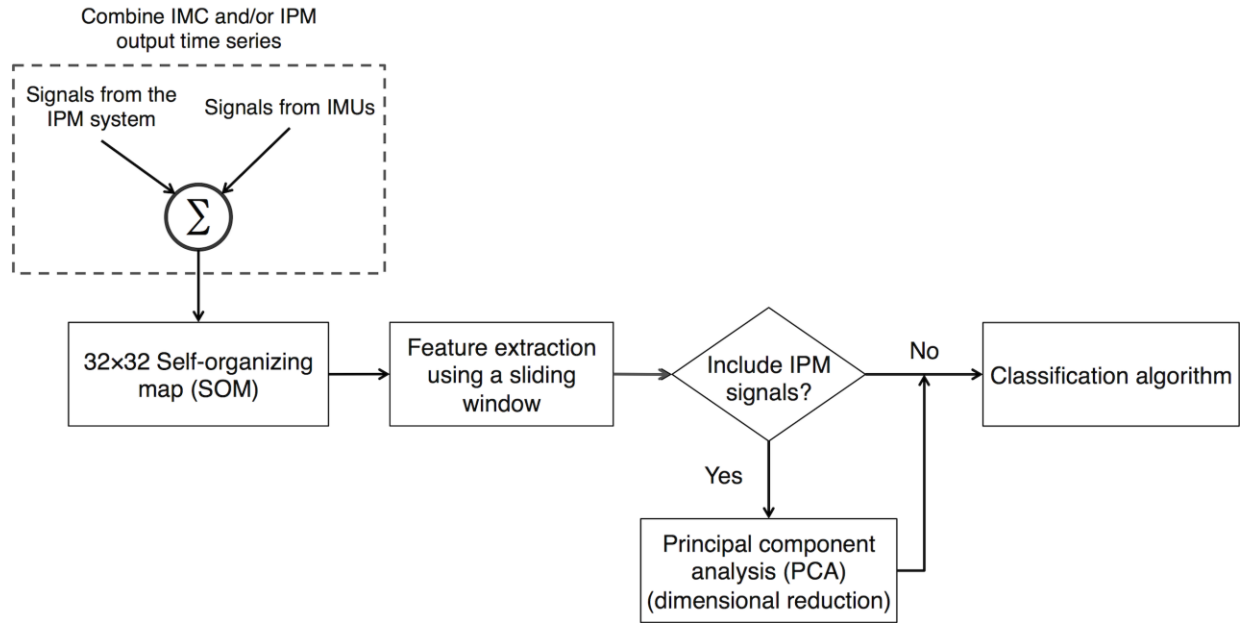


Figure 7. An overview of the process of MMH task classification for each participant.

Quantizing times series of input data sets. An unsupervised clustering algorithm can be used to explore hidden structures in a set of data, and such structures could enable a reliable

identification of tasks with a subsequent supervised task classification algorithm (Preece *et al.*, 2009b). A self-organizing map (SOM) is a neural network based on an unsupervised clustering algorithm (Kohonen, 1990). Here, a SOM was constructed with 1024 neurons in a 32 x 32 hexagonal grid [using the SOM Toolbox (Vesanto *et al.*, 1999)], and which was used to cluster the time series within the input data set. Then, each frame of the time series was replaced with a corresponding cluster centroid vector from the SOM (i.e., quantized).

Feature extraction and data reduction. Feature extraction is a typical pre-processing step for characterizing time series using, for example, descriptive statistics, fast Fourier transform components, and others. From this, extracted features are used as inputs to classification algorithms (Preece *et al.*, 2009b). Here, to extract statistical features, a sliding window of size 10 frames (0.17 sec.) was moved over each time series vector of the input data set with 50% overlapping. In each window, five descriptive statistics were obtained – mean, variance, min, max, and kurtosis. Thus, for example, each frame of the WB_{ANG} data set became a 105-dimensional feature vector (5×21), and the time series length was reduced by one fifth. In the case of a data set including IPM outputs, the dimension of a feature vector became rather large (≥ 990). Principal component analysis (PCA), a well-established statistical dimension reduction technique (Jolliffe, 2002), was therefore performed to reduce the dimensions of a feature vector. This indicated that the first 150 PCs explained > 99.5% of the variance in data set, so that the dimension of a feature vector for all data sets including IPM outputs was reduced to 150 (from ≥ 990).

Classification algorithms. Three different conventional classification algorithms were used to classify MMH tasks. A brief description of each algorithm is given below, with references for additional information. The three classification algorithms are:

- Linear discriminant analysis (LDA): a representative subspace analysis technique to find discriminant functions that maximize the ratio of the between-class separability and the within-class variability (Webb & Copsey, 2011).
- k -nearest neighbor (k -NN): a widely-used distance-based technique, which assigns an unclassified input vector to the nearest known class (Webb & Copsey, 2011). It is rather

exploratory to select the number of nearest neighbor k ; thus, k -NN was performed with $k = 3$ and 5 in this study.

- Multilayer feedforward neural network (MFNN): in a simplified view, a nonlinear mapping structure that typically consists of an input, a hidden, and an output layer of “neurons”, with transfer functions between layers. Inter-connections, or weights, between neurons are determined for a given data set (Bishop, 1995; Haykin, 1999). In this study, a MFNN was developed with sigmoid transfer functions, while the size of one hidden layer was set to be 20 or 30.

Each MMH classifier was trained and tested with each input data set, using 3-fold cross-validation (CV) at the participant level. That is, for each participant, training and testing were performed three times using two replications of MMH tasks for training and the remaining one replication for testing. An example of classification outputs is presented in Figure 8. The performance of MMH-task classifiers was assessed with two common performance measures (Fawcett, 2004): precision and recall. The former is the percentage of cases that a task is correctly classified [i.e., positive predictive value = true positives/(true positives + false positives)], and the latter is the percentage that a classified task is correct [i.e., true positive rate = true positive/total positives]. In addition, the time proportions of each of the MMH tasks were estimated from outputs of selected MMH-task classifiers with different performance levels, to explore the potential use of the classifiers in a task-based exposure assessment. The percentage difference was calculated as an outcome measure, compared to “ground truth” time proportions determined by direct observations.

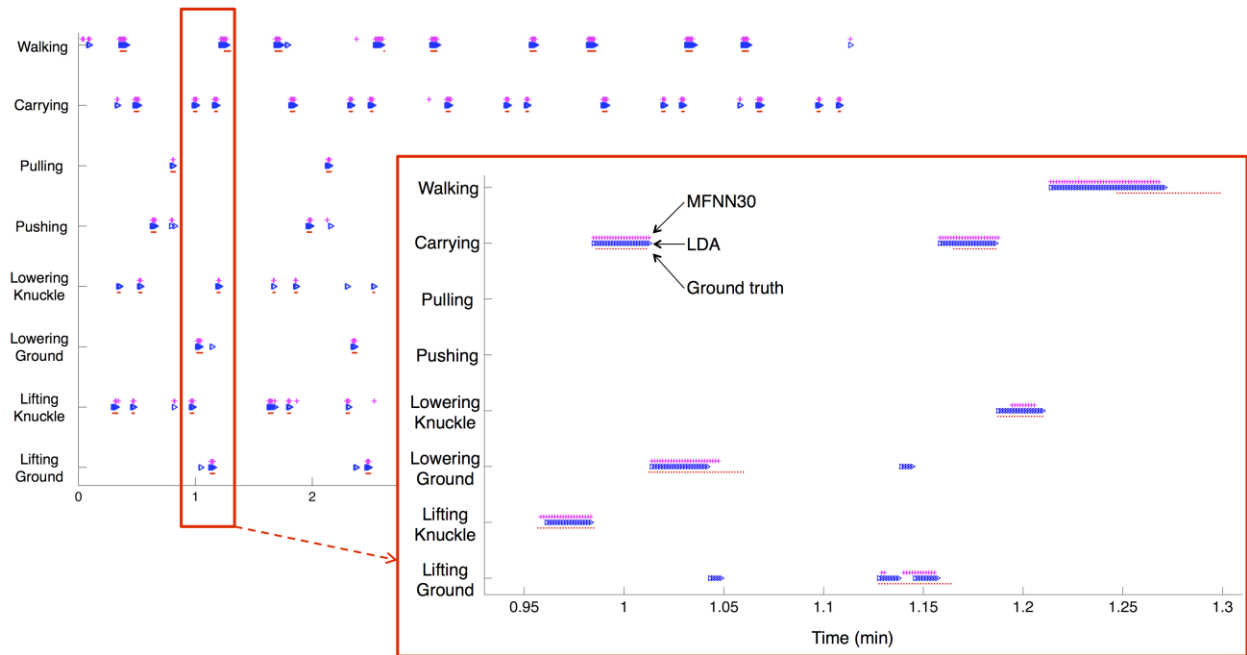


Figure 8. An example of classification outputs using the $WB_{ANG+VEL}$ data set (whole body joint angles and angular velocities). Classification algorithms used here were linear discriminant analysis (LDA) and multilayer feedforward neural network with the hidden layer size = 30 (MFNN30). The vertical axis shows eight tasks classified, and connected dots indicate tasks performed or identified.

Statistical analyses

Three-way repeated-measures analyses of variances (RANVOAs) were performed to assess the main and interactive effects of input data sets (*Data set*), MMH-task classifiers (*Classifier*), and MMH tasks (*Task*) on precision and recall values. Where relevant, post-hoc comparisons were conducted using Tukey's Honestly Significant Difference (HSD) tests. Interpretations of statistical results centered on the predominant emerging patterns in classification performance with respect to *Data set*, *Classifier*, and *Task*, rather than on specific differences across the levels of independent variables. All statistical analyses were complete using JMP 9.0 (SAS Institute Inc., Cary, NC, USA) with statistical significance determined when $p \leq .05$. All summary data are presented as means (SD).

Results

All main and interaction effects of *Data set*, *Classifier*, and *Task* were significant for precision ($p < 0.0001$) and recall values ($p < 0.0001$). A summary of precision and recall values is illustrated in Figure 9 and 10, in which it is evident that task classification performance varied substantially with input data sets, classifiers, and tasks. Two specific input data sets, PELV+IPM and IPM, generally led to the worst performance, and MFNN classifiers appeared to perform relatively worse than the other two algorithms. Overall, the highest precision/recall values achieved were 93% / 80% for Lifting_{GROUND}, 87% / 83% for Lifting_{KNUCKLE}, 95% / 91% for Lowering_{GROUND}, 87% / 77% for Lowering_{KNUCKLE}, 93% / 89% for Pushing, 91% / 87% for Pulling, 89% / 95% for Carrying, and 89% / 79% for Walking.

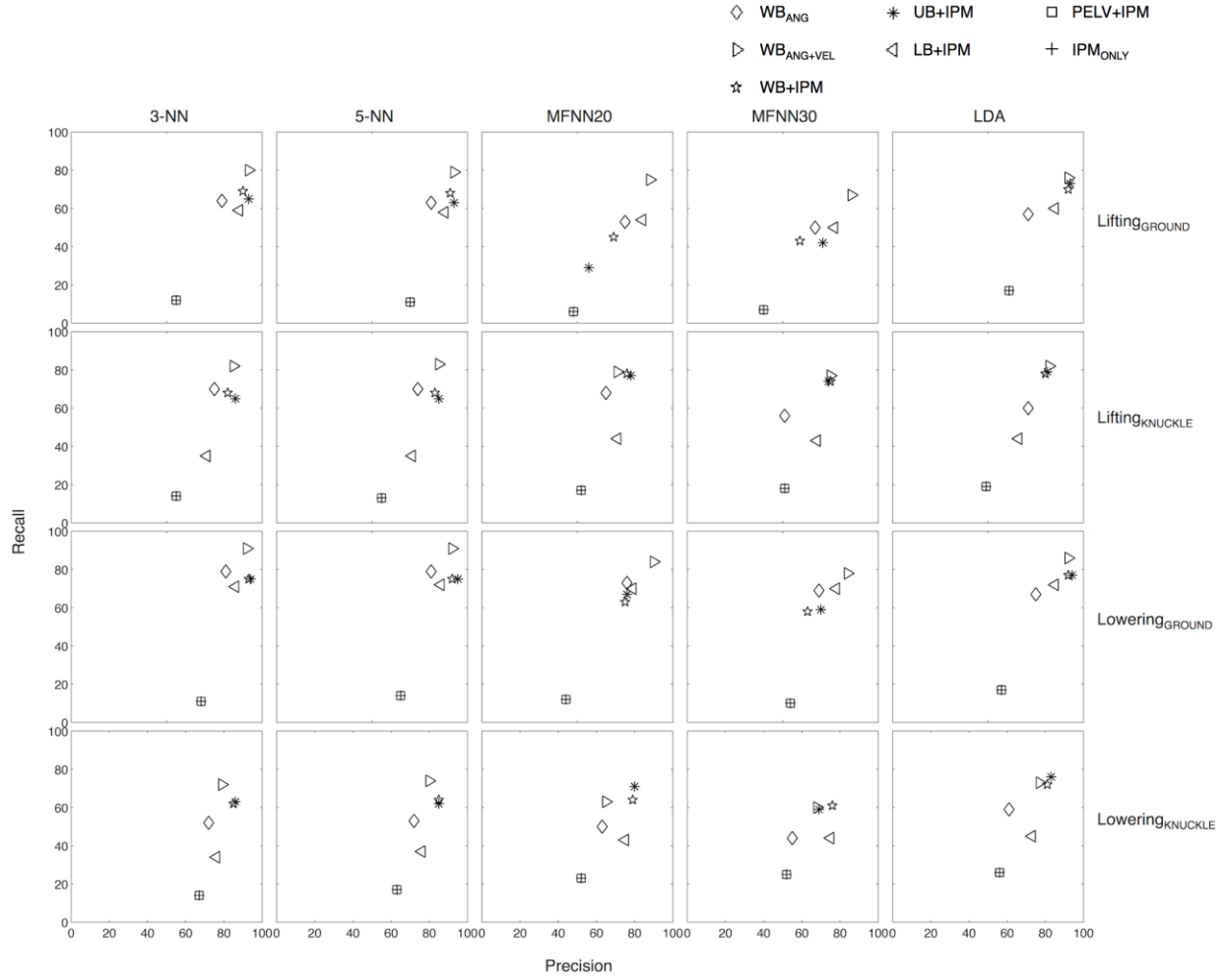


Figure 9. Precision/recall plots for each input data set, MMH-task classifier, and task type (Lifting from/Lowering to the ground or knuckle height). Please see the methods for detailed descriptions of the input data sets (WB_{ANG} , $WB_{ANG+VEL}$, $WB+IPM$, $UB+IPM$, $LB+IPM$, $PELV+IPM$, and IPM_{ONLY}). NN is nearest neighbor, MFNN20 and MFNN30 are multilayer feedforward neural networks with hidden layer size = 20 and = 30, and LDA is linear discriminant analysis.

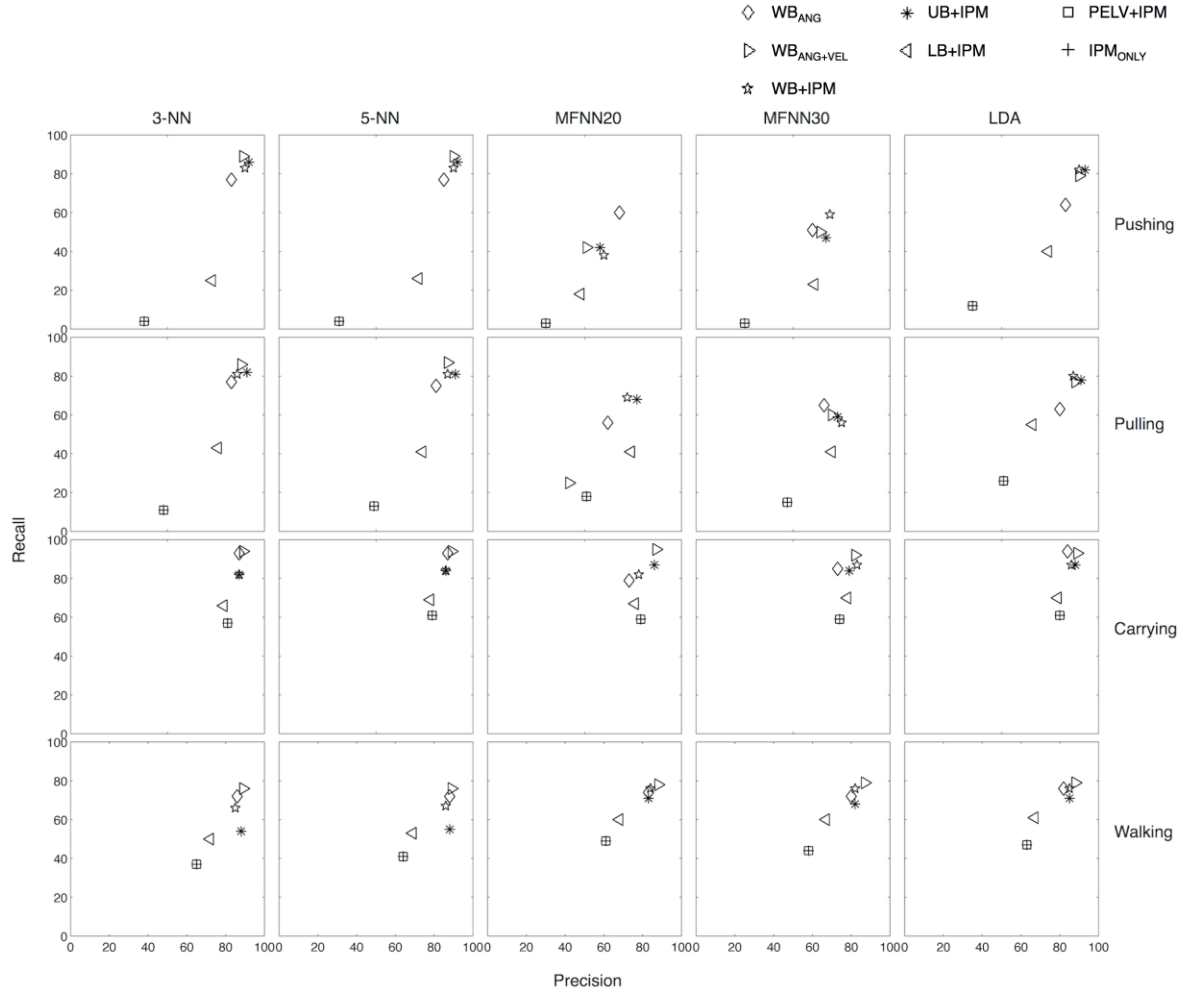


Figure 10. Precision/recall plots for each input data set, MMH-task classifier, and task type. The task types presented are Pushing, Pulling, Carrying, and Walking.

Percentage differences in the time proportions of MMH tasks are summarized in Table 7, for three selected input data sets ($WB_{ANG+VEL}$, $WB+IPM$ and IPM_{ONLY}) with 5-NN, MFNN20 and LDA classifiers. The time proportion for a given task, as derived from a classifier appears, to be typically underestimated.

Table 7. Summary [mean (SD)] of percentage differences in the time proportions of MMH tasks estimated using MMH-task classifiers, compared to “ground truth” time proportions from direct observations. Note 5-NN, MFNN20, and LDA respectively indicate 5-nearest neighbor, multilayer feedforward neural network with the hidden layer size = 20, and linear discriminant analysis. WB_{ANG+VEL} data set is whole body joint angles and angular velocities, WB+IPM is whole body joint angles and IPM pressure outputs, and IPM_{ONLY} is IPM pressure outputs.

	5-NN			MFNN20			LDA		
	WB _{ANG+VEL}	WB+IPM	IPM _{ONLY}	WB _{ANG+VEL}	WB+IPM	IPM _{ONLY}	WB _{ANG+VEL}	WB+IPM	IPM _{ONLY}
Lifting _{GROUND}	-14.2 (17.4)	-24.0 (24.0)	-50.6 (24.1)	-12.7 (21.5)	-47.6 (36.7)	-49.62 (32.2)	-17.3 (21.7)	-23.8 (12.42)	-50.9 (24.1)
Lifting _{KNUCKLE}	-1.1 (19.0)	-17.0 (19.0)	-63.0 (17.0)	10.8 (34.1)	4.8 (21.9)	52.8 (22.5)	2.9 (20.6)	-1.4 (19.0)	-40.6 (23.2)
Lowering _{GROUND}	0.8 (17.5)	-17.8 (16.5)	-61.7 (18.5)	-4.6 (19.2)	-21.0 (36.6)	-52.3 (31.5)	-3.8 (22.1)	-14.8 (15.8)	-50.9 (22.8)
Lowering _{KNUCKLE}	-7.2 (26.3)	-25.2 (18.1)	-53.1 (31.9)	-2.7 (41.2)	-22.3 (24.5)	-38.5 (39.2)	-2.9 (30.2)	-11.0 (20.2)	-41.8 (25.9)
Pushing	2.7 (26.2)	-6.9 (20.5)	-40.8 (57.4)	-34.3 (62.9)	-55.6 (42.9)	-58.7 (38.5)	-9.8 (25.2)	-6.0 (22.9)	-36.5 (33.6)
Pulling	2.4 (27.9)	-4.2 (24.1)	-32.1 (60.9)	-69.5 (36.8)	3.5 (40.4)	-34.7 (50.4)	-11.4 (17.4)	-4.1 (27.3)	-10.4 (64.9)
Carrying	7.5 (16.8)	-0.3 (18.9)	-3.9 (35.5)	11.6 (19.3)	-1.3 (32.6)	-12.4 (33.1)	5.8 (15.7)	1.5 (17.1)	-12.4 (33.1)
Walking	-13.9 (20.7)	-22.5 (19.3)	-35.6 (24.7)	-9.6 (22.4)	-9.4 (18.5)	-19.9 (27.7)	-8.5 (20.2)	-10.0 (18.3)	-17.9 (29.9)

Discussion

This study explored the potential use of two commercially-available portable measurement (IMU and IPM) systems for exposure assessments in the field. To extract contextual information (i.e., task types and their time proportions) during the simulated job, five different MMH-task classifiers were developed to automatically classify MMH tasks, and each was used with seven different combinations of IMU and/or IPM output time series as inputs. Depending on the specific MMH-task classifier, precision and recall values could be $\geq \sim 87\%$ and $\sim 79\%$ across the MMH tasks, and the percentage difference in estimated time proportion for an MMH task were up to $\sim 14\%$ (Table 10).

That the performance in task classification depended on the specific input data sets, classification algorithms, and task types (Figure 9 and 10) has been similarly demonstrated in existing studies

(e.g., Altun *et al.*, 2010; Blanke & Schiele, 2009; Gyllensten & Bonomi, 2011; Ogris *et al.*, 2008; Pärkkä *et al.*, 2006). These studies reported classification precision of ~30% to ~99%, and it indicate that a lower precision is associated with fine-motor and/or complex tasks (e.g., check hood gaps, preparing food, walking while carrying an object), and tasks performed in less-controlled environments (e.g., outside of a laboratory). In the present study, participants performed the sequences of MMH tasks in self-selected, comfortable styles, while being allowed to move freely during rest periods. Given this minimal control, the precision and recall values of ~87% and ~79% achieved across all MMH tasks, therefore, support the potential use of these portable measurement systems in the field, to collect not only numerically detailed exposure data but also contextual information of a job. Moreover, having both detailed and contextual information could enhance task-based exposure assessment, in that task characteristics (e.g., measurement outputs, task durations) can be functionally related to task exposures, as discussed by Mathiassen *et al.* (2005), and task proportions can be monitored continuously without additional labor costs. The latter is particularly important in practice, since inaccurate information on task proportions is an important error source for task-based exposure estimation (Mathiassen *et al.*, 2005), and labor costs are a major factor in observational posture assessment methods (Rezaghali *et al.*, 2012).

Considering that the current study was exploratory in nature, there exists room for improving the performance of MMH-task classifiers. First, feature extraction and selection methods affects the performance of classification (Jiménez-Rodríguez *et al.*, 2007; Preece *et al.*, 2009b). While we used several descriptive statistics to characterize input data in a sliding window, more informative features could be derived from the frequency (e.g. fast Fourier transform components) or the time-frequency domains (e.g., wavelet parameters), as reviewed by Preece *et al.* (2009b). For example, two of the input data sets, PELV+IPM and IPM_{ONLY}, resulted in almost the same classification performance (Figures 9 and 10), suggesting that the pelvis angles provided limited additional information to MMH-task classification. Alternatively, it may be that the relevant information regarding pelvis angles for classification was not effectively extracted by the descriptive statistics. Further, for effective classification, an optimal set of features can be selected using heuristic approaches (Dash & Liu, 1997); these include sequential forward selection, sequential backward selection, and cross validation, or dimension reduction

techniques (Preece *et al.*, 2009a) such as principal component analysis, and independent component analysis. Second, the performance of k -NN and MFNN can be improved by selecting the number of nearest neighbors and the hidden layer size heuristically. Particularly in this study, the MFNN generally performed poorer than other algorithms (see Figure 9 and 10), and which may be due to an inadequate hidden layer size. Third, more modern classification algorithms can be explored such as Bayesian decision making, support vector machines, and hidden Markov models. Though modern algorithms do not necessarily lead to better classification performance, existing studies (Altun *et al.*, 2010; Liu *et al.*, 2011; Preece *et al.*, 2009b) have demonstrated that modern algorithms can outperform conventional classification algorithms.

This study explored using two commercially-available portable systems to classify MMH tasks during a simulated job. While the performance in task classification varied with input data sets, classification algorithms, and task types, the results overall indicate that precision and recall values of $\geq \sim 87\%$ and $\sim 79\%$ could be achieved across the diverse MMH tasks. This, along with additional results indicating that the time proportion for an MMH task in a job can be estimated using an MMH-task classifier, supports the potential for using the portable measurement systems during *in situ* exposure assessments. Specifically, using the portable measurement systems with an MMH-task classifier has been argued to improve the performance of a task-based exposure assessment. However, as discussed above, more efforts should be made to improve classification performance using different feature extraction and selection methods, and/or modern classification algorithms. To facilitate easy use of portable measurement systems in exposure assessments, future work is also needed to develop MMH-task classifiers for a population, not for an individual (as in the current study), and to evaluate such classifiers with actual worker data obtained in the field.

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Chapter 5: Conclusions and recommendations

Work-related musculoskeletal disorders (WMSDs) are an important health concern in the workplace. These disorders account for ~30% of all lost work days (BLS, 2010; 2011) and have substantial associated costs (Liberty Mutual, 2012). How changes in the levels of exposure to work-related risk factors affect the risk of adverse health outcomes should be understood, to help more effectively control and prevent WMSDs. To find and understand such relationships, exposure data need to be obtained in the workplace, so that a comprehensive range of actual exposures that workers undergo can be captured. However, quantifying exposures to physical risk factors (e.g., non-neutral postures, high forces/moments) has been considered to be challenging in various work places, and improvements are clearly needed (Burdorf *et al.*, 1997; Garg & Kapellusch, 2009; Marras *et al.*, 2009).

With a long-term goal of facilitating direct quantification of physical exposures in the workplace, this dissertation provided groundwork through basic investigations using two wearable (portable) measurement systems – an inertial motion capture (IMC) system and in-shoe pressure measurement (IPM) system. As reviewed in Chapter 1, the IMC and the IPM systems are emerging wearable sensor technologies that could, respectively, facilitate monitoring of whole body kinematics and external forces applied to the body (i.e., ground reaction forces) in actual work settings. Two laboratory-based studies were designed and completed to:

- assess the measurement performance of the IMC system during several manual material handling (MMH) tasks against an optical motion capture (OMC) system (“gold standard”).
- address two practical concerns when using the IMC and the IPM systems. These are calibrating the IPM system without an OMC system outside of a laboratory, and automatically extracting descriptive information of a job (e.g., task type, duration) from quantitatively detailed outputs of the portable measurement systems (i.e., MMH-task classification). Potential application of the latter in task-based exposure assessments was also discussed.

Summary of Major Results

Performance of a commercially-available IMC system in exposure assessments

To quantify physical exposures (e.g., joint kinematics, moments), one needs some combination of body kinematic and/or external kinetic data. These can be monitored with high accuracy and precision, using mature technologies such as an OMC system and force platforms. Such technologies, however, are rather non-portable, and not especially flexible or configurable for use in actual work settings. As such, use of an OMC system and force platforms are typically limited to laboratory settings. In fact, few studies (Faber, Kingma, Delleman, & van Dieën, 2008; Marras *et al.*, 1993; Morlock *et al.*, 2000; Norman *et al.*, 1998) have obtained detailed kinematics and/or kinetics *in situ*.

Wearable sensor technologies, such as IMC systems, have been widely explored as an alternative for monitoring body kinematics in actual (field) settings, though primarily in more basic, clinical and sports-related research (e.g., Cutti *et al.*, 2007; Favre *et al.*, 2008; Goodvin *et al.*, 2006; Luinge *et al.*, 2007). Therefore, we evaluated the measurement performance of an IMC system in terms of quantifying physical exposures during five different MMH tasks repeated over an extended (2 hour) time period (Chapter 2). Stability in performance over time was a particular interest, since non-routinized jobs often require prolonged observations to describe exposure variability (Gold *et al.*, 2006; Paquet *et al.*, 2005). Estimated joint kinematics (i.e., joint angles and angular velocities) and the resulting joint moments at selected body parts were evaluated, by comparison with an OMC system.

Based on the results obtained, the IMC performance was generally stable over time, although there existed some significant but minor changes in performance (e.g., the magnitude of performance changes for joint angles over time was $\leq \sim 3.6^\circ$). Moreover, the accuracy of kinematics captured by the IMC system varied, in some cases substantially, across different MMH tasks, and this variability was generally consistent with the movement characteristics involved for different tasks (cf. Tables 1 and 2). Specifically, if a task involved relatively large movements about a given axis and joint, kinematic and kinetic errors for this axis/joint were typically relatively large. The IMC system yielded peak kinematic values that differed by up to 28% from the OMC system. The IMC system, in some cases, incorrectly reflected the actual

extremity positions of a participant, and which can cause relatively large errors in joint moment estimation. Therefore, though caution is needed when using the IMC system in exposure assessments, the IMC system seems to have a reasonable capacity to monitor whole body kinematics in the field for a prolonged period.

Application of an IPM system in exposure assessments

Force platforms are a typical measurement technology to capture ground reaction forces (GRFs) and moments, and which are often required to quantify physical exposures (i.e., lower-extremity and low-back joint kinetics). However, and as noted in several studies (e.g., Savelberg & de Lange, 1999; Veltink *et al.*, 2005), using force platforms in actual work settings can be challenging, since the platforms need to be fixed in the floor or other structures, and their size, placement, and/or available quantities can limit the foot placement of an individual.

As noted in Chapter 3, an IPM system measures the plantar pressure distribution below the foot sole (i.e., only vertical loading is registered). Thus, such vertical loading and center-of-pressure (COP) locations estimated from the pressure distribution need to be functionally related to 3D GRFs (and frictional moment if needed) and COP locations captured by the force platform under the shoe (Forner-Cordero *et al.*, 2004; Fradet *et al.*, 2008; Rouhani *et al.*, 2010; Savelberg & de Lange, 1999). More importantly, to calculate joint kinetics, the IPM system should be spatially synchronized with a motion capture system to calculate joint kinetics. Thus, to use the IPM system in exposure assessments, there exists a need for a field-based approach to spatially synchronize the IPM system with an ambulatory motion capture system, and also a need to estimate 3D GRFs and COP locations.

To address such needs, we introduced *ad hoc* global coordinate systems for the IPM and the motion capture system that were defined using anatomical landmarks of a foot (Figure 4). Further, three different regression methods were explored to estimate GRFs, and COP locations during several MMH tasks. For each task, the performance of the IPM system was compared with data from force platforms (“gold standard”), using three comparative measures of errors obtained in 3D GRFs, COP, and resulting 3D lumbosacral (L5/S1) joint moments. Errors varied significantly with the regression method and MMH task (see Tables 4-6). Only the vertical

component of GRFs and the sagittal L5/S1 moment showed relatively small errors – for example the vertical GRF estimated using a least squares method yielded < ~4% errors in peak values – while other components showed relatively larger errors. Thus, the results suggested a need for improving the quality of COP and shear GRFs estimates using IPM outputs during MMH tasks.

Evaluation of task-classification methods using wearable technologies

Portable measurement systems potentially provide physical exposure data that is as “fine-grained” as laboratory-based systems (i.e., optical motion capture systems and force platforms). However, lacking from these portable systems is contextual information of a given job, including aspects such as what tasks are performed, when, how frequently, and if/how exposures changes over time for a given task, etc. For example, task types and their time proportions for a given job are required to estimate task-based job exposures. Related to this, using both an observational method and a direct measurement system has been suggested to provide more complete exposure data than either alone (Juul-Kristensen *et al.*, 2001; Teschke *et al.*, 2009; Wells *et al.*, 1994). However, using both systems is more costly, time consuming, and resource demanding than using either alone.

Task classification is a data mining technique that often uses information yielded by wearable sensors to automatically recognize varying levels of human behaviors, and which has been an active and fast growing research area as wearable sensor technologies advance. Largely in the fields of healthcare-related research and pervasive computing, different types of wearable sensors (e.g., accelerometer, gyroscope, IMU) have been used successfully to classify daily activities (Allen *et al.*, 2006a; Ermes *et al.*, 2008; Pärkkä *et al.*, 2006). Since MMH tasks are high-level behaviors, one can presume that task classification can be used to recognize MMH tasks performed in the workplace, so as to provide contextual information about a job (e.g., task types and their time proportion) without additional labor costs.

In Chapter 4, we thus examined the potential of using the IMC and the IPM systems for classification of MMH tasks during a simulated job (Figure 6). Seven different combinations of IMC and/or IPM output time series were explored as inputs to a task classifier, while five different MMH-task classifiers were developed using three different conventional classification

algorithms (i.e., k -nearest neighbor, multilayer feedforward neural network, and linear discriminant analysis). Depending on the specific MMH-task classifier, the results suggested that precision and recall values achieved can be $\geq \sim 87\%$ and $\sim 79\%$ across the MMH tasks (Figures 9-10), and that the percentage difference in an estimated time proportion for an MMH task can be $\leq \sim 14\%$. Such outcomes suggest that using portable measurement systems with MMH-task classifiers could be viable for task-based exposure assessments.

Suggestions for future research

The current research has addressed some basic concerns, and sought to facilitate more effective and efficient assessments of physical exposures in actual work settings. The results have demonstrated the potential of portable measurement systems as useful alternatives not only to laboratory systems (Chapters 2-3), but also to direct observation (Chapter 4), although the measurement performance of portable measurement systems still needs improvement in some cases. Indeed, improving the performance of portable measurement systems (e.g., IMUs) has been an active research topic in other domains (Brodie *et al.*, 2008; Finch *et al.*, 2011; Jiang *et al.*, 2012; Luinge *et al.*, 2007; Schepers *et al.*, 2010). Thus, in parallel to this, we see that future efforts need to be directed toward potential practical issues in using the portable measurement systems, and a comprehensive understanding of the level, patterns, and pathways of physical exposures in “real” work environments. Some specific suggestions are:

- Improve regression model(s) for COP and GRFs estimation using IPM outputs, and MMH-task classifiers. A few conventional regression and classification models were explored with suboptimal model parameters, to assess the potential of COP and GRFs estimation with the *ad hoc* global coordinate system approach (Chapter 3), and task classification for MMH tasks (Chapter 4). Thus, to improve model performance, more systematic studies should be performed to select optimal models and their parameters for work-related tasks.
- Minimize/eliminate the training phase for regression models used for COP and GRFs estimation and MMH-task classifiers. In Chapters 3 and 4, models trained were participant-specific (i.e., intra-participant training), so that these models are not directly applicable to other individuals. This intra-participant training could be time-consuming or/and challenging in some workplaces. To address this, the studies of Chapter 3 and 4

can be extended to incorporate inter-participant training – training based on data from other individuals. Alternatively, and to minimize the need for training data collection in the workplace, an adaptive training approach could be explored, which updates the pre-trained models using a small set of participant-specific data (Allen *et al.*, 2006b).

- Investigate detectable differences in physical exposures measured in various work environments. The measurement performance of the IMC and the IPM systems was assessed, compared to laboratory systems (Chapter 2 and 3). This approach provided a basic understanding of the performance of the systems during several MMH tasks. However, in practice, one often needs to assess changes in the level of exposures, such as those associated with modifications in work environments and strategies (e.g., shift schedule, physical changes in workstation, use of team MMH, etc.). Therefore, a series of studies needs to be conducted to understand the measurement sensitivity of the IMC and the IPM systems to modified work environments and strategies, in terms of changes in physical exposures.
- Investigate time-related aspects of physical exposures. Time is an important factor in exposure assessments (Krajcarski & Wells, 2011; Wells *et al.*, 2007), and the time variation and duration of physical exposures typically requires considerable resources to capture (Krajcarski & Wells, 2011). Use of wearable portable measurement systems can enable monitoring of physical exposures in the workplace for extended periods. Such an application could help in understanding potential differences in time-related exposure changes between different work groups (e.g., novices vs. experienced, healthy vs. unhealthy, etc.), and which would be of benefit for designing effective and/or targeted training and ergonomic intervention programs. In addition, prolonged monitoring of physical exposures in the workplace could, ultimately, help in developing more detailed dose-response relationship.

Overall conclusions

This research sought to contribute to bringing more efficient and effective assessments of physical exposures to the workplace. As a whole, the results demonstrated the potential for using wearable technology (i.e., IMC and IPM systems) to collect both detailed and descriptive information regarding physical exposures, and to do so *in situ*. It is expected that with further

research and development we will be able to better control and prevent WMSDs, specifically by understanding better the relationships between physical exposures and health outcomes and by developing targeted training/interventions.

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Appendix A: Informed Consent Form

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

Informed Consent for Participants in Research Projects Involving Human Subjects

Title of Project: A Decision Support System for Ergonomic Construction Design

Investigators: *Dr. Maury Nussbaum, Dr. John Shewchuk, Dr. Michael Agnew, Mr. Sunwook Kim, Mr. Bochen Jia, Ms. Courtney Haynes, and Mr. Sourish Sarkar.*

I. Purpose

The long-term goal of our work is to improve the productivity and safety of residential building construction using prefabricated (panelized) walls. To this end, we have developed a prototype software system that allows panel designer, manufacturers, and builders to proactively improve process efficiency and quantify and reduce the physical demands on construction workers using panels. The purposes of the current work, in which you have been asked to participate, are to obtain input to help us refine and improve the system, based on assessing the physical demands involved in a wide range of manual material handling tasks (lift, lower, carry, pull and push).

II. Procedures

The study will take place in the Industrial Ergonomics and Biomechanics Lab, in the Department of Industrial and Systems Engineering. Upon arriving, you will be briefed of the study protocol, asked if you have any further questions, and asked to review and sign this informed consent form.

Prior to the experiment, several non-invasive position sensors will be placed on your body using double-sided tape, along with sensors to measure the levels of activity of certain muscles. The experimental session will be videotaped to help the investigators analyze your movement patterns during the experiment.

Prior to the actual experiment, in a preliminary session, you will be given a full description on manual material handling tasks. You will then be given practice in performing these tasks until you feel you can do them comfortably. You may also be asked to perform several strength tests, so that we can determine the capacity of your low back muscles. This preliminary session is expected to take about ½ hour. In the main portion of the experiment, you will be asked to attend additional session(s), during which we'll ask you perform the manual material handling tasks you practiced earlier. While doing so, we will record measures of your postures, motions, muscle activity, and your perceptions of the physical demands in different body regions. We will also ask you to provide a numerical rating of the level of physical effort you perceive during each task. Each session is expected to take approximately 3-4 hours to complete.

It is important for you to understand that we are not evaluating you or your performance in any way. You are helping us to collect data that will be used to estimate physical behaviors and loads on the musculoskeletal system during several common occupational tasks. Results from this may help in the future to improve the design of such tasks or for training purposes. Any tasks you perform, or opinions you have, will only help us do a better job. Therefore, we ask that you perform normally and be as honest as possible. The information and feedback that you provide is very important to this project.

III. Risks and Benefits

There are minimal risks to you from participating in this study, which include:

- 1) minor muscle strain resulting from the experimental tasks (pushing/pulling and repetitive lifting/lowering).
- 2) delayed onset muscle soreness, in the 24-48 hours following the experiment.
- 3) minor skin discomfort from surface marker attachment.

Participants in a study are considered volunteers, regardless of whether they receive payment for their participation. Under Commonwealth of Virginia law, workers compensation does not apply to volunteers. Appropriate health insurance is strongly recommended to cover these types of expenses.

This research project will quantify the physical demands occurring during common residential construction tasks. This information may have future benefit in identifying safe working methods and/or the development of worker training methods. While this research may yield such benefits, no promise or guarantee of benefits will be made to participants. Participants may contact the investigators listed at the end of Consent Form to inquire about the results and conclusions of this research.

IV. Extent of Anonymity and Confidentiality

Participant's personal information and identity will be kept in the strictest of confidence. A coding system will be used to associate their identity with individual's data. The list associating names with answers will be destroyed one month after completion of data collection. Photographing or videotaping might occur for assisting in the assessment of participant's postures. However, any images used in documentation will have faces blacked out to maintain confidentiality. All individual information will be collected in a file and locked when not being used, and experimental data will be stored in password-secured computers. Only the investigators have access to the data. It is possible that the Institutional Review Board (IRB) may view this study's collected data for auditing purposes. The IRB is responsible for the oversight of the protection of human subjects involved in research.

V. Informed Consent

You will receive two informed consent forms to be signed before beginning the experiment; one for your records and one for the experimenter's records.

VI. Compensation

You will be compensated for your participation at a rate of \$10 per hour, and with an additional \$10 if complete all sessions. Compensation will be limited to time spent in the experimental session (e.g., you will not be compensated for your travel to or from the study). Your total payment will vary, depending on the duration required, but the total compensation will be approximately \$75.

VII. Freedom to Withdraw

You are free to withdraw from this study at any time without penalty or reason stated, and no penalty or withholding of compensation will occur for doing so. If you choose to withdraw, you will be compensated for the portion of time of the study for which you participated. Furthermore, you are free not to answer any questions or to decline to respond to experimental situations without penalty. There may be circumstances under which the investigator may determine that the experiment should not be continued. In this case, you will be compensated for the portion of the project completed.

VIII. Approval of Research

The Department of Industrial and Systems Engineering has approved this research, as well as the Institutional Review Board (IRB) for Research Involving Human Participants at Virginia Tech.

IX. Participant's Acknowledgments

Check in the box if the statement is true:

- ☐ I have U.S citizenship.
 - ☐ I am not under the influence of alcohol or drugs.
 - ☐ I have no current or recent (past year) musculoskeletal problems (the experimenter will discuss this with you).

X. Participant's Responsibilities

I voluntarily agree to participate in this study. I have the following responsibilities:

1. To read and understand the aforementioned instructions
2. To answer questions, surveys, etc. honestly and to the best of my ability
3. Be aware that I am free to ask questions or terminate participation at any point time

XI. Participant's Permission

I have read and understand the Informed Consent and conditions of this research project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent for participation in this project.

If I participate, I reserve the right to withdraw at any time without penalty. I agree to abide by the responsibilities noted above, to the best of my ability, or to inform the investigators if I am unable to comply with these.

Participant's Signature	Date
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Experimenter's Signature	Date
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Should I have any pertinent questions about this research or its conduct, and research subjects' rights, and whom to contact in the event of a research-related injury to the subject, I may contact:

<u>Sunwook Kim</u> Investigator	<u>540-231-6656/ sunwook@vt.edu</u> Telephone/e-mail
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<u>Dr. Maury A. Nussbaum</u> Faculty Advisor Professor Department of Industrial and Systems Engineering 521 Whittemore Hall (0118) Blacksburg, VA 24061	<u>540-231-6053/ nussbaum@vt.ed</u> Telephone/e-mail
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<u>David M. Moore</u> Telephone/e-mail Chair, Virginia Tech Institutional Review Board for the Protection of Human Subjects Office of Research Compliance 2000 Kraft Drive, Suite 2000 (0497) Blacksburg, VA 24061	<u>540-231-4991/moored@vt.edu</u>
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**Appendix B: Training data fit of the regression methods (using IPM outputs)
to center of pressure locations, ground reaction forces, and resulting L5/S1
moments**

Table 8. Summary statistics [mean (SD)] of the training-data fit of center of pressure locations. Note, the subscripts X and Y indicate the direction of the laboratory coordinate system: positive x-axis rightward and y-axis forward. For each trial, participants initially stood along the x- and y-axis, while facing in the positive y direction. The units for the mean absolute error (MAE) and the absolute error at the peak (AEP) are mm, whereas the index of agreement (IOA) ranges from -1 to 1.

	LL _{GROUND}		LL _{KNUCKLE}		LL _{ASYM}		PushPull	
	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}
MAE _X	7.6 (1.3)	10.1 (3.5)	5.4 (1.3)	5.2 (2.6)	30.6 (24.7)	31.5 (26.3)	7.2 (1.1)	5.6 (3.4)
MAE _Y	5.4 (1.2)	14.5 (2.5)	3.9 (1.1)	13.9 (3.1)	32.3 (27.0)	36.8 (28.0)	5.5 (1.2)	21.2 (4.3)
AEP _X	8.8 (6.5)	10.0 (8.1)	5.2 (2.2)	2.5 (5.8)	7.5 (2.8)	3.3 (5.9)	6.9 (2.6)	5.1 (7.4)
AEP _Y	3.6 (7.3)	4.5 (12.6)	3.1 (5.6)	10.1 (11.5)	6.1 (4.9)	6.7 (8.7)	5.5 (8.0)	13.2 (10.2)
IOA _X	0.4 (0.3)	0.2 (0.3)	0.2 (0.4)	0.1 (0.5)	0.01 (0.6)	0.05 (0.6)	0.04 (0.5)	0.4 (0.4)
IOA _Y	1.0 (0.03)	0.9 (0.06)	1.0 (0.04)	0.7 (0.13)	0.5 (0.4)	0.3 (0.4)	1.0 (0.02)	0.8 (0.06)

Table 9. Summary statistics [mean (SD)] of the training-data fit of ground reaction forces. Note, the subscripts X, Y, and Z indicate the direction of the laboratory coordinate system: positive x-axis rightward, y-axis forward and z-axis upward. The subscript T indicates the frictional moment. The units for $MAE_{X,Y,Z}$ and $AEP_{X,Y,Z}$ are Newton, and the units for MAE_T and AEP_T are Nm.

	LL _{GROUND}		LL _{KNUCKLE}		LL _{ASYM}		PushPull	
	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}
MAE_X	11.1 (6.9)	14.2 (7.8)	4.6 (2.6)	6.1 (3.4)	9.6 (2.5)	13.0 (4.3)	5.5 (2.2)	5.3 (3.1)
MAE_Y	6.6 (2.0)	7.7 (2.2)	5.0 (1.8)	4.5 (2.3)	5.7 (1.6)	7.0 (2.1)	8.6 (3.8)	11.1 (4.0)
MAE_Z	17.1 (6.7)	15.4 (4.5)	11.1 (4.9)	10.4 (3.6)	27.9 (10.9)	27.1 (9.9)	13.1 (4.7)	12.4 (4.0)
MAE_T	2.4 (1.0)	2.9 (1.5)	2.1 (1.1)	1.7 (1.0)	1.9 (0.6)	3.5 (1.5)	2.1 (0.6)	3.1 (1.5)
AEP_X	24.4 (13.1)	30.6 (13.1)	6.0 (4.6)	10.3 (6.0)	21.2 (10.6)	33.5 (14.9)	5.4 (3.5)	7.8 (6.3)
AEP_Y	19.3 (9.0)	23.6 (9.8)	11.9 (8.7)	13.3 (7.0)	8.4 (4.3)	14.4 (7.0)	23.1 (8.5)	32.8 (11.3)
AEP_Z	20.5 (12.6)	17.7 (11.8)	14.1 (11.4)	15.7 (14.3)	23.2 (18.6)	25.2 (16.6)	11.9 (8.2)	9.5 (6.3)
AEP_T	6.2 (3.0)	5.8 (4.9)	3.7 (2.1)	2.0 (2.0)	3.1 (3.1)	8.3 (3.3)	4.9 (1.7)	3.8 (3.3)
IOA_X	0.6 (0.1)	0.5 (0.1)	0.2 (0.4)	0.1 (0.4)	0.7 (0.1)	0.6 (0.1)	0.0 (0.4)	0.1 (0.4)
IOA_Y	0.6 (0.1)	0.5 (0.1)	0.3 (0.3)	0.4 (0.1)	0.7 (0.1)	0.6 (0.1)	0.7 (0.1)	0.6 (0.04)
IOA_Z	0.9 (0.1)	0.9 (0.1)	0.8 (0.1)	0.9 (0.1)	1.0 (0.03)	1.0 (0.04)	0.7 (0.1)	0.7 (0.1)
IOA_T	0.5 (0.2)	0.3 (0.3)	0.0 (0.4)	0.1 (0.4)	0.7 (0.1)	0.5 (0.2)	0.3 (0.3)	0.1 (0.4)

Table 10. Summary statistics [mean (SD)] of the training-data fit of L5/S1 moments. Note, here the subscripts X, Y, and Z indicate, respectively, the sagittal, frontal, and transverse planes of the pelvis. The units for MAE and AEP are Nm.

	LL _{GROUND}		LL _{KNUCKLE}		LL _{ASYM}		PushPull	
	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}	f_{LSQ}	f_{MFNN}
MAE _X	11.8 (3.0)	14.3 (2.8)	10.2 (3.8)	13.4 (7.1)	15.1 (4.3)	19.8 (4.0)	16.6 (5.4)	19.3 (6.8)
MAE _Y	13.0 (7.6)	16.2 (9.3)	10.2 (11.1)	12.5 (7.7)	13.8 (5.7)	24.9 (10.5)	12.0 (11.6)	13.6 (7.9)
MAE _Z	11.2 (5.0)	12.1 (7.1)	3.9 (3.8)	5.7 (2.4)	6.3 (2.4)	11.4 (6.1)	6.2 (5.3)	9.6 (3.8)
AEP _X	17.6 (12.5)	21.3 (10.9)	22.8 (10.5)	36.9 (16.9)	22.6 (20.1)	24.7 (22.4)	13.7 (8.5)	16.4 (14.0)
AEP _Y	22.5 (18.9)	27.9 (19.7)	11.5 (10.0)	18.7 (14.1)	24.6 (17.8)	29.6 (21.0)	13.4 (11.7)	13.1 (15.1)
AEP _Z	19.5 (14.1)	21.0 (12.0)	4.7 (4.0)	5.5 (3.3)	6.8 (6.6)	13.4 (9.8)	11.8 (9.0)	6.2 (4.7)
IOA _X	0.9 (0.04)	0.9 (0.1)	0.6 (0.2)	0.3 (0.4)	0.8 (0.1)	0.7 (0.2)	0.8 (0.1)	0.7 (0.2)
IOA _Y	0.5 (0.2)	0.3 (0.3)	0.3 (0.3)	0.1 (0.5)	0.8 (0.1)	0.6 (0.2)	0.4 (0.4)	0.1 (0.5)
IOA _Z	0.7 (0.4)	0.6 (0.1)	0.4 (0.3)	0.1 (0.5)	0.7 (0.3)	0.6 (0.1)	0.6 (0.4)	0.4 (0.3)