Journal of Biomechanics xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Short communication

Influence of proximal trunk borne load on lower limb countermovement joint dynamics

Bernard X.W. Liew [a,*], Nathaniel E. Helwig [b,c], Susan Morris [d], Kevin Netto [d]

[a] Centre of Precision Rehabilitation for Spinal Pain (CPR Spine), School of Sport, Exercise and Rehabilitation Sciences, College of Life and Environmental Sciences, University of Birmingham, Birmingham, UK
[b] Department of Psychology, University of Minnesota, Minneapolis, MN, USA
[c] School of Statistics, University of Minnesota, Minneapolis, MN, USA
[d] School of Physiotherapy and Exercise Sciences, Curtin University, GPO Box U1987, Perth, WA 6845, Australia

ARTICLE INFO

Article history:
Accepted 10 August 2018
Available online xxxx

Keywords:
Load carriage
Jumping
Kinematics
Kinetics
Multivariate statistics

ABSTRACT

Vertical jumping involves coordinating the temporal sequencing of angular motion, moment, and power across multiple joints. Studying the biomechanical coordination strategies that differentiates loaded from unloaded vertical jumping may better inform training prescription for athletes needing to jump with load. Common multivariate methods (e.g. Principal Components Analysis) cannot quantify coordination in a dataset with more than two modes. This study aimed to identify coordinative factors across four modes of variation using Parallel Factor (Parafac2) analysis, which may differentiate unloaded (body weight [BW]) from loaded (BW + 20% BW) countermovement jump (CMJ). Thirty-one participants performed unloaded and loaded CMJ. Three-dimensional motion capture with force plate analysis was performed. Inverse dynamics was used to quantify sagittal plane joint angle, velocity, moment, and joint power across the ankle, knee, and hip. The four-mode data were as follows: Mode A was jump cycle (101 cycle points), mode B was participant (31 participants by two load), mode C was joint (two sides by three joints), and mode D was variable (angle, velocity, moment, power). Three factors were extracted, which explained 95.1% of the data's variance. Only factors one ($P = 0.001$) and three ($P < 0.001$) significantly differentiated loaded from unloaded jumping. The body augmented hip-dominant at the start, and both hip and ankle dominant behaviors at the end of the ascending phase of the CMJ, but kept knee-dominant behavior invariant, when jumping with a 20% BW load. By studying the variation across all data modes, Parafac2 provides a holistic method of studying jumping coordination.

1. Introduction

In terraneous racing such as orienteering, jumping is required to successfully navigate natural obstacles (Hebert-Losier et al., 2014). Also, during such races, jumping performance may be impaired from the need to carry external load (Leontijevic et al., 2012; Marais and de Speville, 2004). Optimal vertical jump performance relies on the body coordinating the temporal sequencing of angular motion, moment, and power across multiple joints (Bobbert and van Ingen Schenau, 1988). To better inform jump training prescription, an understanding of the biomechanical coordination strategies that differentiates loaded from unloaded vertical jumping is required.

Current research of loaded and unloaded jumping biomechanics have employed independent ("univariate") analysis (Jandacka et al., 2014; Moir et al., 2012; Williams et al., 2018). This is less optimal for studying coordination, as it does not account for co-variation between different data-points within a waveform, joints (e.g. hip, knee, ankle), and biomechanical variables (e.g. angle and power). For example, constant joint power can emerge from an opposite change in joint moment and velocity (Williams et al., 2018). An independent analysis thus requires a qualitative synthetization of how individual elements of data-points, joints, and biomechanical variables may coordinate, which becomes increasingly challenging as the number of elements increase. In contrast, multivariate analysis yields a parsimonious set of coordinative units (termed as "factors" presently) between individual elements.

Multivariate methods such as Principle Components Analysis (PCA), are designed to analyze two-mode data (e.g. joints × data-points), while biomechanical data can have up to four modes (e.g. data-points × participant × joints × biomechanical variables). Using two-mode methods on four-mode data, investigators must either perform multiple analysis (Hug et al., 2011), or perform a

* Corresponding author.
E-mail address: LiewB@adf.bham.ac.uk (B.X.W. Liew).

https://doi.org/10.1016/j.jbiomech.2018.08.009
0021-9290/

single analysis by "collapsing" the data into two-modes (Federolf et al., 2013). The first solution reduces between-participant reliability in identified factors (Shourijeh et al., 2016). The second solution does not capture co-variation between all data modes and the interpretation of extracted factors vary depending on the choice of post-hoc rotations (Helwig et al., 2012). Parallel Factor Analysis (Parafac) (Harshman, 1970) is a straightforward extension of PCA for data collected across multiple modes of variation. In this paper, we use the Parafac2 model, which has been proven useful for analyzing multi-modal data involving different biomechanical variables (Harshman, 1972; Helwig et al., 2013). Based on prior work (Williams et al., 2018), we hypothesized that loaded versus unloaded jumping should be distinguished at the hip (moment and velocity), the knee (velocity and power), and the ankle (velocity). However, unlike past studies, we leverage novel tensor models to simultaneously understand how loaded versus unloaded jumping differs across all joints and waveforms simultaneously, which provides a more complete understanding of the interrelations between the joints and various biomechanical signals.

2. Methods

2.1. Participants and design

Sixteen male and 15 female healthy adults [mean (standard deviation [SD]) age of 30.17 (9.20) years, mass of 68.41 (12.21) kg, height of 1.72 (0.77) m] provided written informed consent to participate. This study was approved by the Curtin University Human Research Ethics Committee (RD-41-14).

2.2. Jump assessment

Countermovement jump (CMJ) data were captured using an 18 camera system (Vicon T-series, Oxford Metrics, UK) (250 Hz), synced to two in-ground force plates (AMTI, Watertown, MA) (2000 Hz). CMJ was performed with and without a 20% bodyweight (BW) backpack (CAMELBAK, H.A.W.G.® NV, 14L), henceforth termed "load", with both arms at a 90° abducted posture, with one foot on each force plate. This load magnitude has been reported to be carried during dynamic movement tasks (Carlton and Orr, 2014; Liew et al., 2016). The sequence of load was randomized. The load was fastened to the posterior trunk via the chest strap and waist belt. In the CMJ, participants were verbally instructed to jump from a depth of a visually estimated 90° knee flexion posture. Practice trials were provided till consistent visual achievement of the required depth was achieved. Three unloaded and three loaded CMJ trials were required, with each trial separated by at least a 30 s standing rest, and each condition separated by at least a minute seated rest.

2.3. Biomechanical modelling and processing

All biomechanical processing were performed in Visual 3D (C-motion, Germantown, MD), using a previously published model (Liew et al., 2016). The reflective marker set used is found in the supplementary material. Raw kinematic and ground reaction force (GRF) data were filtered at 8 Hz (4th order, zero-lag, Butterworth) (Raffalt et al., 2016).

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jbiomech.2018.08.009.

Joint angles, velocities, and moments were calculated using a XYZ Cardan rotation sequence (Schache and Baker, 2007; Sinclair et al., 2013). Velocities and moments were expressed relative to the proximal segment (Schache and Baker, 2007). Joint power was derived by the dot product of the three-dimensional joint moment and velocity. Only sagittal plane angles, velocities and moments were analyzed to fit a 4 mode array. Biomechanical waveforms from each joint were time normalized to 101 points between CMJ onset (drop in GRF > 2.5% BW) (Meylan et al., 2011) and toe-off (GRF < 20 N). Joint power, and moment were scaled to the participant's body mass (M) and standing leg length (L) measured at static calibration, and gravitational constant (g) (power by $M.g^{1.5}.L^{0.5}$ and moment by MgL) (Pinzone et al., 2016). 1% $M.g^{1.5}.L^{0.5}$ equates to a mean (SD) of 1956.4 (377.9) W, and 1% MgL equates to 567.1 (120.2) Nm.

2.4. Statistical analysis

Parafac2 analysis was performed in R software (v 3.2.5), using the "*multiway*" package (Helwig, 2017). The input data was organized into a four mode array, with Mode A being cycle (101 points), Mode B being participants (31 participants by two load conditions), Mode C being joints (right ankle, right knee, right hip, left ankle, left knee, left hip), and Mode D being variable (angle, velocity, moment, power). Scale differences between each biomechanical variable type were removed (Helwig et al., 2013). Substantive interpretations of the factors were determined by examining Modes A, C, and D weights, which reveal the salience of each cycle point, joint, and biomechanical variables, respectively, for each factor. A higher absolute weighting indicates a greater contribution of the mode to the factor.

An Alternating Least Squares (ALS) algorithm was used to find an optimal solution, using 500 random starts with 500 maximum iterations of the ALS algorithm for each start. An orthogonality constraint was applied to the Mode C (Helwig et al., 2013). A paired Wilcoxon signed-ranks test was used on the "participant" mode, to compare which factors differentiated between jumping conditions (Helwig et al., 2013).

3. Results

Based on locating the 'elbow' of a scree plot of number of factors against variance accounted for (VAF), three factors were extracted (factor one = 69.6% VAF, two = 19.2% VAF, three = 6.3% VAF). Factors one (V = 407, P = 0.001) and three (V = 472, P < 0.001) significantly weighted higher during loaded compared to unloaded jumping (Table 1) – where "V" represents the sum of ranks assigned to the differences with positive sign.

The highest joint weighting was the hip for factor one, the knee for factor two, and the ankle for factor three (Table 2). Factor one had angle and moment waveforms which peaked, with identical

Table 1
Mean (standard deviation) and effect size of participant weightings for each extracted factors, and for each jump task.

Factor 1		Factor 2		Factor 3	
Unloaded	Loaded	Unloaded	Loaded	Unloaded	Loaded
0.985 (0.065) ES = 0.38	1.010 (0.071)	0.977 (0.189) ES = 0.04	0.984 (0.208)	0.959 (0.125) ES = 0.53	1.025 (0.128)

ES (Effect size) of difference = $(\text{Mean}_{\text{Loaded}} - \text{Mean}_{\text{Unloaded}})/\text{Standard Deviation}_{\text{Unloaded}}$