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Effects of IMU Sensor Location and Number on the Validity of Vertical Acceleration Time-Series Data in Countermovement Jumping

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EFFECTS OF IMU SENSOR LOCATION AND NUMBER ON THE VALIDITY OF VERTICAL

ACCELERATION TIME-SERIES DATA IN COUNTERMOVEMENT JUMPING

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Abstract

Many devices are available for measuring the height of a CMJ. An inertial measurement unit (IMU) measures linear acceleration, orientation, and angular velocity. As an alternative to using IMU estimates of flight time, CMJ height could be estimated by integrating the IMU time-series signal for vertical acceleration to derive CMJ take-off velocity in order to track whole-body center of mass (WBCoM) movement, yet this approach would require valid IMU acceleration data. Thus, the purpose of this study was to quantify the effects of IMU sensor location and number on the validity of vertical acceleration estimation in CMJ. Thirty young adults from a university setting completed this study. Seven IMUs were placed at the approximate center of mass of the trunk, thighs, shanks, and feet. A total of 15 WBCoM models were created from the 7 IMUs. Using the four segments of the lower body, 1-,2-,3-, and 4-segment IMU models were constructed. Root mean square error (RMSE) was estimated between the acceleration derived from each IMU model against acceleration derived from a force platform. RMSE values from the best performing 1-,2-,3-, and 4-segment IMU models were analyzed for main effects using a 1-way analysis of variance. Notably, all of the best performing models contained IMU acceleration data from the trunk. The best performing 2- and 3-segment IMU models returned significantly lower RMSE values, on average, than the 4- segment model ($p = 0.041$, $p = 0.021$, $p = 0.061$). The average RMSE of the best performing 2- and 3-segment models produced an error of 20% relative to gravitational acceleration, with this error likely to be lower when viewed within the context of specific CMJ events and peak forces. Further investigation into improving IMU technology, procedures, and data processing are needed to reduce RMSE errors to a more acceptable level of validity relative to force platform dynamometry.

Introduction

Scientists in Kinesiology often use physical tests to derive data which can be used to measure human strength, power, and fatigue. Measures of strength, power, and fatigue are critical for understanding a person's physical health and mobility, particularly as they relate to tasks of daily living. The countermovement jump (CMJ) is a common physical performance test (Jaitner et al., 2014; Rantalainen, Finni, &Walker, 2020) which is used across an array of applications to measure strength, power, and fatigue. Specifically, the CMJ can be used as an assessment for lower extremity stretch-shortening cycle (SSC) function and mechanical power (Markovic, Dizdar, Jukic, & Cardinale, 2004; Toft Nielsen, Jørgensen, Mechlenburg, & Sørensen, 2019), a monitor for neuromuscular fatigue (Patterson & Caulfield, 2010), and a benchmark to support the rehabilitation of skeletal muscle strength post-injury (Souissi et al., 2011; Holsgaard-Larsen, Jensen, Mortensen, & Aagaard, 2014). Since there is comprehensive interest in CMJ testing among researchers, clinicians, and sport practitioners, it is important that the field continues to improve the practicality, accuracy, and validity of CMJ measurement technologies.

Presently, there are many devices available for measuring CMJ performance. In lab settings, force platform dynamometry and optical motion capture are accepted as criterion devices (Aragón-Vargas, 2000; Buckthorpe, Morris, & Folland, 2012; Corazza, Mündermann, Gambaretto, & Ferrigno, 2010; Hall, Fleming, Dolan, Millbank, & Paul, 1996; List, Hitz, Angst, Taylor, & Lorenzetti, 2017; Pinto & Callaghan, 2021; van der Kruk & Reijne, 2018; Windolf, Götzen, & Morlock, 2008). These devices sample kinematic and kinetic data which when processed (i.e., integrating acceleration to obtain take-off velocity, manipulating Newton's second law to find force from acceleration and mass, etc.) provide useful information into joint rotations and ground reaction forces (GRFs). Generally, data sampled from force platforms and optical motion capture are highly accurate; however, these systems are expensive, require training to use, and are restrained by several limitations relating to the practicality of sampling data in real-world situations and environments outside of the lab. Force platforms and optical motion capture can be bulky and difficult to assemble outside of a lab setting (Aragón-Vargas, 2000; Buckthorpe et al., 2012; van der Kruk & Reijne, 2018). For example, both devices require a reliable power supply, interface with hardware such as a desktop computer and data acquisition modules, and a high level of proficiency to operate. Further, both devices normally correspond with small collection volumes which limit the nature of movement tasks that can be evaluated. This presents a barrier for capturing valid data on the linear mechanics of CMJ performance, such as the vertical displacement of the whole-body center of mass (WBCoM; e.g., CMJ height), in field/real-world situations and environments.

There are several practical technologies for measuring CMJ performance that are commonly used in the field and do not have the limitations of force platforms and optical motion capture. For instance, the Vertec (Jump USA, Sunnyvale, CA, USA), contact mats, and optoelectronic devices are much less prohibitive to use since they address the portability, economics, and ease of use concerns associated with optical motion capture and force platform dynamometry. While these devices are generally accepted to provide estimates of CMJ height outside of the lab, they do not measure vertical displacement of the WBCoM. Contact mats and optoelectronic devices, in particular, use the flight time method to estimate jump height. Flight time measurements can be accurate and valid when comparing successive jumps of the same participant; however, researchers should be cautious when comparing flight time measurements between participants. For instance, postural changes between takeoff and landing can create a significant overestimation of CMJ height (Yamashita, Murata, & Inaba, 2020).

With the recent development of microelectromechanical systems sensors, inertial measurement units (IMUs) have been made accessible for application across a broad range of human movement analyses. The IMU is an electronic device which encloses tri-axial accelerometers, gyroscopes, and magnetometers that sample linear acceleration, angular velocity, and heading relative to magnetic north, respectively. When data streams from the various sensor components are fused, IMUs can provide reasonable estimates of 2- or 3-dimensional linear acceleration and angular velocity against a global reference frame. Relative to force platforms and optical motion capture systems, IMUs are a small, portable, and affordable technology that may give a practical solution for gathering lab quality data outside of the lab setting.

There have been several investigations into the validity of estimating CMJ height using a single IMU. From these investigations, researchers have reported over- or underestimations of CMJ height (3% - 12% error) derived from IMU data using either an estimate of flight time or proprietary algorithms, when compared against force plates or video motion capture systems (Lesinski, Muehlbauer, & Granacher, 2016; MacDonald, Bahr, Baltich, Whittaker, & Meeuwisse, 2017; Manor, Bunn, & Bohannon, 2020; Skazalski, Whiteley, Hansen, & Bahr, 2018). It is suggested the measurement error could be due to changes in posture, twisting motions, the difference in the WBCoM starting and stopping positions, too much upper body movement, or too small of movements made by the participants (Lesinski et al., 2016; MacDonald et al., 2017; Manor et al., 2020; Morrow, Fortune, Kaufman, & Hallbeck, 2017; Skazalski et al., 2018).

Flight time is easily skewed by poor form in the CMJ. If a participant lands from the jump with greater flexion of lower extremity joints, this lengthens the time in between feet leaving and feet landing on the force plate, leading to an overestimation of true jump height. As an alternative to using IMU estimates of flight time to derive CMJ height, CMJ height could be estimated by integrating the IMU time-series signal for vertical acceleration to derive CMJ take-off velocity. It is important to mention that IMU estimates of jump height from take-off velocity requires the capture of valid IMU acceleration data. Thus, there is a need to investigate the validity of IMU acceleration data using vertical acceleration data from a force platform as the criterion. Within this approach, it is important to consider that data from a single IMU may not sufficiently represent the linear mechanics acting through the WBCoM. Further, the location at which the IMU is affixed to the body will affect the information that can be derived from time-series signals. Consequently, it is reasonable to suggest the linear mechanics acting through the WBCoM may be more accurately modelled through data acquired from multiple IMUs attached to body segments that are known to contribute substantially to CMJ performance (Al-Amri et al., 2018; Lapinski et al., 2019; Morrow et al., 2017; M. A. O'Reilly et al., 2017; M. O'Reilly, Whelan, Delahunt, Ward, & Caulfield, 2017).

The purpose of this study was to quantify the effects of IMU sensor locations and number on the validity of vertical acceleration estimation in CMJ. It was hypothesized that the use of seven strategically placed IMUs, as opposed to one or two, would yield the most valid IMU WBCoM acceleration data when compared against vertical acceleration acquired via a force platform. It was also hypothesized that affixing IMUs to body segments with a greater mass proportion relative to the whole-body would improve the validity of IMU vertical acceleration data.

Methods

Participants

Thirty young adults from a university setting agreed to volunteer as participants in this study (Table 1). All participants completed this study. Participants met inclusion criteria if they were between the ages of 18 and 35 years of age. They were required to self-report if they engaged regularly in sports or other moderate-to-vigorous physical activity. Participants could be recreationally active, meaning they were involved in sports and other modest physical activity; however, participants could not be strength training more than three times a month or perform aerobic activities more often than 30 minutes a day, five days per week. Participants were excluded from the study if they had a lower limb injury or surgical intervention on the lower extremity or trunk within a year prior to enrollment in the study. Participants were also excluded from the study if they reported having a musculoskeletal or neurological disorder which may have affected their ability to successfully perform maximal effort jumping. The study was approved by the university's Institutional Review Board and all participants read and signed an informed consent document prior to their enrollment in the study.

Table 1. Participant characteristics

Sex	n	Age (years)	Height (cm)	Body Mass (kg)
Female	10	21.3 (3.8)	166.1 (4.1)	67.6 (11.3)
Male	20	22.0 (2.6)	179.2 (6.4)	83.5 (17.1)

Data are reported as mean (SD).

Procedures

Participants reported to a Human Performance Laboratory for a single data collection session which lasted approximately 1 hour. Participants were affixed with seven IMUs (Blue Trident, Vicon Motion Systems Ltd, Oxford, UK). The IMUs were placed at the approximate CoM for the trunk, thighs, shanks, and feet according to the de Leva (1996) anthropometric model. The IMUs were attached directly to the skin using hypoallergenic, double-sided, motion capture tape (B&L Engineering, Santa Ana, CA, USA). To reduce movement artifacts, IMUs were secured to the trunk, thighs, and shanks by a covering sheet of Fixomull® polyurethane film (BSN medical GmbH, Hamburg, Germany). To secure the IMUs to the feet, participants were asked to wear anti-slip neoprene socks (OMgear) over the sensor.

Once the IMUs were placed, participants were provided with a visual demonstration and verbal instruction of proper CMJ technique. Participants performed three practice jumps followed by three maximal-effort CMJ performed with the feet positioned on a tri-axial force platform (Model OR6-WP, Advanced Mechanical Technology Inc., Watertown, MA, USA). The force platform was zeroed without the participant standing on the platform in between each maximal-effort CMJ. To minimize contribution of the arms, participants were asked to perform each jump akimbo (Picerno, Camomilla, & Capranica, 2011). Immediately prior to each maximal-effort CMJ, participants were given the following standard verbal cue: “After I say go, perform a jump upwards as high and as quickly as possible”. Participants were given a 1-minute rest between each maximal-effort CMJ. CMJ technique was monitored in real-time by a member of the research team. Successful CMJ trial criteria required participants to 1) jump upwards with maximal effort with both feet positioned on the force platform, 2) keep their arms in akimbo position during the jump, 3) land from the jump with both feet impacting the force platform at approximately the same time, and 4) perform the jump with no extra steps, hops, or loss of balance.

Data Acquisition

Vertical GRF data was captured from a tri-axial force plate (1000 Hz sampling rate) using a signal conditioner (Gen 5, Advanced Mechanical Technology Inc., Watertown, MA, USA) and data acquisition software (NetForce, Advanced Mechanical Technology Inc., Watertown, MA, USA). The force platform was set to collect for a time period of 10 seconds. Sampling was initiated using a manual trigger to ensure each CMJ trial was captured in full. Each IMU logged tri-axial angular velocity data from 16-bit MEMS gyroscopes (range = ±2000°s^{-1}, sampling frequency = 1600 Hz) in addition to tri-axial linear acceleration data from 16-bit low-g (range = ±16g, sampling frequency = 1600 Hz) accelerometers to internal memory. Time synchronization and IMU sampling were controlled manually using data acquisition software (Capture.U, Vicon Motion Systems Ltd., Oxford, UK) that was loaded to an iPad Pro (Apple Inc., Cupertino, CA, USA).

Data Analysis

Signal processing of vertical GRF data was conducted using a custom MATLAB® (The Mathworks Inc., Natick, MA, USA) script. GRF data was first converted to vertical acceleration using Newton's Second Law. More specifically, GRF data was converted to vertical acceleration by dividing out participant total body mass. Total body mass was also found using Newton's Second Law. Vertical acceleration data was then passed through a 4th order recursive low-pass Butterworth filter. A filter cut-off frequency of 50 Hz was selected following residual analysis optimization (Winter, 2009). Lastly, filtered vertical acceleration data was pared to begin at the initiation of the countermovement and end at the beginning of the CMJ flight phase. The timing of CMJ initiation was determined by first estimating a 5 standard deviation range around 0.5 s of static data. CMJ initiation was then defined as the time point where GRF magnitude crossed the lower-bound of the standard deviation range (Pérez-Castilla, Fernandes, Rojas, & García-Ramos, 2021). CMJ take-off was determined using a rate of GRF development method described previously (Louder, Thompson, & Bressel, 2021).

Signal processing of IMU data was conducted using a custom MATLAB® (The Mathworks Inc., Natick, MA, USA) script. For each IMU, angular velocity and acceleration data were fused using an error-state Kalman filter. The Kalman filter output an estimate of vertical acceleration aligned to the global reference frame. After aligning vertical acceleration signals to the global vertical, the signals were then passed through a 4th order recursive low-pass Butterworth filter (50 Hz cut-off frequency).

Filtered vertical acceleration signals from the IMUs were combined by weighting each signal according to segment-mass weighting coefficients adapted from de Leva (1996); Table 2-5). Vertical acceleration signals from the 4-segment (trunk, thighs, shanks, and feet) IMU model of the WBCoM were aligned with vertical acceleration signals acquired from the force platform using cross-correlation performed in MATLAB. Following signal alignment, vertical acceleration signals from the IMUs were combined into 1-, 2-, 3-, and 4-segment IMU models of the whole-body COM according to segment-mass weighting coefficients adapted from de Leva (1996); (Tables 2-5).

Table 2. Segment-mass weighting percentages for a 4-segment WBCoM IMU model

Sex	Model	Trunk	R. Thigh	L. Thigh	R. Shank	L. Shank	R. Foot	L. Foot
Male	1	52.25	17.02	17.02	5.21	5.21	1.65	1.65
Female		50.48	17.53	17.53	5.70	5.70	1.53	1.53

WBCoM = whole-body center of mass; IMU = inertial measurement unit.

Table 3. Segment-mass weighting percentages for 1-segment WBCoM IMU models.

Sex	Model	Trunk	R. Thigh	L. Thigh	R. Shank	L. Shank	R. Foot	L. Foot
Both*	2	100	-	-	-	-	-	-
	3	-	50	50	-	-	-	-
	4	-	-	-	50	50	-	-
	5	-	-	-	-	-	50	50

*Weighting percentages are equivalent across sexes. WBCoM = whole-body center of mass; IMU = inertial measurement unit.

Table 4. Segment-mass weighting percentages for 2-segment WBCoM IMU models.

Sex	Model	Trunk	R. Thigh	L. Thigh	R. Shank	L. Shank	R. Foot	L. Foot
Male	6	60.54	19.73	19.73	-	-	-	-
	7	83.38	-	-	8.31	8.31	-	-
	8	94.07	-	-	-	-	2.97	2.97
	9	-	38.29	38.29	11.71	11.71	-	-
	10	-	45.59	45.59	-	-	4.41	4.41
	11	-	-	-	37.98	37.98	12.02	12.02
Female	6	59.02	20.49	20.49	-	-	-	-
	7	81.57	-	-	9.22	9.22	-	-
	8	94.29	-	-	-	-	2.86	2.86
	9	-	37.72	37.72	12.28	12.28	-	-
	10	-	45.99	45.99	-	-	4.01	4.01
	11	-	-	-	39.43	39.43	10.57	10.57

WBCoM = whole-body center of mass; IMU = inertial measurement unit.

Table 5. Segment-mass weighting percentages for 3-segment WBCoM IMU models.

Sex	Model	Trunk	R. Thigh	L. Thigh	R. Shank	L. Shank	R. Foot	L. Foot
Male	12	54.03	17.60	17.60	5.38	5.38	-	-
	13	58.32	19.00	19.00	-	-	1.84	1.84
	14	79.22	-	-	7.89	7.89	2.50	2.50
	15	-	35.65	35.65	10.90	10.90	3.45	3.45
Female	12	52.07	18.08	18.08	5.88	5.88	-	-
	13	56.98	19.78	19.78	-	-	1.73	1.73
	14	77.73	-	-	8.78	8.78	2.36	2.36
	15	-	35.39	35.39	11.52	11.52	3.09	3.09

WBCoM = whole-body center of mass; IMU = inertial measurement unit.

In total, the combination of IMU vertical acceleration signals yielded 15 unique models of the WBCoM comprised of either 1, 2, 3, or 4 body segments. For each model, root mean square error (RMSE) was estimated between IMU vertical acceleration data and vertical acceleration data acquired from the force platform. The 1-, 2-, 3-, and 4-segment models that returned the lowest RMSE, on average, were selected for statistical analysis.

Statistical Analysis

Statistical analysis was conducted using RStudio (Version 2.1) open-source software. A 1 × 4 Analysis of Variance was used to evaluate for a main effect of segment number (1-segment IMU model × 2-segment IMU model × 3-segment IMU model × 4-segment IMU model) on RMSE. A main effect was observed between the RMSE of the models and a post-hoc analysis was performed using the Tukey HSD pairwise comparison. For all hypothesis tests, an alpha type I error threshold of $p < 0.05$ was used to determine statistical significance.

Results

Using the above methods, RMSE data for each IMU model are presented in Table 6. Models 1, 2, 7, and 13 returned the lowest RMSE, on average, and thus were included as the 1-, 2-, 3-, and 4- segment models in the ANOVA, respectively.

Table 6. Central tendency and dispersion.

Model	Segments	RMSE ($m*s^{-2}$)
1	Trunk, Thighs, Shanks, Feet	2.2 (1.1)
2	Trunk	3.0 (1.4)
3	Thighs	4.3 (1.2)
4	Shanks	9.0 (2.3)
5	Feet	15.1 (3.3)
6	Trunk, Thighs	2.2 (1.2)
7	Trunk, Shanks	2.1 (1.3)
8	Trunk, Feet	2.5 (1.4)
9	Thighs, Shanks	4.5 (1.1)
10	Thighs, Feet	4.2 (1.1)
11	Shanks, Feet	9.9 (2.4)
12	Trunk, Thighs, Shanks	2.1 (1.1)
13	Trunk, Thighs, Feet	2.0 (1.2)
14	Trunk, Shanks, Feet	2.2 (1.3)
15	Thighs, Shanks, Feet	4.7 (1.1)

Data are presented as mean (SD). RMSE = root-mean-square error.

ANOVA

There was a main effect of segment number on RMSE ($F = 6.0$, $p = 0.016$). Tukey HSD pairwise comparisons revealed that the RMSE for the best performing 1-segment IMU model was significantly greater than the RMSE for the best performing 2-segment ($p = 0.041$; Table 7) and 3-segment IMU models ($p = 0.021$; Table 7). No other significant differences were observed ($p = 0.061 – 0.999$); however, the comparison between the best performing 1-segment model and the 4-segment model approached statistical significance ($p = 0.061$).

Table 7. ANOVA Results

Model Type	Model	RMSE ($m*s^{-2}$)
4-Segment	1	2.2 (1.1)
3-Segment	13	2.0 (1.2)*
2-Segment	7	2.1 (1.3)*
1-Segment	2	3.0 (1.4)

*Significantly different from 1-Segment (Model 2; $p < 0.05$)

Discussion

The purpose of this study was to quantify the effects of IMU sensor location and number on the validity of vertical acceleration estimation in CMJ. A total of 15 unique IMU models were constructed from de Leva (1996) anthropometrics. Using acceleration acquired from a force platform as a criterion reference, it was hypothesized that IMU models comprised of acceleration data that was representative of a greater proportion of body mass relative to the whole-body (e.g. multiple body segments, body segments with larger mass proportions) would yield the most valid estimate of CMJ vertical acceleration. The results of this study partially supported this hypothesis.

Our hypothesis was based on the concept that a model representing more segments, and thus comprising a greater overall proportion of mass relative to the whole-body would better characterize whole-body acceleration and so the 4-segment model constructed from IMU acceleration data corresponding with the approximate segmental centers of mass of the trunk, thighs, shanks, and feet was expected to yield the lowest RMSE values. This was not observed in the present investigation, as the RMSE values for the best performing 2-segment (Trunk, Shanks) and 3-segment (Trunk, Thighs, Feet) IMU models did not differ statistically from the 4-segment IMU model (see Table 7). There was no significant difference in RSME values for the 4-segment model when compared against the best performing 2- and 3-segment models. Notably, significantly lower RMSE values were observed for the best performing 2- and 3-segment models, but not for the 4-segment model, when compared with the 1-segment model comprised of trunk acceleration data (see Table 7). This suggests that the best performing 2- and 3-segment models were marginally better than the 4-segment model.

The observation that a 2-segment IMU model has the potential to perform equally well against a 4-segment IMU model would simplify methods for gathering CMJ GRF data via IMUs. There is practical value in developing IMU technology so as to provide access to laboratory grade assessments in the field. Within this scope, minimizing the number of IMUs a researcher would need for application in CMJ could facilitate the efficiency and convenience of measurements collecting in field or real-world settings.

On average, RMSE values for the best performing 2-segment and 3-segment IMU models was 2.1 and 2.0 m/s^2, respectively. This can be interpreted as these IMU models having an average error of roughly 20% of the acceleration of gravity (e.g., 2/9.81) when compared against acceleration captured via a force platform. Therefore, it can also be extrapolated that these IMU models could be expected to represent CMJ GRF data within an average error of approximately 20% of body weight, given that body mass is a constant value. While the level of acceptable measurement error in instrument validity is highly contextual, a 5% IMU measurement error relative to force platform data would likely be considered acceptable by the broader research and practitioner communities. The average RMSE of roughly 20% observed in the present investigation may be viewed as too large, however, it is important to note that this error was interpreted in relation to body weight. During the CMJ, peak forces are substantially greater than body weight, which suggests that it is likely for RMSE values to be much less than 20% when viewed within the context of specific CMJ events (e.g., peak GRF).

In support of the hypothesis, IMU models including vertical acceleration of the trunk segmental center of mass tended to yield lower RMSE values. For instance, the best performing 1-, 2-, 3-, and 4-segment models all included trunk acceleration data. This is not surprising since the trunk comprises roughly 43.5% and 42.5% of overall body mass in males and females, respectively (de Leva, 1996). Within this same context, it was hypothesized that the thighs, given their proportion of overall body mass, would yield acceleration data which was important to include to the IMU models from the perspective of maximizing instrument validity. Contrary to the hypothesis, the best performing 2-segment model included acceleration data from the trunk and shanks. It is important to note the best performing models were selected based on the lowest RMSE values returned, on average. RMSE values from model 7 (Trunk, Shanks) were lower than model 6 (Trunk, Thighs) (see Table 6). Therefore, the movement of the shanks may be more beneficial to track even though the thighs contain a higher percent of body mass.

The results of the present investigation support the potential for using IMUs in place of the “gold standard” force plate when capturing CMJ data. There is practical value in using IMUs to collect valid CMJ data in field settings. IMUs are small, they are easy to transport and store, and they allow the subject to move rather than standing overtop a force platform. Yet, there is also a need to improve upon the validity of data captured from IMU sensors. There are various ways in which the validity of IMU data could be improved. One approach could be to improve upon the IMU technology currently available for application in kinesiology. Improving the technology would be achieved through minimizing systematic sensor errors such as bias, scaling, sensitivity, and nonlinearity (Martin, Groves, & Newman, 2016).

Martin et al. (2016) provides an in-depth overview of the different types of systematic (fixed) and stochastic (random) errors associated with IMUs. They found the most important error to minimize is the gyroscope bias which can be improved through static calibration. The Kalman filter, as discussed in the methods session, was used to transform the data from the IMU axes to align with the global vertical (downward acceleration of gravity). It is noted by Martin et al. (2016) that the performance of the Kalman filter degrades with greater magnitudes of systematic sensor error. This was addressed in the present investigation by conducting a static calibration of the IMUs. The simplest approach to calibration involves placing the IMUs on a table to obtain static estimates of systematic sensor error, including gyroscope and accelerometer bias and noise (Martin et al., 2016). In this study, the IMUs were calibrated by collecting static data with the sensors suspended on a planar surface that was floated on the surface of water. By using this approach to optimize the Kalman filter, the average sensor orientation error was reduced from 2.8 degrees to 1.8 degrees. Though there was a substantial drop in error, the calibration did not eliminate the error.

Lastly, this study used de Leva (1996) anthropometrics to weight IMU signals according to the mass proportions of individual body segments. These measurements were based on average measurements taken and do not relate to every participant. Fat stores and torso-to-legs ratios can skew the CoM in body segments; therefore, a more participant-specified mass proportioning method could beneficial. Perhaps a more optimal mass weighting strategy which does not follow the anthropometric norms. Methods such as DEXA scans or 3D imaging, though both of these are expensive and require training, would provide more specified measurements per participant than average CoM measurements.

There were a few limitations to this study. First, it is likely that there was movement artifact in the IMU acceleration data relating to the fat, skin, and muscle on which the IMUs are attached. While the use of the Fixomull® polyurethane film was intended to help minimize movement artifact, there may be better approaches for securing the IMUs. In the present investigation, we passed time-series data through a 4^{th} order, recursive Butterworth filter that was set to a cut-off frequency of 50 Hz. It may also be possible to develop a time-series data filter that is more suitable for removing movement artifact from IMU signals, yet this would need to be addressed through additional study.

Conclusion

The purpose of this study was to quantify the effects of IMU sensor location and number on the validity of vertical acceleration estimation in CMJ. Contrary to the hypothesis, the use of a 2-segment IMU model has the potential to perform equally well against a 4-segment IMU model, which would simplify methods for gathering CMJ acceleration data. The average RMSE of the best performing 2- and 3-segement models produced an error of approximately 20% relative to gravitational acceleration. This error is high compared to a generally acceptable 5% error margin; however, the percent error observed may be lower when viewed within the context of specific CMJ events and peak acceleration. It was hypothesized that IMUs placed over segments with a greater mass proportion relative to the whole-body would contribute most to achieving a valid estimate of vertical acceleration in comparison with the force platform. This was supported, with the trunk included as a segment in all of the best performing models. While the results of the present investigation are promising, there is a continued need to further improve IMU technology, procedures, and data processing in effort to reduce RMSE values relative to force platform dynamometry to a more acceptable level.

References

Al-Amri, M., Nicholas, K., Button, K., Sparkes, V., Sheeran, L., & Davies, J. L. (2018). Inertial measurement units for clinical movement analysis: Reliability and concurrent validity. *Sensors*, *18*(3), 719. https://doi.org/10.3390/s18030719

Aragón-Vargas, L. (2000). Evaluation of four vertical jump tests: Methodology, reliability, validity, and accuracy. *Measurement in Physical Education and Exercise Science*, *4*, 215–228. https://doi.org/10.1207/S15327841MPEE0404_2

Buckthorpe, M., Morris, J., & Folland, J. P. (2012). Validity of vertical jump measurement devices. *Journal of Sports Sciences*, *30*(1), 63–69. https://doi.org/10.1080/02640414.2011.624539

Corazza, S., Mündermann, L., Gambaretto, E., Ferrigno, G., & Andriacchi, T. (2010). Markerless motion capture through visual hull, articulated ICP and subject specific model generation. *International Journal of Computer Vision*, *87*, 156–169. https://doi.org/10.1007/s11263-009-0284-3

de Leva, P. (1996). Adjustments to Zatsiorsky-Seluyanov's segment inertia parameters. *Journal of Biomechanics*, *29*(9), 1223–1230. https://doi.org/10.1016/0021-9290(95)00178-6

Hall, M. G., Fleming, H. E., Dolan, M. J., Millbank, S. F. D., & Paul, J. P. (1996). Static in situ calibration of force plates. *Journal of Biomechanics*, *29*(5), 659–665. https://doi.org/10.1016/0021-9290(95)00109-3

Jaitner, T., Schmidt, M., Nolte, K., Rheinländer, C., Wille, S., & Wehn, N. (2014, October 24). *A wearable inertial sensor unit for jump diagnosis in multiple athletes*. icSPORTS 2014 - Proceedings of the 2nd International Congress on Sports Sciences Research and Technology Support. https://doi.org/10.5220/0005145902160220

Lapinski, M., Brum Medeiros, C., Moxley Scarborough, D., Berkson, E., Gill, T. J., Kepple, T., & Paradiso, J. A. (2019). A wide-range, wireless wearable inertial motion sensing system for capturing fast athletic biomechanics in overhead pitching. *Sensors*, *19*(17), 3637. https://doi.org/10.3390/s19173637

Lesinski, M., Muehlbauer, T., & Granacher, U. (2016). Concurrent validity of the Gyko inertial sensor system for the assessment of vertical jump height in female sub-elite youth soccer players. *BMC Sports Science, Medicine and Rehabilitation*, *8*. https://doi.org/10.1186/s13102-016-0061-x

List, R., Hitz, M., Angst, M., Taylor, W. R., & Lorenzetti, S. (2017). In-situ force plate calibration: 12 years' experience with an approach for correcting the point of force application. *Gait & Posture*, *58*, 98–102. https://doi.org/10.1016/j.gaitpost.2017.07.111

Louder, T., Thompson, B., & Bressel, E. (2021). Association and agreement between reactive strength index and reactive strength index-modified scores. *Sports*, *9*, 97. https://doi.org/10.3390/sports9070097

MacDonald, K., Bahr, R., Baltich, J., Whittaker, J. L., & Meeuwisse, W. H. (2017). Validation of an inertial measurement unit for the measurement of jump count and height. *Physical Therapy in Sport*, *25*, 15–19. https://doi.org/10.1016/j.ptsp.2016.12.001

Manor, J., Bunn, J., & Bohannon, R. W. (2020). Validity and reliability of jump height measurements obtained from nonathletic populations with the VERT device. *Journal of Geriatric Physical Therapy*, *43*(1), 20–23. https://doi.org/10.1519/JPT.0000000000000205

Markovic, G., Dizdar, D., Jukic, I., & Cardinale, M. (2004). Reliability and factorial validity of squat and countermovement jump tests. *The Journal of Strength and Conditioning Research*, *18*, 551–555. https://doi.org/10.1519/00124278-200408000-00028

Martin, H., Groves, P., & Newman, M. (2016). The limits of in-run calibration of MEMS inertial sensors and sensor arrays. *NAVIGATION*, *63*(2), 127–143. https://doi.org/10.1002/navi.135

Morrow, M. M. B., Lowndes, B., Fortune, E., Kaufman, K. R., & Hallbeck, M. S. (2017). Validation of inertial measurement units for upper body kinematics. *Journal of Applied Biomechanics*, *33*(3), 227–232. https://doi.org/10.1123/jab.2016-0120

O'Reilly, M. A., Whelan, D. F., Ward, T. E., Delahunt, E., & Caulfield, B. M. (2017). Classification of deadlift biomechanics with wearable inertial measurement units. *Journal of Biomechanics*, *58*, 155–161. https://doi.org/10.1016/j.jbiomech.2017.04.028

O'Reilly, M., Whelan, D., Delahunt, E., Ward, T., & Caulfield, B. (2017). Classification of lunge biomechanics with multiple and individual inertial measurement units. *Sports Biomechanics*, *16*. https://doi.org/10.1080/14763141.2017.1314544

Patterson, M., & Caulfield, B. (2010). A method for monitoring reactive strength index. *Procedia Engineering*, *2*, 3115–3120. https://doi.org/10.1016/j.proeng.2010.04.120

Pérez-Castilla, A., Fernandes, J. F. T., Rojas, F. J., & García-Ramos, A. (2021). Reliability and magnitude of countermovement jump performance variables: Influence of the take-off threshold. *Measurement in Physical Education and Exercise Science*, *25*(3), 227–235. https://doi.org/10.1080/1091367X.2021.1872578

Picerno, P., Camomilla, V., & Capranica, L. (2011). Countermovement jump performance assessment using a wearable 3D inertial measurement unit. *Journal of Sports Sciences*, *29*(2), 139–146. https://doi.org/10.1080/02640414.2010.523089

Pinto, B. L., & Callaghan, J. P. (2021). An appropriate criterion reveals that low pass filtering can improve the estimation of counter-movement jump height from force plate data. *Measurement in Physical Education and Exercise Science*, *25*(4), 344–352. https://doi.org/10.1080/1091367X.2021.1906253

Rantalainen, T., Finni, T., & Walker, S. (2020). Jump height from inertial recordings: A tutorial for a sports scientist. *Scandinavian Journal of Medicine & Science in Sports*, *30*(1), 38–45. https://doi.org/10.1111/sms.13546

Skazalski, C., Whiteley, R., Hansen, C., & Bahr, R. (2018). A valid and reliable method to measure jump-specific training and competition load in elite volleyball players. *Scandinavian Journal of Medicine & Science in Sports*, *28*(5), 1578–1585. https://doi.org/10.1111/sms.13052

Souissi, S., Wong, D. P., Dellal, A., Croisier, J.-L., Ellouze, Z., & Chamari, K. (2011). Improving functional performance and muscle power 4-to-6 months after anterior cruciate ligament reconstruction. *Journal of Sports Science & Medicine*, *10*(4), 655–664.

Toft Nielsen, E., Jørgensen, P. B., Mechlenburg, I., & Sørensen, H. (2019). Validation of an inertial measurement unit to determine countermovement jump height. *Asia-Pacific Journal of Sports Medicine, Arthroscopy, Rehabilitation and Technology*, *16*, 8–13. https://doi.org/10.1016/j.asmart.2018.09.002

van der Kruk, E., & Reijne, M. M. (2018). Accuracy of human motion capture systems for sport applications; state-of-the-art review. *European Journal of Sport Science*, *18*(6), 806–819. https://doi.org/10.1080/17461391.2018.1463397

Windolf, M., Götzen, N., & Morlock, M. (2008). Systematic accuracy and precision analysis of video motion capturing systems—Exemplified on the Vicon-460 system. *Journal of Biomechanics*, *41*(12), 2776–2780. https://doi.org/10.1016/j.jbiomech.2008.06.024

Winter, D. A. (2009). *Signal Processing. In bomechanics and Motor Control of Human Movement, 4th ed.* John Wiley & Sons.

Yamashita, D., Murata, M., & Inaba, Y. (2020). Effect of landing posture on jump height calculated from flight time. *Applied Sciences*, *10*(3), 776. https://doi.org/10.3390/app10030776