Journal of Biomechanics 85 (2019) 218–223

Contents lists available at ScienceDirect

Journal of Biomechanics

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

Short communication

Recommendation for the minimum number of steps to analyze when performing the uncontrolled manifold analysis on walking data

Noah J. Rosenblatt [a,*], Christopher P. Hurt [b]

[a] Rosalind Franklin University of Medicine and Science, Center for Lower Extremity Ambulatory Research (CLEAR) at the Dr. William M. Scholl College of Podiatric Medicine, 3333 Greenbay Road, North Chicago, IL 60064, United States
[b] University of Alabama at Birmingham, Department of Physical Therapy, United States

ARTICLE INFO

Article history:
Accepted 8 January 2019

Keywords:
Synergy index
Center of mass
Stability
Older adults
Gait
UCM
Foot trajectory
Mediolateral

ABSTRACT

The uncontrolled manifold (UCM) analysis quantifies the extent to which co-variation among a set of variables facilitates consistent performance by partitioning variance in those variables into two components then calculating their normalized difference (i.e., the synergy index). Although UCM-derived measures are thought to depend on the number of data points analyzed, the minimum number needed to reasonably approximate true values of these measures is unknown. For each of two performance variables related to mechanical stability of gait, we evaluated changes in UCM-derived measures when increasing the number of analyzed points, here steps. Fourteen older adults walked on a treadmill while motion capture tracked movement. For each subject, n steps (where $n = 2$–99) were randomly sampled from the first 100, then used to calculate UCM-derived variables. For each subject, variables were expressed as a percent of the subject-specific value with $n = 100$ and averaged across 50 simulations. For each n, 95% confidence intervals (CIs) were calculated from group data. The minimum number of steps to “reasonably approximate” a variables was defined as the value of n for which the lower CI was >90% of the value with $n = 100$. Regardless of performance variable, reasonable approximations of the synergy index were attained with $n = 16$ steps, whereas $n = 50$ steps were needed for each of the variance components However, the differences between using 16 steps and 50 steps were small. Collecting 15–20 steps is recommended for a reasonable approximation of the synergy indices considered herein, particularly when data collection is constrained to a limited number of steps.

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1. Introduction

The production of human movement inherently involves more degrees of freedom (DoFs) than required by constraints of the action (Bernstein, 1967), and the ability to exploit such redundancy may be important to maintaining a heathy motor system. Motor redundancy ensures that multiple solutions exist for a given motor problem, e.g., no single combination of muscle forces produces a given joint moment, which provides flexibility to the system (Latash, 2018; Latash, 2012). The exploitation of motor redundancy may help to reduce variance in motor performance in the presence of system noise or varying initial conditions, and to facilitate performance of secondary actions and appropriate reactions to challenging circumstances (Hsu and Scholz, 2012; Latash et al., 2007). The extent to which redundancy is exploited to accomplish a motor task can be evaluated using the uncontrolled manifold (UCM) analysis, which in essence quantifies coordination – i.e. how variations in all of the DoFs that contribute to performance (termed elemental variables) co-vary in order to produce consistent output in a performance variable.

As suggested in a 2010 review on UCM analysis: “when applying the UCM approach…the number of data points used in the analysis is an important consideration…Ideally the more data points…. the better” (Latash et al., 2010). In the case of gait, every step is equivalent to a data points and the UCM analysis is performed across steps at comparable time-normalized points within the step. While more steps may be “better”, the number that can be captured during an experiment may be limited by the population or the experimental manipulation. An “informal analysis” from a single subject performing a reaching task suggested including “at least 20 trials for UCM analysis to increase the chances of having a stable (output) estimate” (Latash et al., 2010), which is consistent with the number of steps analyzed in prior gait studies (Eckardt and Rosenblatt, 2018; Krishnan et al., 2013; Papi et al., 2015; Robert et al., 2009; Rosenblatt et al., 2014a,b; Verrel et al., 2010).

* Corresponding author.
E-mail address: noah.rosenblatt@rosalindfranklin.edu (N.J. Rosenblatt).

https://doi.org/10.1016/j.jbiomech.2019.01.018
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However, whether 20 steps provides stable estimates of UCM measures during gait has yet to be tested. In light of the insights UCM analysis can offer into strategies used by non-impaired (Eckardt and Rosenblatt, 2018; Hsu et al., 2013; Kapur et al., 2010; Olafsdottir et al., 2007; Papi et al., 2015; Qu, 2012; Robert et al., 2009; Shim et al., 2004) and clinical populations (Black et al., 2007; Latash et al., 2002; Papi et al., 2015; Park et al., 2012) to generate movement solutions during everyday activities, it is important to know the number of observations needed to characterize these movements.

The purpose of this study was to evaluate the minimum number of steps needed to obtain a "reasonable approximation" of the "true" value of three UCM-derived measures – two variance components and the synergy index. Here we use the term "reasonable approximation" rather than "reliable" or "accurate", which utilize specific methodologies. Specifically, we will "approximate" – i.e., obtain values that are $\geq$90% the "true value", or the value obtained with a "large" number of steps – with "reasonable" certainty – i.e., 95% confidence.

2. Methods

This study is a secondary analysis of data from fourteen healthy community-dwelling older (>65 years) adults (7 female; 71.4 ± 6.8 years; 1.69 ± 0.09 m; 67.4 ± 7.5 kg) who participated in a larger study focused on the effects of obesity on fall risk. Only data from subjects with body mass index of 17.5–25.0 kg/m^2 is included. All subjects were screened for neuromusculoskeletal health (e.g., normal range of motion, no joint replacements or history of neurodegenerative disease) and provided written informed consent before participating in this study approved by the Rosalind Franklin University IRB.

Participants walked on a motorized treadmill (Motek; Amsterdam, Netherlands) for 10 min at a self-selected velocity, determined using a previously described approach (Rosenblatt et al., 2014a,b). An 8-camera motion capture system (Vicon; Oxford, UK) tracked the motions of passive reflective markers placed on body landmarks according to the full body plug in gait model. Marker data was processed using commercial software (Nexus; Oxford, UK) to obtain locations of the lower limb joint centers and segment lengths. Two performance variables related to mechanical stability of gait were then considered in the analysis. One variable, the mediolateral (ML) trajectory of the swing limb (Krishnan et al., 2013; Rosenblatt et al., 2015; Rosenblatt et al., 2014a,b) - defined as the mediolateral position of the swing limb ankle joint center relative to that of the stance limb (AJC_{ML}) - was chosen due to the importance of mediolateral foot placement in the control of mechanical stability while walking (Bauby and Kuo, 2000; Donelan et al., 2004). We also considered the frontal plane position of whole body center of mass (CoM) relative to the stance limb ankle joint center (CoM_{ML}), given the importance of ML CoM control in the maintenance of upright gait (Hurt et al., 2010; Papi et al., 2015). For both performance variables, elemental variables were segment angles of the lower limbs and trunk. For the AJC_{ML} analysis, motion data was normalized from 0 to 100% corresponding to each left-leg swing; for CoM_{ML} analysis, motion data was normalized to each left-leg swing and ensuing double support. Normalized data was then entered into custom code (Matlab; Cambridge, MA) to calculate the UCM measures, using a four step process (Scholz and Schoner, 1999):

1) A geometric model was created to express the performance variables as functions of 7 or 9 elemental variables (Greek letters in Eqns. (1) and (2)), for AJC_{ML} and CoM_{ML} respectively (see Fig. 1 for definitions of elemental variables). We used a previous described model for the former (Krishnan et al., 2013) and a similar model for the latter, with the addition of trunk mediolateral and frontal plane flexion.

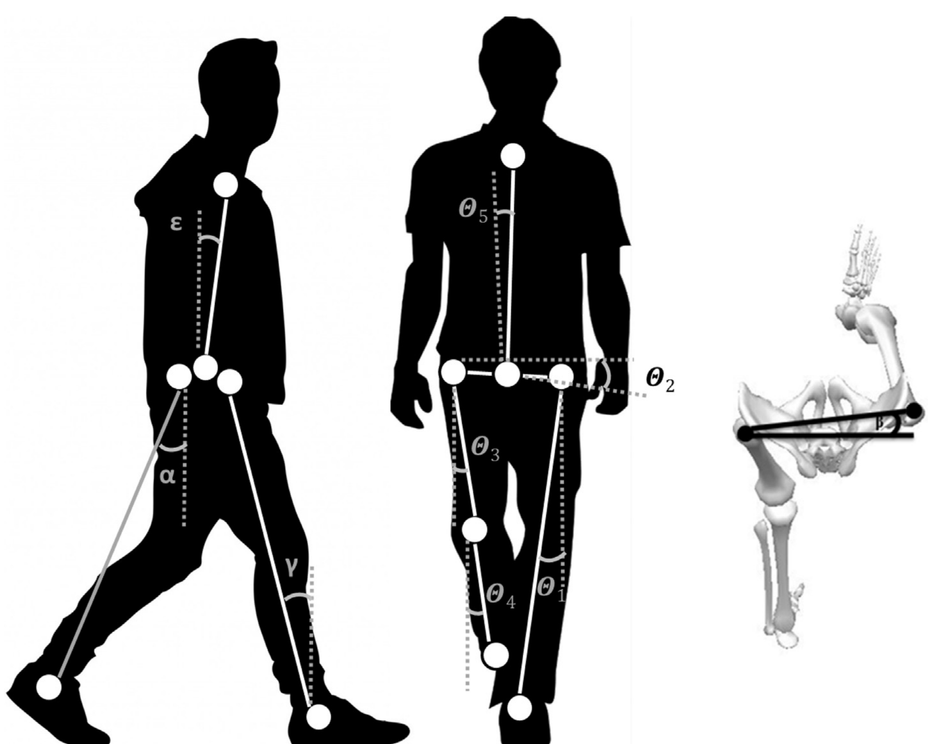

Fig. 1. Definition of elemental variables used in the UCM analyses. (left) sagittal plane view where white circles represent the hip and ankle joint centers as well as the center of the pelvis and the shoulders; (middle) frontal plane view with white circles representing similar locations, with the addition of a circle representing the knee joint center on the swing; (right) blank circles represent hip joint centers.

Anthropometric tables (Winter, 2005) were used to approximate the positions of the segmental CoMs relative to their ends ($y_{1,3,4,5}$ in Eq. (2)) and the magnitudes of segmental CoMs ($m_{1,3,4,5}$ in Eq. (2)). The terms $L_{1,-4}$ represent the lengths of model segments.

$$\mathbf{AJC_{ML}} = L_1 \cos\alpha \sin\theta_1 + L_2 \cos\beta \cos\theta_2 + L_3 \cos\gamma \sin\theta_3 + L_4 \cos\gamma \sin\theta_4 \quad (1)$$

$$\mathbf{COM_{ML}} = \frac{1}{m_1 + m_5 + m_3 + m_4} * [m_1 * y_1 * L_1 \cos\alpha \sin\theta_1 + \cdots$$

$$m_5 * (L_1 \cos\alpha \sin\theta_1 + 0.5 * L_2 \cos\beta \cos\theta_2 + y_5 * L_5 \cos\varepsilon \cos\theta_5) \cdots$$

$$m_3 * (L_1 \cos\alpha \sin\theta_1 + L_2 \cos\beta \cos\theta_2 + y_3 * L_3 \cos\gamma \sin\theta_3) + \cdots$$

$$m_4 * (L_1 \cos\alpha \sin\theta_1 + L_2 \cos\beta \cos\theta_2 + y_3 * L_3 \cos\gamma \sin\theta_3 + y_4 * L_4 \cos\gamma \sin\theta_4)] \quad (2)$$

2) A Jacobian matrix was derived from the model to relate changes in elemental variables to changes in the performance variable. At every percent of the normalized gait cycle, the Jacobian was evaluated at the mean values of the elemental variables. The null space of the evaluated Jacobian defined the UCM.
3) For each left-step, deviation vectors were independently calculated at every percent of swing as the difference between the elemental variables at that point and their respective means. These vectors were projected onto the UCM and a space orthogonal to it. The squared length of the projected vectors in each space, relative to the number of DoFs in that space, was averaged across multiple steps to define two variance components (V_{UCM} and V_{ORT}, respectively).
4) The synergy index was calculated at each percent as the difference between V_{UCM} and $V_{ORT,}$ relative to the total variance. The index was then z-transformed (Robert et al., 2009). All outcomes were averaged across 0–100%

For each participant, we ran the four-step process within a larger Monte Carlo simulation to generate subject-specific curves of the synergy index, V_{UCM} and V_{ORT} as a function of number of steps. This was done to visually verify that the curves plateaued after some "large" number of steps (N_{max}). Within the simulation, we performed the following actions: (1) set $N_{max} = 100$; (2) randomly selected $n = 2$ steps from the first N_{max} steps; (3) calculateed UCM-derived variables for n steps using the four-step process; (4) repeated actions 2 and 3 over 50 replications (above which limited improvements in simulation accuracy were expected) (Efron and Tibshirani, 1986); (5) calculated an average value across replications for the synergy index, V_{UCM} and V_{ORT}; (6) increased n to $n + 1$ and repeat actions 2–5 until $n = N_{max}$; (7) visually identified a plateau in the synergy index, V_{UCM} and V_{ORT} curves; if none existed then we would increase N_{max} and repeat actions 1–7.

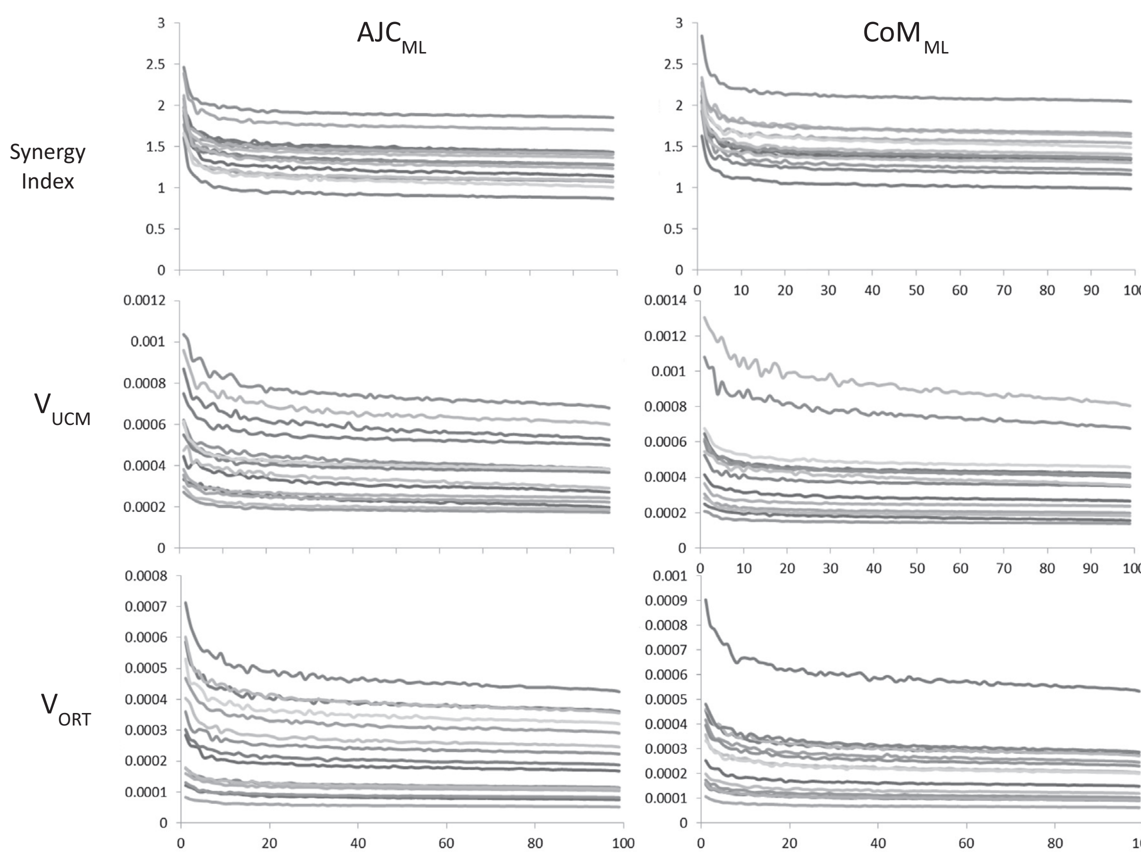

Fig. 2. UCM-related variables for two performance variables plotted as a function of number of steps (n) included in the UCM analysis. For each n, 50 Monte Carlo repetitions were conducted and the output was averaged across repetitions. Each curve represents averaged result for a given subject. All curves plateau at $n < 100$.

After determining an appropriate N_{max}, the values for the synergy index, V_{UCM} and V_{ORT} obtained within a given replication, for a given n, were expressed as percentages of the values attained with N_{max}. For each subject these percentages were then averaged across all 50 simulation replications. From these subject-specific averages, at each n we calculated 95% confidence intervals (CIs) then calculated the grand mean curves by averaging subject-specific curves. The minimum number of steps needed to provide a "reasonable approximation" of a measure was defined as the lowest value of n, above which all lower CIs were ≥90% of the grand mean values.

3. Results

In general, regardless of performance variable, the curves for each of the UCM-related variables as a function of number of steps in the analysis plateaued prior to $n = 100$ (Fig. 2). Therefore we set $N_{max} = 100$ for all ensuing analyses when determining the minimum n needed to approximate "plateau" values (Fig. 1).

Regardless of the performance variable, the synergy index sharply increased for small step counts then leveled out (Fig. 3); with 16 steps in the analysis, the 95% CIs for the synergy index were ≥90% of the values obtained when 100 steps were analyzed. (Fig. 2). Thus 16 steps provides a reasonable approximation of the synergy index.

In contrast, with 16 steps in the analysis, we could be 95% confident that the values of the variance components were 78–81% of the values with $n = 100$ (Fig. 2). We required $n = 49$ steps to obtain "reasonable approximations" for both variance components for each performance variable (Fig. 2). The average absolute change in the variance components for $n = 16$ compared to $n = N_{max}$ varied from 3.4e-5 to 6.4e-5, depending on the component and performance variable (Fig. 1).

4. Discussion

The purpose of this study was to evaluate the minimum number of steps needed to obtain a "reasonable approximation" for three

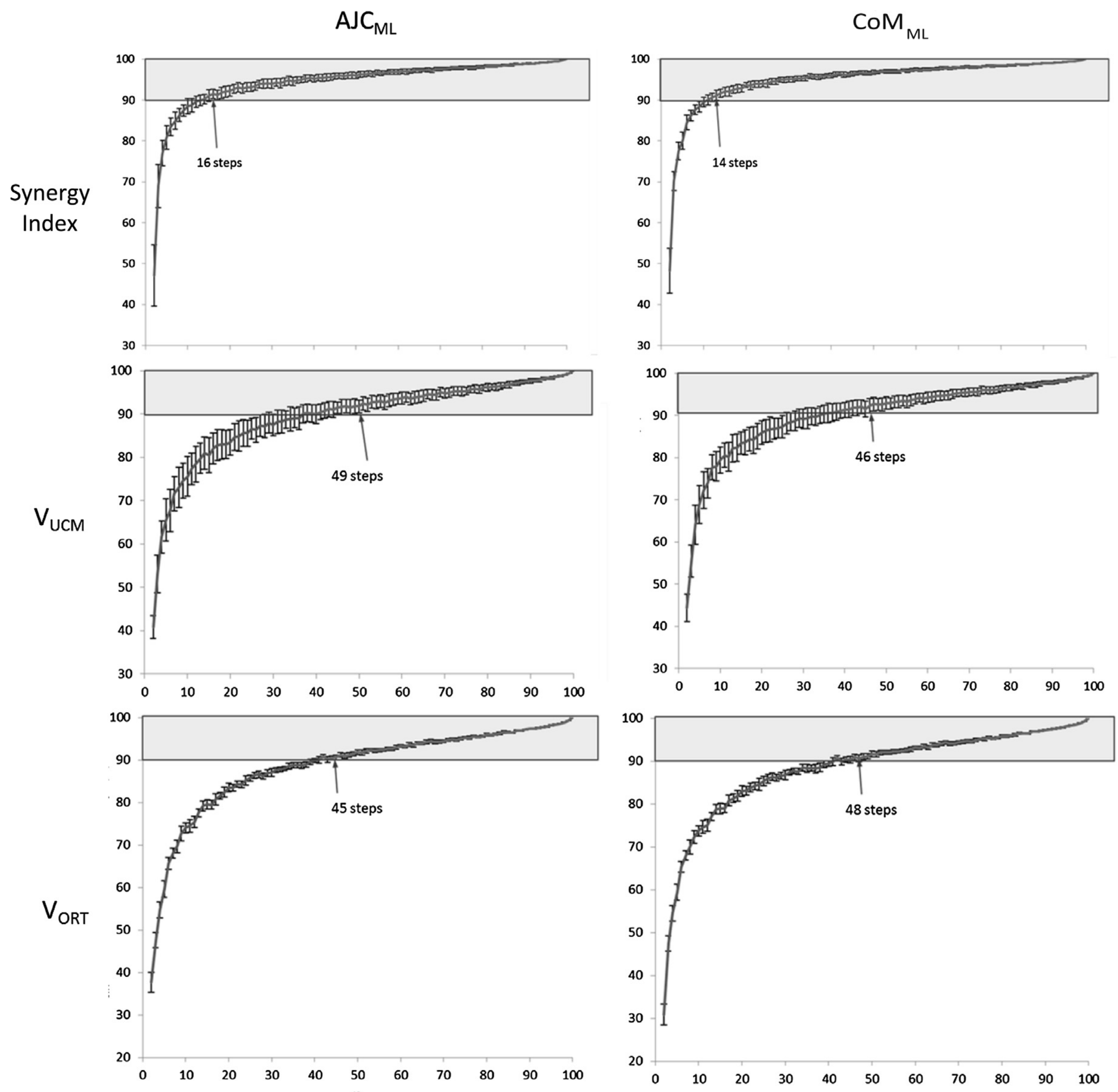

Fig. 3. Grand-mean curves of UCM-related variables as a percent of the value with $N_{max} = 100$, for two performance variables plotted as a function of number of steps (n). For each subject, for each n, 50 Monte Carlo repetitions were performed and the outputs were expressed relative to the values with $n = N_{max}$. Normalized values were then averaged across the 50 repetitions. Each curve represents the grand mean of the normalized curves. Error bars are 95% CI obtained from the subject-specific normalized curves. The number of steps that provide a "reasonable approximation" of values at N_{max} is noted by the arrow.

UCM-derived measures. Regardless of performance variable, 16 steps was sufficient to obtain a "reasonable approximation" of the synergy index. While nearly 50 steps were needed to reasonably approximate the variance components, the two proportionally changed from $n = 16$ to $n = 50$, explaining the lower number of steps for the synergy index. Importantly, previous results regarding variance components from studies using $n < 50$ (Krishnan et al., 2013; Papi et al., 2015; Robert et al., 2009; Rosenblatt et al., 2014a,b; Verrel et al., 2010) should not be dismissed. While reported values from these studies may not represent the "true values" (i.e. those obtained with N_{max}), the difference between reported and "true" values is expected to be relatively small; average absolute changes in variance components with $n = 16$ vs. $n = 100$ were an order of magnitude less than the smallest subject-specific values for these same variables (1e-5 vs. 1e-4, respectively). Because the magnitudes of the variance components are small relative to the synergy index, small deviation from N_{max} may manifest as larger percentage differences. As there is no reason to believe differences between reported and "true" values should depend on experimental conditions, previous reports of between-condition effects would be expected to persist even with more data points. However additional work is needed to demonstrate this.

Several factors may limit generalizability of the current findings. This study utilized treadmill walking, which could limit generalizability to overground conditions, although foot placement and CoM motion relative to the foot may be independent of walking modality (Rosenblatt and Grabiner, 2010). Moreover, in the current study, the 95% CI for the synergy index for AJC_{ML} with $n = 16$ overlaps with previous data from overground walking (Krishnan et al., 2013) (95% CIs: 1.22–1.47 vs. 1.23–1.51, respectively). Results from the current study may not generalize to other performance variables, although findings were similar for AJC_{ML} and COM_{ML}. Generalizability across performance variables (and tasks) is not trivial in light of the wide variety of tasks to which the UCM analysis has been applied (Black et al., 2007; Eckardt and Rosenblatt, 2018; Hsu et al., 2013; Kapur et al., 2010; Latash et al., 2002; Olafsdottir et al., 2007; Papi et al., 2015; Park et al., 2012; Qu, 2012; Robert et al., 2009; Shim et al., 2004). Given that thresholds for "reasonable approximations" depend on intersubject variability, results may differ with a different sampling of subjects. While variance component curves show considerable intersubject variability (Fig. 1) their shapes, and thus values at a given n relative to N_{max} (used to calculate thresholds) tend to be consistent across subjects.

The ability to obtain a "reasonable approximation" for UCM-derived measures using a relatively small number of steps is important if these measures are to be employed within clinical settings where time, space and patient mobility may be constrained. However, it is first critical to evaluate reliability using interclass coefficients, to establish the functional implication of smaller/larger synergy index during gait and, relatedly, to estimate the minimum clinical important difference. Once accomplished, clinical implementation may be possible; similar measures have demonstrated sensitivity to functional changes in patient populations (Falaki et al., 2016; Lewis et al., 2016).

In conclusion, the individual components used to calculate the synergy index required 50 steps to provide "reasonable approximations", however the differences between using 15–20 steps and 50 steps were small (i.e. 20%). The collection of 15–20 steps results in a reasonable approximation of the synergy index related to frontal plane foot placement and CoM control, which is advantageous when the data collections are constrained to a limited number of steps.

Conflict of interest

The authors have no conflicts of interest to declare.

Acknowledgments

Research reported in this publication was supported by the National Institute of Arthritis and Musculoskeletal and Skin Diseases award number 1R03AR066326-01A1. The content in this publication is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The funding sources had no role in the study design, collection, analysis or interpretation of data.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2019.01.018.

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