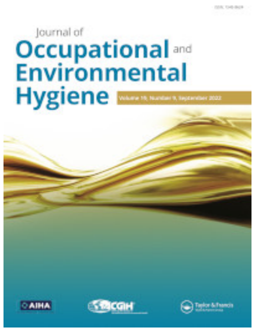

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Wearable inertial sensors for objective kinematic assessments: A brief overview

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Ergonomics; exposure assessment; inertial measurement unit; musculoskeletal disorders; sensors; wearables

Introduction

Approximately 1.71 billion people were affected by debilitating musculoskeletal disorders (MSDs) in 2019 (WHO 2021). The personal and societal burdens of MSDs are well-documented and considerable, and immediate action is needed to address their underlying risk factors (Briggs et al. 2018, 2020; Cieza et al. 2020; Wu et al. 2020). Occupational exposure to kinematic risk factors such as non-neutral postures and high movement speeds have been associated with the development of MSDs (NRC-IOM 2001; Punnett and Wegman 2004; Driscoll et al. 2014; van der Molen et al. 2017; Balogh et al. 2019). Accurately measuring worker kinematics and reducing exposure to harmful movements through intervention is one of several potential paths to preventing MSDs (Buckle and Devereux 2002; Mathiassen et al. 2015; Howard et al. 2022).

Accelerometers (a.k.a. inclinometers) emerged in the 1980s and 1990s as a preferred method for objectively quantifying some worker kinematics and estimating energy expenditure in epidemiological research (Bussmann et al. 1995; Li and Buckle 1999; Bassett 2000; Janz 2006). Measurements from accelerometers may be combined with angular velocity measurements from gyroscopes and local magnetic field information from a magnetometer to provide more accurate kinematic assessments than accelerometers alone (Luinge and Veltink 2005; Madgwick 2010). This complementary arrangement of sensors in a single device is generally known as an inertial measurement unit (IMU).

The use of IMUs in ergonomics has increased substantially in recent years, particularly among researchers (Lim and D'Souza 2020). Applications range from characterizing non-neutral postures such as extreme shoulder elevation or trunk flexion and associated movement speeds (Fethke et al. 2020; Schall et al. 2021) to classifying types of materials handling tasks (Hosseinian et al. 2019; Porta et al. 2021) to monitoring the development of fatigue based on gait kinematics and smoothness of motion (jerk) (Zhang et al. 2014; Maman et al. 2017; Baghdadi et al. 2021; Hostler et al. 2021). Readers are directed to three recent reviews that detail the applications of IMUs for ergonomic assessment (Ranavolo et al. 2018; Lim and D'Souza 2020; Stefana et al. 2021).

Occupational safety and health professionals have reported interest in using wearable IMUs to assess and monitor kinematic risk factors at work (Schall et al. 2018). Several companies sell systems of IMU sensors with proprietary software to facilitate "plug-and-play" kinematic assessment (e.g., Xsens MTw Awinda (Paulich et al. 2018); APDM Opal (Horak et al. 2011)). IMUs have also been shown to perform accurately when operated independently with open-source resources (Chen et al. 2020; Nazarahari and Rouhani 2021). Despite their potential value to organizations and the expanding body of studies supporting their efficacy, occupational safety and health professionals have reported concerns that the data provided by IMUs may be perceived as insufficiently accurate for use in their workplaces (Reid et al. 2017; Schall et al.

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2018). Their concerns may result from misconceptions regarding the fundamentals of IMU operation, a potential lack of understanding regarding how IMU systems are often evaluated, and limited familiarity with real-world applications.

This commentary paper aims to provide a brief overview of the critical principles of IMU operation for performing kinematic assessments. We intend to draw attention to resources and recommendations helpful in using IMUs to support wearable inertial sensors for objective kinematic assessment in the workplace to an audience that may be less familiar with the technology.

Principles of IMU operation

An accelerometer uses the direct current of gravitational acceleration and its projection on the axes of the accelerometer to determine the angle of inclination of an object (Fisher 2010). Accelerations other than that associated with gravity (e.g., body movements) contribute noise to the signal (Chen et al. 2018). Accelerometers are, thus, best suited for "quasi-static" kinematic assessments. Also, accelerometers cannot provide inclination information around the gravity vector (i.e., heading). Therefore, they are best used to estimate human motion in two dimensions (e.g., trunk bending and arm elevation, not for motions such as twisting).

A magnetometer, a device that measures the strength and direction of Earth's local magnetic field surrounding an object, is needed to assess heading information (Chen et al. 2018). Conceptually, a magnetometer functions as a compass in an IMU. A gyroscope measures the angular velocities of an object. The orientation of a gyroscope in three-dimensional space can be calculated by integrating the angular velocities with respect to time (Bergamini et al. 2014).

Thus, at its simplest, an IMU reports an object's orientation in three-dimensional space by using the strengths of each sensor component to compensate for the weaknesses of the other components. The gyroscope is typically used as the base measurement device, and gyroscopic drift is eliminated by fusing it with acceleration and magnetometer measurements (Yun et al. 2008; Bergamini et al. 2014; Chen et al. 2017).

Sources of IMU measurement error

When using IMUs for kinematic assessments, "accuracy" typically refers to the similarity between the output of an IMU or system of IMUs and a reference such as a "gold-standard" laboratory-based optical motion capture (OMC) system (Cuesta-Vargas et al. 2010). "Error' refers to the magnitude of disagreement in these measurements. Studies indicate that error magnitudes of IMUs vary within and across studies (Lebel et al. 2013; Schiefer et al. 2014; Robert-Lachaine et al. 2017). Variations in reported error magnitudes may be attributed to differences in the design of the IMU(s) as well as methodological differences in (i) system operation between IMUs and the reference device and (ii) empirical conditions.

IMU design

Differences in the design and manufacture of IMUs represent one source of potential disagreement in studies of IMU accuracy (Lebel et al. 2013). The differences may be attributed to the performance of the software (i.e., sensor fusion algorithm) embedded in the sensor and the quality of the component hardware (e.g., gyroscope) comprising the sensor. Nazarahari and Rouhani (2021) summarize the development of sensor fusion algorithms for orientation tracking, and Chen et al. (2020) describe considerations for modeling sensor error (i.e., biases).

Differences between IMU and OMC operation

The error between an IMU and OMC system may be quantified at the *system* and the *sensor* level (Robert-Lachaine et al. 2017). *System* error may be thought of as differences in joint angles between the OMC- and IMU-based systems when both systems are used following their recommended data collection and post-processing protocols. Error magnitudes in this context can be substantial, as the error consists of differences in how the coordinate frame of a given body segment is defined by each system and the error associated with individual sensors themselves (Robert-Lachaine et al. 2017). Alternatively, studies that assess *sensor error* represent error magnitudes of IMUs while controlling for several methodological differences. Specifically, reflective markers are attached to the IMU to control for soft tissue artifacts (e.g., relative motion between reflective markers attached directly to the skin of the body segment and IMU) (Chen et al. 2020). Furthermore, offsets between the measurement systems are calculated and applied to mitigate misalignment between the two systems.

Empirical conditions

The experimental conditions of a study can have a substantial effect on the error magnitudes reported for an IMU. These include the following:

Magnetic disturbance

Bachmann et al. (2004) and Chen et al. (2017) are helpful resources that explain the effects of magnetic disturbance on the accuracy of IMU-based measurements. Sensor fusion algorithms can detect and discard magnetometer measurements identified as erroneous (Roetenberg et al. 2005; Sabatini 2006; Ligorio and Sabatini 2016; Fan et al. 2017). Magnetic disturbances not removed quickly (i.e., on the order of seconds to a few minutes) will manifest as gyroscopic drift (Ligorio and Sabatini 2016).

Many studies take precautionary measures to control magnetic disturbance (i.e., maintaining a set distance between the system and known sources of disturbances) when evaluating the accuracy of IMUs (Kim and Nussbaum 2013; Lebel et al. 2013; Schiefer et al. 2014; Robert-Lachaine et al. 2017). However, this may limit study generalizability beyond the laboratory environment. Furthermore, the results may also be affected by unforeseen sources of magnetic disturbance (e.g., metal below the floor) (de Vries et al. 2009).

Measurement duration

Given the propensity for gyroscopic drift, measurement duration can affect error magnitudes. Bergamini et al. (2014) observed that gyroscopic drift did not have a noticeable effect until measurement timeframes exceeded 20 sec. However, deviations >25° were observed after only 2 min. When designing a data collection protocol, the duration and time resolution for analysis should be chosen considering the implications of drift.

Speed of movement

The accuracy of an IMU will be adversely affected by acceleration, which is a function of body segment lengths and movement speeds (Amasay et al. 2009). Therefore, it is expected that IMUs attached to distal segments will report higher magnitudes of sensor error with tasks requiring higher movement speeds. It should be noted that error magnitudes will differ based on the sensor fusion algorithm applied and how the algorithm leverages either the magnetometer or sensor motion to determine relative orientation and exposure metrics (Chen et al. 2017; 2018; Lee and Jeon 2019; Weygers et al. 2020; Fan et al. 2021; Nazarahari and Rouhani 2021).

Recommendations for selecting and using IMUs in the field

The selection of an IMU or system of IMUs for kinematic assessment should be based on the needs and resources of the user. It is critical to choose the sensor type and wear location appropriate for the industry and the problem of interest. The first step is to have a well-defined question to be addressed by the assessment. For example, rather than stating a general goal of exploring employees' postures and motions, a more focused objective could be framed as "what are the shoulder motions present during a specific material handling task?" Defining a straightforward question will allow for determining the duration of needed data collection and the best means for ensuring consistent sensor wear by the worker (e.g., a suit *vs.* straps *vs.* direct skin placement). Additionally, a straightforward question supports identifying what data is most relevant, how many sensors are required to get that data, how the data needs to be stored, and how the data should be aggregated for analysis.

Once the specific question is defined, the sensor or sensor system can be selected. In cases where a more complex, three-dimensional, full-body analysis is needed (e.g., critically examining a particular aspect of a job known to be of substantial risk to a worker), a commercial IMU system with an integrated software solution is likely the preferred option. The software can potentially save months of algorithm and user interface development. However, the complexity of three-dimensional analysis is also typically accompanied by the need for wireless linking of multiple sensors. Connection issues between sensors and the supporting computer system may arise and necessitate relatively short measurement durations. For example, 15–17 sensor Xsens systems have been used to measure worker motions in field environments such as banana harvesting (Merino et al. 2019), tree planting (Granzow et al. 2019), and warehouse order picking (Robert-Lachaine et al. 2020). These three studies had mean measurement durations of 5, 11.5, and 32.2 min, respectively.

The software that accompanies three-dimensional, full-body capable systems will often provide real-time motion tracking and support the extraction of multiple joint angles with high resolution. However, the outputs from most multi-sensor commercial systems are designed for research applications, and it can be challenging to analyze the data efficiently for practical implementation. On the other hand, commercial systems with fewer IMUs (one or two) may be designed with limited application to a single body segment (most typically the back) and often aggregate the data during processing without providing access to the underlying information.

Alternatively, individual IMU-based inclinometers may be preferable for coarser estimations of joint angles, such as determining the occurrence of postures that fall within extreme (e.g., back flexion $> 60°$) *vs.* neutral categories and tracking the variability of exposures over longer durations (i.e., multiple hours to days) (Schall et al. 2021). These devices will be quicker to set up, less obtrusive to the worker(s), and less expensive (Zhang et al. 2022). However, they will typically require expert knowledge to apply effectively since they may not come with a software interface for data processing and visualization.

After making the sensor selection, practical considerations remain regarding the proper sensor use to ensure quality data collection. Regardless of the IMUs selected, it is highly recommended that manufacturer specifications and/or standardized procedures be followed. Members of the Partnership for European Research in Occupational Safety and Health (PEROSH) have published guidance on best practices for measuring and interpreting IMU output for assessing several kinematic risk factors associated with MSDs, with specific publications that include recommendations for evaluating sedentary work and arm elevation (Perosh recommendations for procedures to measure occupational physical activity and workload; Holtermann et al. 2017; Weber et al. 2018). Within the guidance are factors for determining the appropriate system for measurement, the needed sample sizes, data collection durations, and metrics for assessing risk factors. Of particular interest to practitioners may be the example scenarios provided that show how wearable sensors can be applied to specific risk assessment tasks at individual and group levels (Weber et al. 2018). Applications from PEROSH members are also available for using the IMU integrated into an iPhone or Android device as a more accurate inclinometer (Yang et al. 2017; Öhberg et al. 2021).

Assuring alignment of the IMUs to the body segment of interest (Vitali and Perkins 2020) and securing the sensors to prevent shifting during data collection is a considerable challenge in field environments (Schall et al. 2021) and important to increase accuracy and aid interpretation. Aligning IMUs to the body segment is particularly necessary for individual IMU-based inclinometers that may be used to target a single joint of interest but do not have a structured shirt or another system to support proper wear location. Once placed on the worker for measurement, calibration should follow the manufacturer's recommendations if available. If not present, a series of known defined postures, with a combination of static and dynamic components, should be developed to ensure the sensors capture the intended measures. Additional calibrations may be performed throughout the assessment, particularly if the measurement duration is long, to account for the potential shifting of sensors and as a means to mark different activities or situations that occur. For example, in a study designed to assess the effects of a job rotation scheme on kinematic exposures, it may be beneficial to calibrate the sensors to the worker each time the worker rotates to a new work assignment.

The data collected from an IMU sensor can typically be streamed in real-time over a wireless (often Bluetooth) connection to a smartphone/computer or stored on the sensor. If a real-time kinematic assessment is not needed, then on-sensor storage is typically preferred to prevent data loss. The reliability of the sensor system and data quality should be investigated before deployment into a field application. Once in the field, data quality should again be investigated at the start, with a set of pilot workers using the sensors, and periodically throughout the planned data collection. Data quality assessments can be achieved qualitatively by visualizing the collected data via a live stream and comparison with observational measurements (typically recorded with video). The visualization can identify missing data and erroneous measurements (Robert-Lachaine et al. 2020). In addition, issues with comfort and interference with the work task can be identified. Furthermore, using the assumptions of constant magnetic field strength and magnetic field inclination angle at a given geographic location, magnetic disturbances can be indirectly detected if the measured magnetic field measurements exceed these thresholds (Sabatini 2006). However, to our knowledge, this has only been demonstrated under laboratory conditions thus far (Chen 2017).

When feasible, it is recommended that IMU users collect the full complement of raw sensor information possible, including the raw accelerometer, gyroscope, and magnetometer measurements. The raw data from each sensor allows for flexibility when selecting a sensor fusion algorithm in post-processing. Sensor fusion algorithms continue to improve, and many are available in open-source repositories (Nazarahari and Rouhani 2021).

Other practical considerations in sensor management are battery life and the charging process if long-term data collection is needed. With continuous data collection and wireless data transfer, many IMU systems may not have sufficient battery life for an entire work shift. Users should consider whether the sensor has visible battery and data logging status indicators to prevent data loss.

Conclusions

The research community continues to study methods to improve the accuracy of wearable inertial sensors and address gaps in knowledge affecting their practical application and interpretation of the collected data. For example, action levels for full workday median arm speeds measured using accelerometers (and conversions if using IMUs) have recently been proposed to provide specific guidance for evaluating upper arm movement speeds (Balogh et al. 2019; Arvidsson et al. 2021; Forsman et al. 2022). Others have provided recommendations for implementing wearables at work to promote the adoption of the devices among employees and proposed frameworks to facilitate organizational success (Jacobs et al. 2019; Maman et al. 2020). Although wearable inertial sensors have limitations to their application, the objective and unbiased information they provide holds tremendous potential value to organizations and researchers as objective measurements to support an increased understanding of dose-response relationships associated with MSDs. We anticipate that measurement accuracy will improve as wearable inertial sensors are used more frequently in ergonomics and our understanding of the relationship between kinematic risk factors and MSDs advances. We hope that this paper provides valuable information to encourage and facilitate further adoption of the technology and the prevention of MSDs.

Data sharing statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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