MARKERLESS MOTION CAPTURE WITH OPENCAP FOR FIELD-BASED JUMP TESTING: A FORCE TO BE RECKONED WITH?

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Field-based methods to assess external kinetics are essential for regular biomechanical monitoring. The aim of this study was to examine the accuracy of ground reaction forces (GRF) estimated from segmental kinematics, measured with a markerless motion-capture system (OpenCap) during jumping. Full-body segmental kinematics were recorded for fifteen athletes during countermovement, squat, and drop jumps, and used to estimate vertical GRFs with a mechanics-based method. Across jumps, bias and limits of agreement were acceptable (<15%) for 23 and 22 GRF variables, respectively. Within-athlete changes between arm-swing or leg-dominance conditions were adequately detected for multiple GRF variables. These findings show that a low-cost markerless motion-capture system (OpenCap) may be used to estimate and assess force variables of interest in field settings.

KEYWORDS: markerless motion capture; jump testing; biomechanical monitoring; performance assessment; injury screening.

INTRODUCTION: Performance testing and injury-risk screening are important components of athlete monitoring (Thornton et al., 2019). Both performance and injury-risk assessments typically involve the examination of loading patterns during controlled jumping movements (e.g., countermovement or drop jumps), to facilitate sport-specific decision-making. Although such assessments have traditionally been performed in biomechanics laboratories, using motion-capture systems and force platforms, this lab-based approach can be costly, time-consuming and limits the frequency of athlete screening. Alternative solutions, such as portable force platforms, can be used as low-cost options for regular assessment of ground reaction forces (GRFs) in the field, but do not allow for evaluating and monitoring kinematics. Low-cost and field-viable methods that can simultaneously measure GRFs and whole-body kinematics, are, therefore, desirable to further enhance field-based biomechanical assessments (Verheul et al., 2020).

Markerless motion-capture technologies (e.g., OpenCap, Theia 3D) offer a viable alternative to traditional marker-based systems to collect whole-body kinematics non-invasively. Recent work has shown that machine-learning approaches can estimate GRF profiles during sports movements from motion-capture data (Johnson et al., 2018; Mundt et al., 2023). However, examining the underlying kinematics that contribute to the GRF profiles estimated from machine learning is not straightforward. Mechanics-based methods, in which the direct relationship between kinematics and kinetics is used (e.g., $F=m\cdot a$), are thus preferable to allow for examining the kinematic-kinetic relationship (Verheul et al., 2019). However, if markerless measured kinematics can be used to accurately estimate GRFs with such a mechanics-based approach is currently unknown.

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, and 2) provide additional kinematic information to identify performance- and/or injury-related parameters. The aim of this study was, therefore, to validate the accuracy and usability of GRF profiles estimated from segmental kinematics, measured with a low-cost markerless motion-capture system, during common jumping movements.

METHODS: Fifteen injury-free recreational athletes from various sports backgrounds participated in this study (nine males, six females; age 22.4 ± 3.6 yrs; height 1.75 ± 0.07 m; body mass 77.9 ± 12.6 kg). Athletes performed countermovement jumps, squat jumps, bilateral drop jumps, and unilateral drop jumps (dominant and non-dominant leg) – i.e., common performance testing and injury-risk screening jump movements. Each jump was performed three times under two conditions, either with or without an arm swing.
Full-body kinematics were recorded in OpenCap (Uhlrich et al., 2023; v.0.2) sampling at 240 Hz and a ground-embedded force platform (Kistler 9287CA, Kistler, Switzerland) sampling at 1000 Hz recorded GRFs. The OpenCap setup consisted of three tripod-mounted iPads (iPad Pro, Apple, USA) placed around the jump collection area (at ~3.5 m). Videos were recorded, uploaded, synchronised, and processed in the online OpenCap server. Full-body three-dimensional kinematics were determined using the standard OpenPose pose-estimation model and twenty-two-segment full-body musculoskeletal model (Lai et al., 2017). OpenCap data, including inverse kinematics results and athlete-specific model properties, were downloaded and exported to MATLAB (R2022a, MathWorks, USA) for processing and analysis.
Vertical positions of each segment centre of mass were filtered at 4 Hz, using a 2nd-order lowpass Butterworth filter, before double differentiating with respect to time, to calculate the vertical segmental accelerations. The product of vertical accelerations and masses (percentage of total body mass) for each of the twenty-two segments were then summed to estimate the total vertical GRF profile (Verheul et al, 2019), according to:

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

in which GRF_v 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 (9.81 m·s^{-2}). Force variables that are commonly used to assess performance, fatigue, or injury risk (Bishop et al., 2022), were extracted from the measured and estimated GRF profiles, and used for validation purposes. Relevant 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 and jump height).
Bias and limits of agreement were calculated as a percentage difference from the measured GRF values, to assess agreement and interchangeability (Bland and Altman, 2010), categorised as: 1) good accuracy for regular performance or injury monitoring (<5%); 2) sufficiently accurate, likely to provide valuable performance or injury feedback, but caution warranted (5-15%); 3) unlikely to be sufficiently accurate for reliable testing and screening purposes (>15%). In addition, the within-athlete changes between arm-swing conditions and leg dominance were compared for selected GRF variables with a bias <15% – both for measured and estimated values. A between-condition change was defined as a difference larger than the limits of agreement for a GRF variable. If a between-condition change was found for the measured but not the estimated values, this was deemed a false negative. If no between-condition change was found in the measured GRF variable, but estimated values did show a change, this was deemed a false positive.

RESULTS: After visual inspection of the OpenCap videos a total of 34/450 trials (7.6%) were discarded due to poor OpenCap inverse kinematics results (e.g., physiological impossible orientations of segments). Hence, a total of 416 trials were included in the analysis.
A total of six and seventeen GRF variables were estimated with a bias <5% or 5-15% respectively (Figure 1). Limits of agreement were <5% for three variables, and 5-15% for nineteen variables across movements.

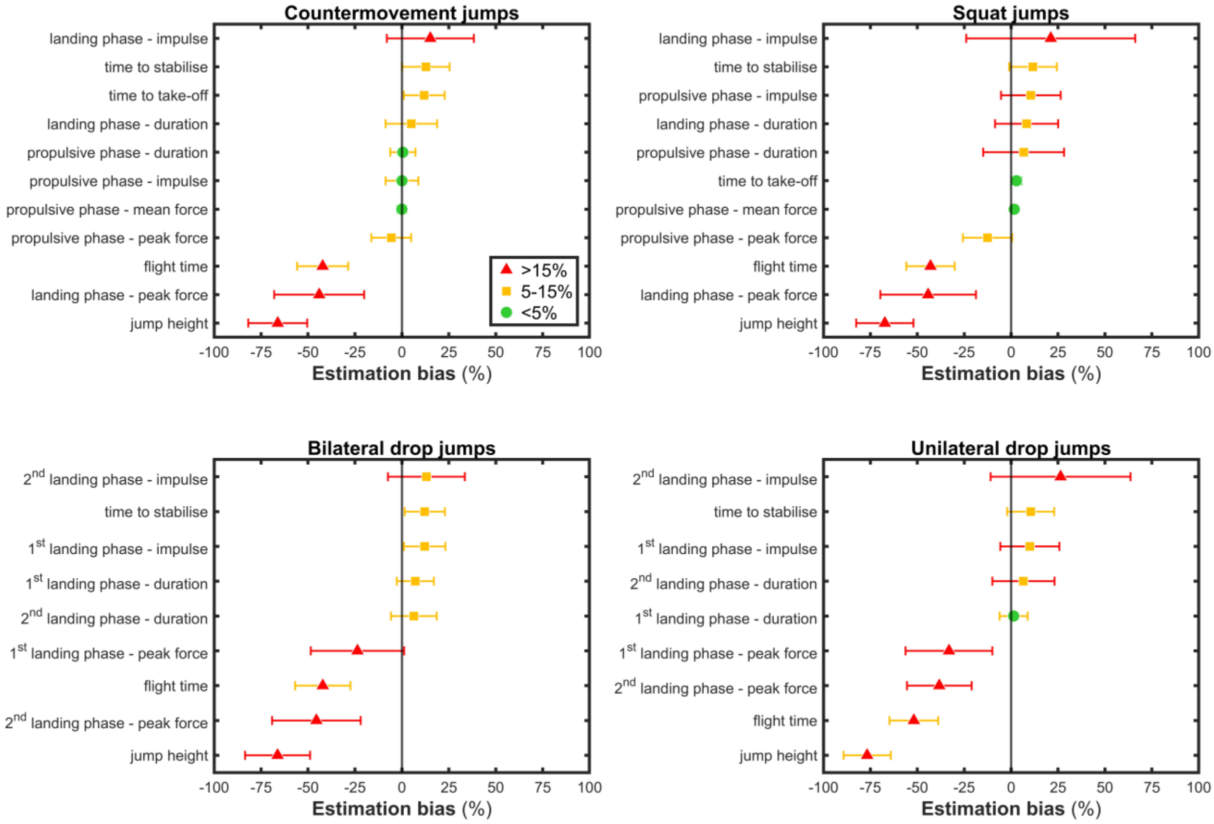

Figure 1: Bias and limits of agreement between measured and estimated vertical ground reaction force variables for four jumping movements. Circles/green, squares/amber, and triangles/red represent respective bias/limits of agreement of <5%, 5-15%, or >15%.

For the 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. Between-condition changes were correctly estimated with OpenCap for 87-93% (countermovement jumps) and 80-93% (unilateral drop jumps) of the participants (Table 1).

Table 1: Within-athlete changes between jumping conditions for six selected GRF variables

Countermovement jumps		Unilateral drop jumps	
propulsive phase – impulse	87% (1FP; 1FN)	1st landing – impulse	93% (1FN)
propulsive phase – mean force	93% (1FN)	2nd landing – duration	80% (1FP; 2FN)
time to take-off	87% (1FP; 1FN)	time to stabilise	93% (1FP)

Percentage of true within-athlete changes detected. FP=false positive, FN= false negative.

DISCUSSION: In this study, we show that an acceptable accuracy level can be achieved for GRF variables estimated from markerless-measured segmental kinematics, across different jumps. We show that several estimated force variables can adequately detect within-athlete changes in force variables between arm-swing conditions or leg dominance.

Across jumps, bias or limits of agreement were <15% for, respectively, 58% and 55% of all GRF variables. Especially propulsive phase characteristics of the countermovement and squat jumps were estimated most accurately (Figure 1). Since the propulsive phase is often used for performance and fatigue assessments (Bishop et al., 2022) the presented method may best suit those purposes. Together with previous work that used markerless kinematics to estimate GRFs for jumping (Colyer et al., 2023), these results are promising for the implementation of markerless motion capture in everyday athlete-monitoring practice. Improvements in capturing high-frequency GRF variables (e.g., landing force) can further enhance overall accuracy.

We found that markerless estimated force variables could assess changes within athletes between slight adjustments in jumping conditions (arm swing or leg dominance) for most athletes (Table 1). This ability to detect subtle within-athlete changes is essential for the method to be usable for screening and monitoring purposes. For example, subtle alterations in force output during the propulsive phase or increased limb asymmetry in the ability to stabilise after a landing can be important indicators of performance and potential risk of injury (Young et al., 1995). Our results, therefore, indicate that GRF variables estimated from OpenCap can form a viable alternative to force platforms for assessing changes in performance, fatigue, or injury risk.
We examined several force variables that are of interest for monitoring performance or injury risk. Further analysis of other GRF characteristics can be performed, depending on individual requirements. Moreover, the presented method allows for analysing force together with underlying segmental kinematics. Depending on the body part of interest, individual segmental contributions to the GRF can be analysed and movement alterations related to relevant GRF characteristics can be identified. Since OpenCap is part of a modelling framework (OpenSim), this approach also allows for estimating muscle and joint-specific loads (e.g., joint moments, muscle-tendon forces). Together these abilities provide novel opportunities for low-cost field-based assessments of biomechanical loading across the levels of the musculoskeletal system.

CONCLUSION: This study shows 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 efficiently, regularly, and extensively in field settings.

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