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Jumping towards field-based ground reaction force estimation and assessment with OpenCap

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ABSTRACT

Low-cost and field-viable methods that can simultaneously assess external kinetics and kinematics are necessary to enhance field-based biomechanical monitoring. The aim of this study was to determine the accuracy and usability of ground reaction force (GRF) profiles estimated from segmental kinematics, measured with OpenCap (a low-cost markerless motion-capture system), during common jumping movements. Full-body segmental kinematics were recorded for fifteen recreational athletes performing countermovement, squat, bilateral drop, and unilateral drop jumps, and used to estimate vertical GRFs with a mechanics-based method. Eleven distinct performance-, fatigue-, or injury-related GRF variables were then validated against a gold-standard force platform. Across jumping movements, a total of six and three GRF variables were estimated with a bias or limits of agreement <5 % respectively. Bias and limits of agreement were between 5 and 15 % for seventeen and nineteen variables respectively. Moreover, we show that estimated force variables with a bias <15 % can adequately assess the within-athlete changes in GRF variables between jumping conditions (arm swing or leg dominance). These findings indicate that using a low-cost and field-viable markerless motion capture system (OpenCap) to estimate and assess GRF profiles during common jumping movements is approaching acceptable limits of accuracy. The presented method can be used to monitor force variables of interest and examine underlying segmental kinematics. This application is a jump towards researchers and sports practitioners performing biomechanical monitoring of jumping efficiently, regularly, and extensively in field settings.

1. Introduction

Performance testing and injury-risk screening are fundamental components of athlete monitoring (Thornton et al., 2019). Performance testing provides objective feedback on athletes' physical capabilities to help design individualised training programmes (Crowcroft et al., 2020). Injury-risk screening is a proactive means to enhance athlete longevity, determine athlete adaption in response to training, and minimise the risk of injury, illness, and/or extended fatigue (Halson, 2014; Thorpe et al., 2017), and can likewise aid (p)rehabilitation strategies to accommodate individual athletes' needs. Both performance and injury-risk assessments commonly involve the examination of loading patterns during controlled jumping movements (e.g., countermovement or drop jumps), to facilitate sport-specific decision-making for coaches and athletes (Bakal et al., 2022; Bates et al., 2013; Kotzamanidis et al., 2005; Marshall and Moran, 2013).

Performance and injury-risk assessments have traditionally been performed in biomechanics laboratories. Such assessments typically use motion-capture systems and ground-embedded force platforms, which together provide a full three-dimensional kinematic and kinetic description of the musculoskeletal system during movement. However, biomechanical equipment is expensive and a need to visit dedicated biomechanics labs does not allow for frequent athlete screening and monitoring. Moreover, marker-based collections of kinematics can be time-consuming due to marker placement and post-processing procedures (Kanko et al., 2021a; Nicholls et al., 2003). Alternative solutions, such as portable force platforms, have been used as a low-cost option for day-to-day in-field performance monitoring and injury-risk screening. Portable force platforms (e.g., Force Decks, Hawkin Dynamics) can measure the external ground reaction force (GRF) during jumping and can help identify specific variables of interest – e.g., propulsive force, landing impulse, flight time and height, or duration of the propulsive and landing phases (Bishop et al., 2022; Painter et al., 2022). Although such information may be used to evaluate performance improvements

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over time or identify injury-related risk factors, force-derived variables do not allow for further analysis of the underlying kinematics that contribute to performance or injury. Methods that are low cost and field viable, and can simultaneously measure GRFs and whole-body kinematics, are thus desirable to further enhance field-based biomechanical assessments (Verheul et al., 2020).

Three-dimensional motion capture technologies have recently made rapid advances. Markerless motion capture systems for measuring kinematics, such as Theia3D (Kanko et al., 2021b), KinaTrax (https://www.kinatrax.com/), OpenPose (Cao et al., 2021), and OpenCap (Uhlrich et al., 2023), offer a viable alternative to traditional marker-based systems. These systems provide new opportunities to non-invasively capture kinematics in sport-specific settings. Recent work has shown that machine-learning can help to estimate GRF profiles during sport movements from motion capture data (Johnson et al., 2018; Komaris et al., 2019; Mundt et al., 2023). However, machine learning requires specialist knowledge to appropriately investigate the links between kinematics and changes in estimated GRF profiles. Mechanics-based methods (e.g., using Newtonian mechanics; $F = m \bullet a$), in which the direct relationship between kinematics and kinetics is used, are thus preferable for estimating GRF profiles to allow for examining the kinematic-kinetic relationship (Bobbert et al., 1991; Verheul et al., 2019a, 2019b). It is unknown, however, if markerless measured kinematics can be used to accurately estimate GRFs with a mechanics-based approach.

A mechanics-based method to estimate GRFs from markerless motion-capture data during jumping movements can 1) provide a low-cost alternative to jump testing with force platforms (i.e., the gold-standard), 2) efficiently assess within-athlete changes in performance- or injury-related GRF characteristics, and 3) allow for examining underlying kinematics. The primary aim of this study was, therefore, to validate the accuracy of GRF profiles estimated from segmental kinematics, measured with OpenCap (a low-cost markerless motion-capture system), during common jumping movements. A secondary aim was to explore the usability of the method for detecting subtle GRF differences between various jumping conditions.

2. Methods

2.1. Participants

Fifteen recreational athletes, who actively participated in various sports for a minimum of three hours per week, took part in this study (nine males and six females; age 22.4 ± 3.6 years; height 1.75 ± 0.07 m; body mass 77.9 ± 12.6 kg; sport participation 8.9 ± 4.2 h/week; experience in sport 10.1 ± 4.4 years). All athletes were healthy at the time of testing and free from any lower-limb injuries for at least six months. Prior to participating, each athlete provided informed consent and confirmed physical fitness through a physical activity readiness questionnaire. This study was approved by the Cardiff School of Sport and Health Sciences Ethics Committee (reference number: Sta-7482).

2.2. Protocol and data collection

Data collections were performed in a dedicated indoor biomechanics laboratory. On arrival, anthropometric measurements were taken for each athlete, and their sport and injury background were assessed. To determine limb dominance, athletes were asked the question: “If you would shoot a ball on a target, which leg would you use to shoot the ball?” (van Melick et al., 2017). Athletes were then verbally briefed on the movements to be performed. A short warm up of fifteen bodyweight squats repeated three times was completed before the main protocol, which consisted of countermovement jumps, squat jumps, bilateral drop jumps, and unilateral drop jumps. These movements were selected based on their common use in performance testing and/or injury-risk screening protocols. Countermovement jumps were performed by

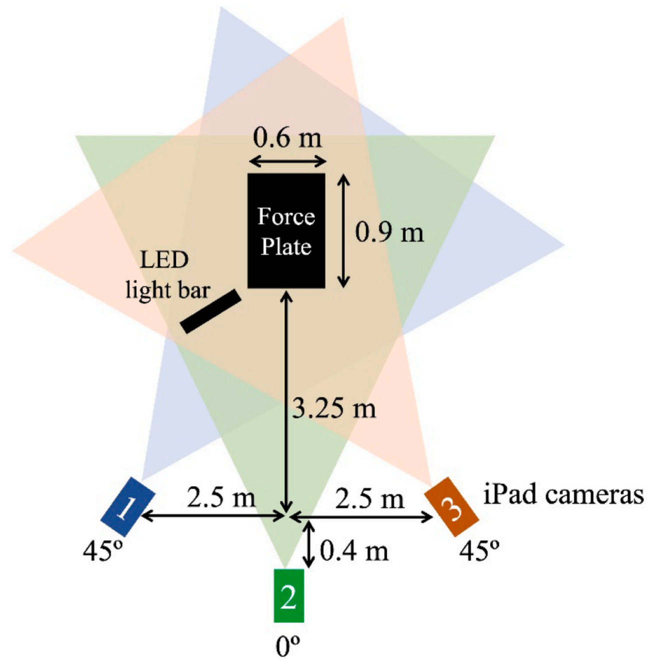

Fig. 1. Visual representation of the iPad cameras, force platform, and synchronisation light bar set-up (not to scale) for data collection.

stepping on the force platform and jumping as high as possible. Squat jumps were performed by lowering into the squat position, holding for three seconds, and jumping as high as possible. Drop jumps were performed by dropping of a 41 cm high box and, after landing, jumping as high as possible, either on both legs (bilateral) or on a single leg (unilateral). The unilateral drop jumps were performed on both the dominant and the non-dominant limb. Each jumping movement was performed under two conditions – either with the use of an arm swing to maximise jump height, or with the hands placed and fixed on the hips. After landing, athletes were required to stabilise on the force platform for a minimum of two seconds to ensure a successful landing. For each jump condition three successful trials were recorded (i.e., a total of 30 trials per participant). A minimum of one minute of rest was observed between trials to minimise the effects of fatigue.

During the jumping movements, GRFs and full-body kinematics were collected. GRF profiles were recorded with a ground-embedded force platform (Kistler 9287CA, 0.6 × 0.9 m, Kistler, Switzerland) sampling at 1000 Hz using Vicon Nexus software (version 2.15, Oxford, United Kingdom). Kinematic data were collected using OpenCap (Uhlrich et al., 2023; version 0.2) sampling at 240 Hz. The setup consisted of three iPads (iPad Pro 11-inch, 4th generation, OS version 16.2, Apple, USA) mounted to a tripod at a height of ~1.2 m, which were positioned around the location where participants performed the jumping movements (in line with the minimal setup requirements described in Uhlrich et al. (2023)), as shown in Fig. 1. An LED synchronisation light bar (Wee Beastie Electronics, Loughborough, UK) was manually triggered during each trial, and positioned to be in the field of view for iPad 3 (Fig. 1). On triggering the light bar, twenty LED synchronisation lights came on sequentially at an interval of one millisecond, whilst a voltage drop was registered in a trigger signal, synchronous with the GRFs.

The cloud-based OpenCap app (Uhlrich et al., 2023; version 0.2) was used to determine full-body three-dimensional kinematics during each jumping trial. Videos were recorded, uploaded, synchronised, and processed in the OpenCap server – hence, the data collection required internet connectivity throughout (Uhlrich et al., 2023). The standard OpenPose model was used for pose estimation and applied to a full-body musculoskeletal model containing 22 segments (Lai et al., 2017; Rajagopal et al., 2016). After the data collections, OpenCap files for each

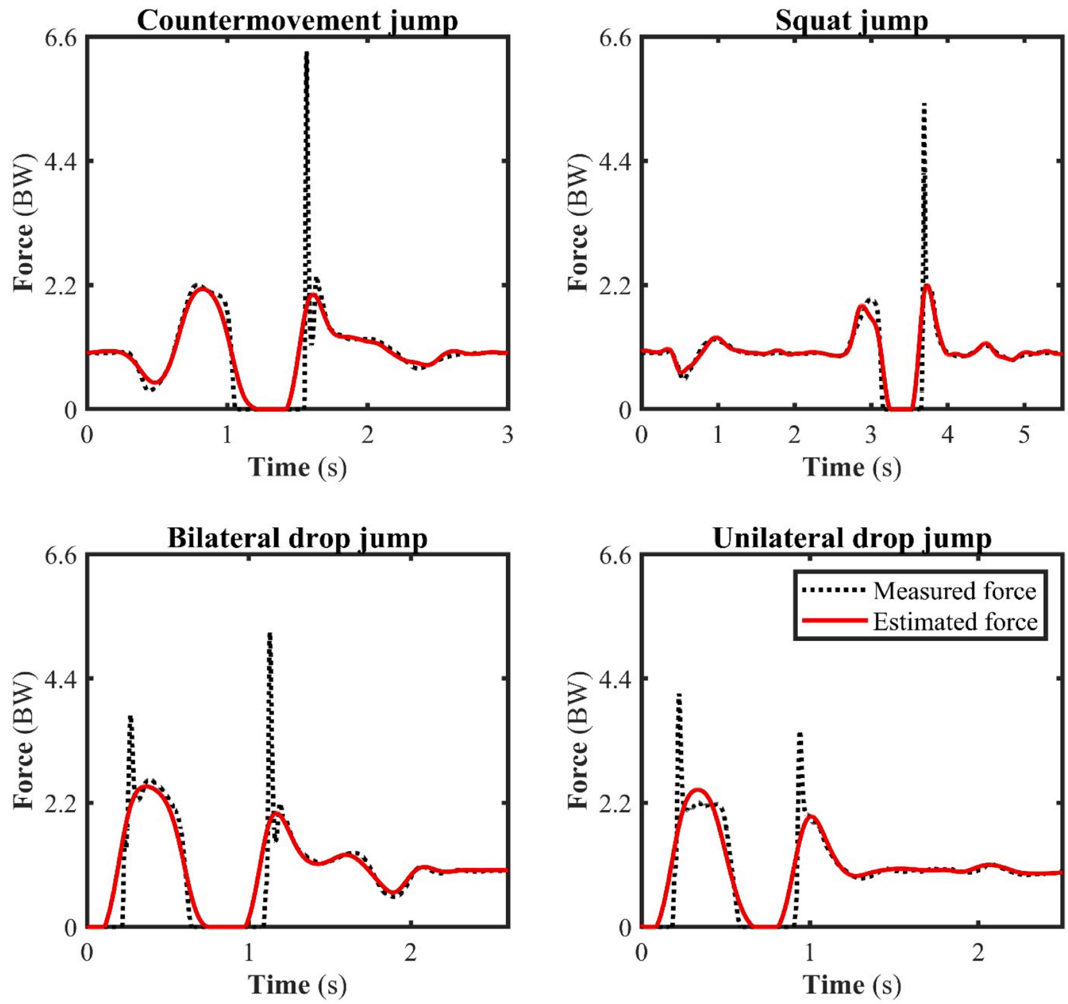

Fig. 2. Representative measured (black dotted line) and estimated (red solid line) vertical ground reaction force profiles for the four jumping movements.

participant were downloaded for offline analysis. The model properties (Lai et al., 2017; Rajagopal et al., 2016) and inverse kinematics results were exported to MATLAB (version R2022a, MathWorks, USA) for further processing.

2.3. GRF estimation and variables of interest

The measured GRFs were filtered at 50 Hz with a second-order Butterworth filter. A custom synchronisation method, using the synchronisation light bar, was then used to synchronise GRFs and body kinematics offline. The location of the light bar in the video of iPad 3 (Fig. 1) was manually identified after which the first frame in which one or more lights were on was automatically detected. The number of active lights in that frame was used to determine the delay between the first video frame with lights on, and the first data point in the GRF signal in which the voltage drop was visible. The force-platform measured GRF was then synchronised and cropped to match the length of the body kinematics signals (up sampled to match the GRF signal).

After synchronisation, the vertical position of each segment centre of mass was filtered at 4 Hz, using a second order lowpass Butterworth filter, before differentiating with respect to time to calculate the vertical segmental velocity. Segment velocities were again filtered at 4 Hz and differentiated over time to get the vertical segmental accelerations. The filter cutoff frequencies were selected based on a qualitative inspection of estimated GRF profiles for one participant, with the aim to reduce baseline noise introduced by the upper-body segments. Each vertical segmental acceleration was then multiplied by its segment mass and summed to provide an estimate of the total vertical GRF profile (Bobbert et al., 1991; Verheul et al., 2019a), according to:

$$GRF_v^{est} = \sum_{j=1}^{22} m_j \bullet (a_{v,j} + g)$$

in which GRF_v^{est} is the vertical GRF estimated from segmental kinematics, m_j and $a_{v,j}$ are the mass and vertical acceleration of each segment j respectively, and g is the gravitational acceleration (i.e., 9.81 m•s^{-2}). Accelerations of each segment, rather than the whole-body centre of mass, were used to allow for future investigations of individual segmental contributions to GRF variables of interest. Forces were normalised to each athlete's body weight, and GRF variables that are commonly used to assess performance, fatigue, or injury risk (e.g., Bishop et al., 2022; Painter et al., 2022), were then extracted from the measured and estimated GRF profiles, and used to validate the accuracy of the estimated vertical GRF profiles. Force variables were determined for the propulsive and landing phases (duration, peak/mean force, impulse, time to take-off/stabilisation), and the jump (flight time, jump height from two calculation methods) (see Appendix A for more details).

2.4. Statistical analyses

For each force variable of interest, derived from the measured and estimated vertical GRF profiles, the mean and standard deviation were determined per jumping movement. Pearson linear correlations were calculated between the measured and estimated force variables.

Table 1
Mean (±standard deviation) measured and estimated ground reaction force variables, differences, and Pearson correlation coefficients (r) for the four jumping movements. Data were combined for all participants per jumping movements and include both arm-swing and limb-dominance conditions. BW = body weight.

	Measured	Estimated	Difference	*r*
Countermovement jumps				
Propulsive phase – duration (s)	0.47 ± 0.08	0.48 ± 0.08	0 ± 0.02	0.97
Propulsive phase – peak force (BW)	2.31 ± 0.28	2.17 ± 0.24	−0.14 ± 0.13	0.90
Propulsive phase – mean force (BW)	1.39 ± 0.13	1.38 ± 0.12	0 ± 0.02	0.99
Propulsive phase – impulse (BW•s)	0.25 ± 0.06	0.25 ± 0.06	0 ± 0.01	0.97
Time to take-off (s)	0.89 ± 0.13	0.99 ± 0.12	0.1 ± 0.05	0.92
Flight time (s)	0.52 ± 0.08	0.3 ± 0.08	−0.21 ± 0.03	0.94
Jump height from flight time (m)	0.33 ± 0.1	0.12 ± 0.06	−0.22 ± 0.05	0.94
Jump height from impulse (m)	0.28 ± 0.09	0.11 ± 0.07	−0.17 ± 0.05	0.88
Landing phase – duration (s)	0.49 ± 0.19	0.51 ± 0.18	0.02 ± 0.03	0.99
Landing phase – peak force (BW)	4.23 ± 1.05	2.26 ± 0.29	−1.97 ± 0.95	0.49
Landing phase – impulse (BW•s)	0.14 ± 0.05	0.16 ± 0.05	0.02 ± 0.02	0.91
Time to stabilisation (s)	0.86 ± 0.25	0.96 ± 0.24	0.1 ± 0.05	0.98
Squat jumps				
Propulsive phase – duration (s)	0.47 ± 0.11	0.52 ± 0.15	0.05 ± 0.09	0.78
Propulsive phase – peak force (BW)	2.22 ± 0.35	1.93 ± 0.23	−0.29 ± 0.19	0.87
Propulsive phase – mean force (BW)	1.18 ± 0.09	1.2 ± 0.09	0.02 ± 0.01	0.99
Propulsive phase – impulse (BW•s)	0.13 ± 0.06	0.14 ± 0.06	0.01 ± 0.01	0.99
Time to take-off (s)	3.52 ± 0.35	3.62 ± 0.36	0.1 ± 0.06	0.99
Flight time (s)	0.5 ± 0.07	0.29 ± 0.07	−0.21 ± 0.03	0.92
Jump height from flight time (m)	0.31 ± 0.09	0.11 ± 0.05	−0.2 ± 0.05	0.93
Jump height from impulse (m)	0.25 ± 0.1	0.11 ± 0.07	−0.14 ± 0.07	0.75
Landing phase – duration (s)	0.5 ± 0.21	0.53 ± 0.21	0.03 ± 0.03	0.99
Landing phase – peak force (BW)	4.2 ± 1.13	2.22 ± 0.26	−1.97 ± 1	0.60
Landing phase – impulse (BW•s)	0.08 ± 0.07	0.1 ± 0.07	0.02 ± 0.01	0.99
Time to stabilisation (s)	0.93 ± 0.36	1.02 ± 0.34	0.09 ± 0.05	0.99
Bilateral drop jumps				
1st ground contact – duration (s)	0.46 ± 0.13	0.49 ± 0.12	0.03 ± 0.02	0.99
1st ground contact – peak force (BW)	3.39 ± 0.83	2.52 ± 0.45	−0.86 ± 0.63	0.67
1st ground contact – impulse (BW•s)	0.27 ± 0.07	0.31 ± 0.07	0.03 ± 0.01	0.99
Flight time (s)	0.51 ± 0.08	0.29 ± 0.08	−0.21 ± 0.04	0.89
Jump height from flight time (m)	0.32 ± 0.1	0.11 ± 0.06	−0.21 ± 0.06	0.90
2nd landing phase – duration (s)	0.45 ± 0.16	0.47 ± 0.17	0.03 ± 0.03	0.98
2nd landing phase – peak force (BW)	4.37 ± 1.02	2.27 ± 0.27	−2.1 ± 0.93	0.45
2nd landing phase – impulse (BW•s)	0.16 ± 0.05	0.17 ± 0.05	0.02 ± 0.01	0.98
Time to stabilisation (s)	0.84 ± 0.24	0.93 ± 0.23	0.09 ± 0.05	0.98
Unilateral drop jumps				
1st ground contact – duration (s)	0.43 ± 0.11	0.43 ± 0.1	0 ± 0.02	0.99
1st ground contact – peak force (BW)	3.42 ± 0.57	2.25 ± 0.33	−1.17 ± 0.54	0.37
1st ground contact – impulse (BW•s)	0.19 ± 0.07	0.21 ± 0.06	0.02 ± 0.02	0.97
Flight time (s)	0.34 ± 0.06	0.16 ± 0.05	−0.18 ± 0.03	0.85
Jump height from flight time (m)	0.15 ± 0.05	0.04 ± 0.02	−0.11 ± 0.04	0.89
2nd landing phase – duration (s)	0.41 ± 0.16	0.43 ± 0.16	0.02 ± 0.04	0.97
2nd landing phase – peak force (BW)	3.22 ± 0.51	1.95 ± 0.16	−1.27 ± 0.46	0.47
2nd landing phase – impulse (BW•s)	0.08 ± 0.04	0.1 ± 0.04	0.02 ± 0.01	0.93
Time to stabilisation (s)	0.86 ± 0.33	0.94 ± 0.33	0.08 ± 0.05	0.99

Correlations were considered to be negligible (0–0.3), low (0.3–0.5), moderate (0.5–0.7), high (0.7–0.9), or very high (0.9–1) (Hinkle et al., 2003). Significance was accepted at $\alpha < 0.05$ and a Bonferroni correction was applied to account for repeated hypothesis testing. Furthermore, Bland-Altman analyses were used to assess the agreement and interchangeability between measured and estimated GRF variables (Bland and Altman, 2010, 1999). Bias (mean difference) and limits of agreement (±1.96 standard deviations of the difference) were calculated as an absolute and percentage difference from the measured GRF values. Outliers were removed before calculating the bias and limits of agreement (~1–5 % of datapoints per GRF variable), to assure a representative calculation of the limits of agreement (Bland and Altman, 2010). Variables were then classed into three *a priori* defined categories of accuracy and interchangeability, both for the bias and limits of agreement: 1) good accuracy for regular performance-monitoring and/or injury-screening purposes (<5 %); 2) sufficiently accurate, likely to provide valuable performance and/or injury feedback, but some caution warranted (5–15 %); 3) unlikely to be sufficiently accurate for reliable testing and screening applications (>15 %). Correlation and Bland-Altman analyses included trials for all participants, arm-swing condition, and leg dominance, per jumping movement.

The ability to detect subtle within-athlete changes in GRF variables is essential for effective performance monitoring or injury screening, and usability of the method. Differences between arm-swing and leg-dominance were, therefore, investigated as a secondary aim. To evaluate if estimated force variables can adequately describe changes (increase or decrease) between jumping conditions, GRF variables with a bias of <15 % were selected and compared between arm swing conditions and leg dominance for each participant – both for measured and estimated values. A between-condition change was defined as a difference that was larger than the limits of agreement for that GRF variable. If there was a change between conditions for the measured but not the estimated values, this was deemed a false negative change. If no between-condition change was found in the measured GRF variable, but the estimated values did show a change, this was considered a false positive change.

3. Results

A total of 450 trials (fifteen participants × five jumping movements × two arm-swing conditions × three trials) were collected and processed. After visual inspection of the estimated GRF and OpenCap videos, 34 trials (one squat jump, two bilateral drop jumps, and 31 unilateral drop jumps) were discarded (7.6 %). For these discarded trials the estimated GRF profiles could not be analysed due to poor OpenCap motion capture results (e.g., physiologically impossible orientations of segments). Hence, a total of 416 trials were used for further analysis.

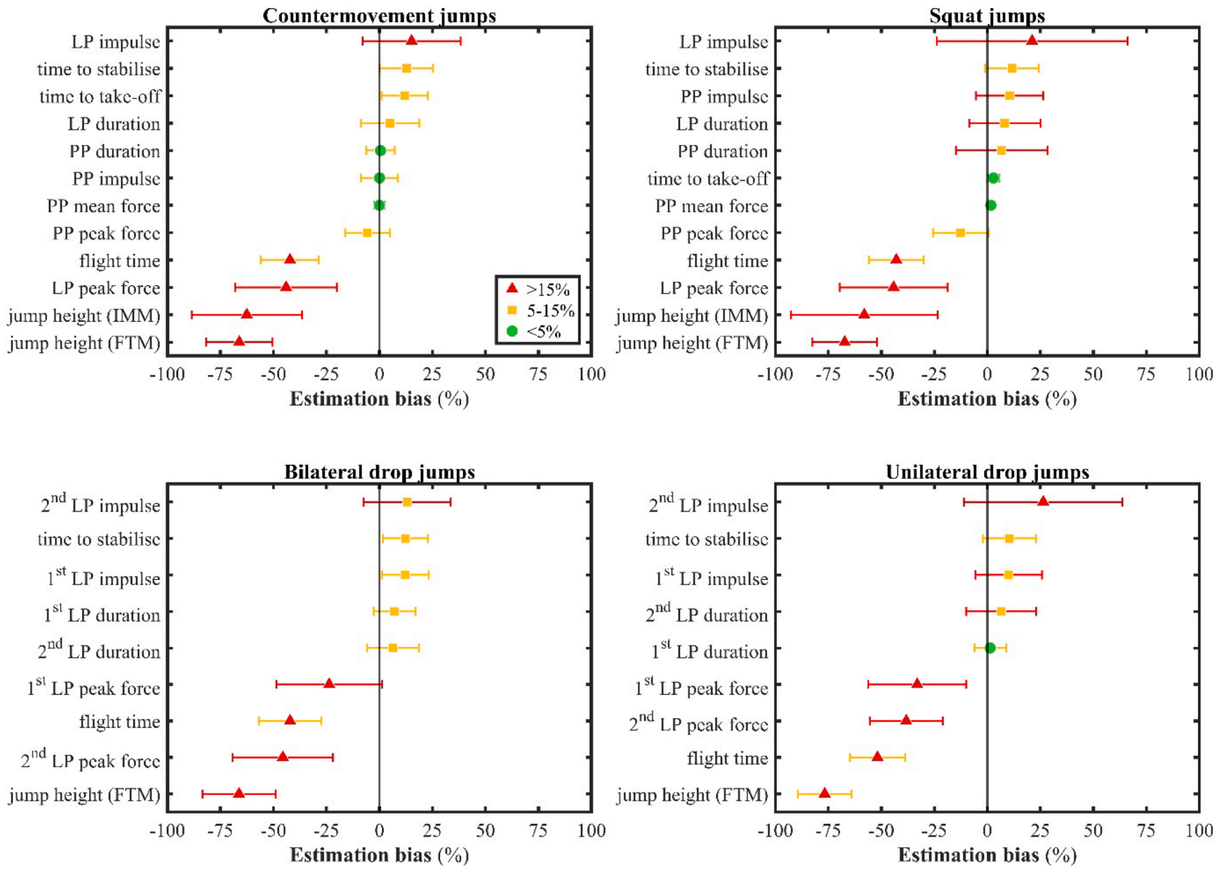

Fig. 3. Percentage bias and limits of agreement between the measured and estimated vertical ground reaction force variables for the four jumping movements. Circles/green, squares/amber, and triangles/red represent a bias/limits of agreement of <5 %, 5–15 %, or >15 % respectively. Bias and limits of agreement values can be found in Appendix B. LP = landing phase, PP = propulsive phase, FTM = flight time method, IMM = impulse-momentum method.

Example GRF force profiles for the four jumping movements of one representative participant are shown in Fig. 2.

3.1. Measured vs estimated GRF variables

Correlations were moderate between the measured and estimated peak force during the landing phase (countermovement and squat jump), and high for the jump height from impulse (countermovement and squat jump) and propulsive phase peak force (squat jump) (Table 1). For all other GRF variables of the countermovement and squat jumps there was a very high correlation. For the drop jumps, there was a low to moderate correlation for the peak force during both landing phases, a high correlation for the flight time and jump height (bilateral drop jump), and a very high correlation for all other GRF variables. All correlations were significant ($p < 0.001$).

A total of six and seventeen GRF variables were estimated with a bias <5 % or 5–15 % respectively (Fig. 3). Limits of agreement were <5 % for three variables, and 5–15 % for nineteen variables across movements. Absolute and percentage bias and limits of agreement results are presented in Appendix B.

3.2. Qualitative comparison of jumping conditions

For all selected force variables with a bias <15 %, estimated values adequately described the direction of change (i.e., increases or decreases) between arm-swing or leg-dominance conditions (Fig. 4). For the countermovement jumps, between-condition changes were correctly estimated with OpenCap for 87–93 % of the participants – propulsive phase impulse (one false positive, one false negative); propulsive phase mean force (one false negative); time to take-off (one false positive, one false negative). For the unilateral drop jumps, between-condition changes were appropriately estimated for 80–93 % of the participants – 1st landing impulse (one false negative); 2nd landing duration (one false positive, two false negatives); time to stabilise (one false positive).

4. Discussion

This study examined the validity and usability of GRF variables, estimated from markerless-measured segmental kinematics during four jumping movements, which are commonly used for performance testing and/or injury-risk screening. We show that an acceptable level of accuracy (i.e., bias or limits of agreement <15 %) can be achieved for several estimated GRF variables across different jumps. Moreover, estimated force variables can effectively reveal the within-athlete changes in force variables between jumping conditions.

Across the four jumping movements and examined force variables, moderate to very high correlations were found between the measured and estimated GRF. Force variables were estimated with a bias or limits of agreement <15 % for, respectively, 58 % and 55 % of all variables. Propulsive phase characteristics of the countermovement and squat jumps especially, were estimated with the highest level of accuracy (Fig. 3). Propulsive phases of these jumps are commonly used for performance profiling and neuromuscular fatigue assessments (Bishop et al., 2022). The presented markerless GRF estimation method may, therefore, be particularly suitable for performance testing and fatigue monitoring.

The absolute accuracy of novel predictive methodologies is important to examine. However, the ability to detect subtle within-athlete changes – e.g., due to performance, asymmetry, or fatigue – is essential for in-field and athlete-specific applications. The analysis shown in

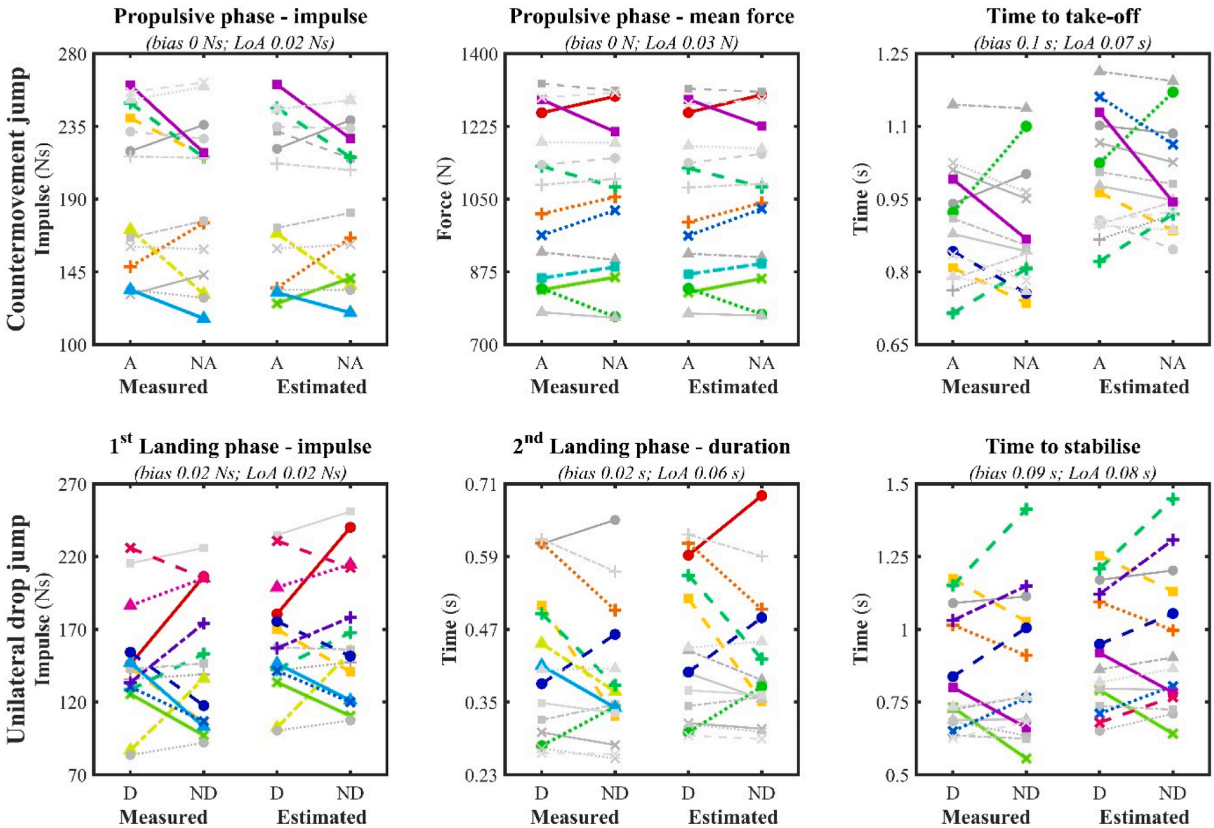

Fig. 4. Selected measured and estimated ground reaction force variables for all fifteen participants, compared between arm-swing conditions (top row) and leg dominance (bottom row). Colours represent participants for which the mean difference between arm-swing conditions or legs was larger than the limits of agreement. Grey represents differences between conditions to be smaller than the limits of agreement. Values are means and standard deviations for three trials per jumping movement and condition. A = arm swing; NA = no arm swing; D = dominant leg; ND = non-dominant leg; LoA = limits of agreement.

Fig. 4 demonstrates that estimated force variables retain the same directionality of change within individual athletes (increase or decrease) between subtle adjustments in jumping conditions – i.e., the (non) use of an arm swing, or landing on the dominant/non-dominant leg. Moreover, between-condition changes (or the absence thereof) were appropriately assessed by the estimated GRF variables for most of the participating athletes. This ability to observe changes in force characteristics is essential for meaningful and effective performance-testing or injury-screening practice. For example, alterations in force output during the propulsive phase or increased asymmetry between legs in the ability to stabilise after a landing can be important indicators of performance potential (Young et al., 1995) or injury risk (Fort-Vanmeerhaeghe et al., 2022) respectively. These results thus indicate that several GRF variables estimated from OpenCap are a viable alternative to force platforms to help evaluate changes in performance, fatigue, or injury risk.

To the best of our knowledge, only one previous study (Colyer et al., 2023) has attempted to estimate GRF profiles from markerless motion capture using a mechanics-based modelling method. Colyer et al. (2023) used the whole-body centre of mass, measured from a bespoke markerless motion capture method (Needham et al., 2022), to estimate vertical GRFs during countermovement jumps and running. Like our results, that study found a very small difference (mean < 1 %) in force impulse, but their estimated peak forces were substantially better (<1 % mean difference). However, that study was limited in scope (e.g., one jumping movement without different conditions) and the markerless motion capture workflow used by Colyer et al. (2023) is not widely accessible. In contrast, this study examined four different jumping movements with two different conditional variations and used a publicly available and user-friendly application (OpenCap), which enhances its scope and opportunities for field-based monitoring. The combination of the findings presented by Colyer et al. (2023) and our results are promising, and we encourage future studies to further examine the use of openly available markerless motion-capture systems for estimating GRF across a wide range of movements.

Characteristics of the GRF profiles that are associated with high frequency content were estimated with the lowest level of accuracy. For example, take-off and touchdown, and the impact peaks of landing were consistently estimated with the largest bias. We suggest that this has two main reasons: 1) the sampling frequency of the kinematic data, and 2) the filtering procedures applied. First, the sampling frequency of OpenCap's kinematics data was 240 Hz. The minimal sampling frequency for capturing the high frequency content of GRF profiles, such as the take-off and touchdown events and the impact peak of landing, has previously been suggested to be >1000 Hz (Kibele, 1998; Owen et al., 2014; Street et al., 2001). It is thus unlikely that GRF estimated from kinematic data sampled at a lower frequency can estimate such information well (for example, the accuracy of GRF estimations from marker-based motion-capture data sampled at a comparable sampling frequency is also limited (Verheul et al., 2019a)). Second, segmental position data was doubly filtered during differentiation to avoid the magnification of noise in the process of deriving segmental accelerations. It is thus not surprising that high-frequency content was not captured well in the estimated GRF profiles. Unless markerless motion capture allows sampling at higher frequencies, extending the present method to more dynamic activities, such as high-speed running or side cutting, where rapid changes in the GRF profile are typically of interest, may not yield valid results.

A total of 34 out of 450 trials (i.e., 7.6 %) were discarded due to poor OpenCap motion capture results. Interestingly, most of the discarded trials were for drop jump movements, and predominantly for the unilateral trials (31/34). The deep learning model used to augment the 3D marker set in OpenCap is trained using existing data and is unlikely to perform well for movements that are not included in the training dataset (Uhlrich et al., 2023). Although unilateral drop jumps were part of the training data (Thompson et al., 2017; Thompson-Kolesar et al., 2018), the inclusion of a larger number of trials for this type of movement may be required to further enhance the pose estimations. In addition, the availability of sampling frequency options is probably another current limiting factor for estimated GRF variables, as discussed above. The performance and breadth of GRF estimation opportunities from markerless motion capture with OpenCap will, therefore, likely further improve with the introduction of new features in the future – e.g., with the use of larger training datasets, or the availability of higher sampling frequencies.

In this study, we have demonstrated a selection of force variables that can be of interest for monitoring performance or injury risk. Further analysis of other GRF characteristics can be performed, depending on individual needs or requirements. More importantly, the presented method allows for analysing force in combination with the underlying segmental kinematics. Depending on the body part of interest (joints or segments), individual segmental contributions to the GRF can be identified and changes in GRF variables can be analysed by considering related changes in movement patterns of the various parts of the musculoskeletal system. Moreover, OpenCap is part of a modelling framework (OpenSim; Seth et al., 2018) that also allows for estimating muscle and joint-specific loading (e.g., joint moments, muscle–tendon forces). Together these abilities thus provide a major jump towards low-cost field-based assessments of whole-body, structure-, and tissue-specific load assessments (Verheul et al., 2020), linking biomechanical loading profiles to individualised movement analysis.

5. Conclusion

Low-cost and field-viable methods that can simultaneously assess external kinetics and kinematics can further enhance current practice for field-based biomechanical monitoring. This study examined the accuracy and usability of GRF variables, estimated from markerless-measured segmental kinematics, during common jumping movements. We show that several GRF variables can be estimated with acceptable limits of accuracy and can effectively reveal the within-athlete changes in GRF variables between jumping conditions. Markerless motion capture with OpenCap can thus be used to estimate GRF profiles during common jumping movements and monitor force variables of interest. Together, these outcomes show that the presented method is a jump towards performing biomechanical monitoring of jumping efficiently, regularly, and extensively in field settings.

CRediT authorship contribution statement

Jasper Verheul: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mark A. Robinson:** Writing – review & editing, Validation, Supervision, Investigation, Formal analysis, Conceptualization. **Sophie Burton:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Appendix A. Supplementary material

Supplementary data (Appendix A and B) to this article can be found online at https://doi.org/10.1016/j.jbiomech.2024.112044.

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