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Movement variability response to change in the rate of hopping

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Movement variability is often considered undesirable, but growing evidence demonstrates positive aspects of variability. During unipedal hopping, control of limb stiffness and limb length are paramount. *Purpose*: The purpose of this study was to compare two methods of measuring movement variability that provide information at the task level, and their capacities to illuminate the neuromotor control system's response to change in hopping rate. *Methods*: The typical task-level movement variability measure of the standard deviation of vertical limb length was compared to uncontrolled manifold analysis. We examined the relationship between change scores in deviation from spring-mass model-type behavior and these two variability measures for the shift from typical (2.3 Hz) to slow (1.7 Hz) hopping. *Results*: The change scores for deviation from spring-mass model-type behavior and vertical limb length standard deviation demonstrated no correlation ($p = 0.784$, $R = 0.051$). In contrast, the change scores for deviation from spring-mass model-type behavior and the uncontrolled manifold analysis measure demonstrated a moderate correlation ($p = 0.004$, $R = 0.502$). *Conclusions*: Uncontrolled manifold analysis considers not just variability in the sense of error, but illustrates how the neuromotor control system distributes movement variability into performance-irrelevant and performance-destabilizing subspaces. As such, this type of analysis may be more effective at illuminating global control aspects of movement variability than the typical variability measure of limb length standard deviation.

Key words: *uncontrolled manifold, spring mass model, segmental coordination*

1. Introduction

Movement variability is often considered the failure of an imperfect human control system, and, therefore, something to be minimized. However, movement variability is found to a surprising degree even in elite athletes [2], [4]. Variability tends to decrease with progression from novice to moderate skill level, but increase with progression from moderate skill to expertise [2], [10], [16], [19]. Furthermore, altered variability is associated with pathology in a variety of injury types and activities [3], [10], [11], [14]. While some of these studies link pathology with excessive variability, others link pathology with insufficient variability.

Findings of decreased variability in pathological populations point to the positive roles of variability. Variability may enable multiple successful performance strategies and make the performer adaptable to small changes in task, equipment, or personal state, and even protect against injury [4], [10], [11], [14]. Most variability studies employ single-joint or dual-joint, or endpoint-only, measures of variability. Such measures provide a magnitude of variability, but no information about quality – whether it promotes or detracts from performance consistency.

Uncontrolled manifold (UCM) analysis parses variability into performance-irrelevant (V_{UCM}) and performance-destabilizing (V_{ORT}) subspaces, providing a distinction in movement variability quality not offered by most other measures of variability [23]. It is plausible that V_{UCM} (vs. V_{ORT}) plays the positive roles of providing adaptability and protection against injury without disrupting performance. This assertion is consis-

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tent with previous findings of a smaller proportion of V_{UCM} (vs. V_{ORT}) variability in elders and persons with neurological disorders compared to younger or healthy counterparts [15], [20]. UCM analysis provides a promising tool to explore individual responses to perturbations or small changes within a task potentially associated with injury risk.

For UCM analysis, variability is measured at two levels. The first is a relatively microscopic examination of variability at the elemental contributor level. This microscopic level typically represents measures of kinematic variability. The second is a relatively macroscopic examination of variability at the task level. This macroscopic level typically represents measures of outcome variability. The elemental contributors may coordinate so that variability in one element cancels out variability in another. This cancelling-out promotes task level measure consistency, and is deemed performance-irrelevant variability (V_{UCM}). In contrast, the elemental contributors may fail to coordinate so that variability in one element is not countered by variability in another. This lack of coordination results in task level measure inconsistency, and is deemed performance-destabilizing variability (V_{ORT}).

The UCM method provides context to the control system's manner of distributing variability at the elemental level, whether it contributes to or detracts from task-level variability. Such detailed content is not available with basic movement variability measures, such as the standard deviation of vertical limb length across hopping trials (VLL_{SD}). While numerous studies examining movement variability from the perspective of single-joint or end-point standard deviation (akin to VLL_{SD}) and others – using the UCM method have been conducted, the authors are unaware of any study comparing these differing movement variability perspectives using the same data set.

This study employs unipedal hopping, a naturally repetitive movement and tightly-controlled proxy for the more ecologically relevant bouncing gait of running. These types of bouncing gait are classically modeled by a spring-mass system ($ma_V + k\Delta L_V = mg$), which accurately predicts all major mechanical parameters despite its apparent oversimplification of the entire lower limb into a spring [5]. The spring-mass model highlights the importance of spring compression (ΔL_V) control, prompting the use of vertical limb length variability as the task-level variability parameter examined in this study. Although not required for UCM analysis, elemental variables that have a straightforward mapping onto the task level variable are highly desirable [23]. For this study, elemental variables of foot-to-floor, ankle and knee local joint-coordinate sagittal plane intersegmental angles were chosen because they have a straightforward mapping onto the task level variable of vertical limb length (Fig. 1).

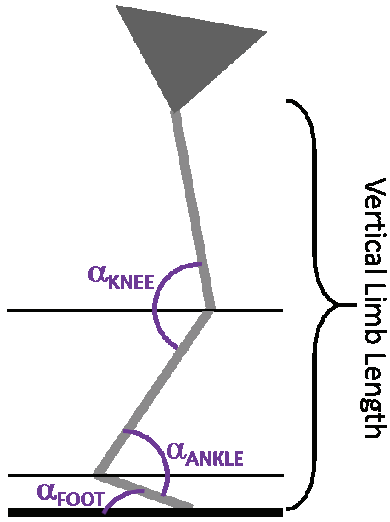


Fig. 1. Vertical limb length model for UCM analysis. The relationship between the elemental variables (sagittal plane foot-to-floor, and ankle and knee intersegmental angles) and the task-level variable (vertical limb length)

Hopping at rates slower than typically preferred presents a challenge to spring-mass model-type behavior, particularly with regards to maintaining linear spring stiffness (k) [5]. However, maintenance of spring-mass model-type behavior has been demonstrated even in the presence of severe perturbations [7], [17]. Change in adherence to spring-mass model-type behavior is used as a representative of the degree of control strategy alteration in response to changing the hopping rate for this study, and is compared to change in the movement variability measures.

The purpose of this study is to compare the relationship between two different methods of measuring movement variability and change in adherence to spring-mass model-type behavior in response to altered hopping rate. The first method is the basic movement variability measure of the standard deviation of vertical limb length across hopping trials (VLL_{SD}). The second method is uncontrolled manifold analysis (UCM) of the degree to which coordination between variability in foot, shank and thigh positioning contributes to stabilization of vertical limb length across hopping trials. Due to the interest in response to change in hopping rate, within-participant change-scores are the primary data analyzed. Correlations between change scores for each movement variability type, and change in adherence to spring-mass model-type behavior (alteration in control strategy) are explored.

2. Materials and methods

Participants

Thirty-four healthy volunteers aged 23–55 (average age 30 yr.; 15 males; body mass 71.23 ± 10.28 kg) participated. All participants were screened by a physical therapist to ensure the ability to participate safely. Limb preference for kicking a ball the greatest possible distance was determined. All procedures performed were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The Institutional Review Board of the Health Sciences Campus of the University of Southern California approved this study. Written informed consent was obtained from all participants.

Task

Typical self-selected *bipedal* hopping rate in humans has been reported as 2.0–2.3 Hz [5]. Pilot testing in our laboratory demonstrated self-selected *unipedal* hopping rates of 2.1–2.4 Hz. Preferred rate differed within-participant between hopping bouts and between days of testing. Participants in this study were tested at 2.3 Hz and 1.7 Hz, providing notable separation between the typical and slow rates examined. All participants reported that 2.3 Hz hopping was easy to maintain and considerably easier to perform than 1.7 Hz hopping. Hopping at 1.7 Hz posed a significant challenge to all participants, but still allowed consistent and uninterrupted hopping. Hopping rate was prescribed by music that had a strong bass-beat at 140 bpm for 2.3 Hz hopping and 100 bpm for 1.7 Hz hopping. All participants were able to remain within ±0.1 Hz of the prescribed hopping rate throughout all trials as measured by individual hop durations. Hop height was not explicitly controlled. However, hop height consistency was expected, given the rate constraint and observation of an implicit constraint of consistent limb stiffness [5].

Biomechanical instrumentation

Participants wore their own athletic shoes and attire, and were outfitted with reflective markers over the following anatomical landmarks: iliac crests, anterior superior iliac spines, space between the L5 and S1 spinous processes, greater trochanters, medial and lateral femoral epicondyles, medial and lateral malleoli, 1st and 5th metatarsal heads, and the distal phalanx of the pedal 2nd rays. Additional rigid reflective marker clusters were placed bilaterally on the lateral surfaces of the thighs, shanks, and heels. 3D kinematic data were collected using an 11-camera motion analysis system (sampling rate: 250 Hz; Qualisys AB, Gothenburg Sweden). Ground reaction force data were collected from a 120 cm × 120 cm force plate embedded in the laboratory floor (sampling rate: 1500 Hz; AMTI Corp., Newton MA, USA).

Experimental protocol

While outfitted with reflective markers as above, each participant completed a standing static trial followed by a series of unipedal hopping trials. Upper extremity movement during hopping trials was constrained by the participants holding a 0.3 kg dowel across their shoulders. Participants performed a minimum of 27 consecutive hops on each lower extremity at 1.7 Hz and 2.3 Hz. The order of limb testing and hopping rates was randomized. In each case, the participant was instructed to "please hop in place to the beat". A familiarization trial was performed at each hopping rate. Rest breaks of at least 1.5 minutes were given between hopping trials.

Data reduction and analysis

The first and last pair of hops from each trial were excluded from analysis. All remaining hops were qualitatively screened for visibly aberrant kinematics by reviewing video footage from the data collection. Visibly aberrant kinematics included notable trunk lean (forward or lateral), letting go of the arm-constraining dowel, or flailing the non-hopping leg. No aberrant kinematics were found in any of the included hopping trials. The accepted hops (23–28 hops per limb per participant) were parsed into stance (ground reaction force ≥20 N) and flight (ground reaction force <20 N) phases. Only data from the stance phase were analyzed, as control of limb length during flight is not an expected neuromotor control system goal. Stance phase data were normalized to 100 frames for UCM analysis, which requires all trials to contain the same number of data points. Preliminary data exploration for the individual measures at the two hopping rates demonstrated no significant difference between the preferred kicking and contralateral limbs at either hopping rate; therefore, limbs were pooled bilaterally for a total of 46–56 hops analyzed per participant.

Kinematic data were filtered with a bidirectional 4th order Butterworth low-pass filter with cutoff frequency of 12 Hz. Movement out of the sagittal plane was found to be minimal, with the sagittal plane projection of the foot, shank, and thigh segment lengths differing from the segment lengths computed from 3D data in the static trial by ≤2% at any given time point. Therefore, the segment lengths computed from the static trial were used during all further calculations.

The exact UCM calculation methods employed in this study have been detailed elsewhere [8]. Briefly, the referent joint configuration vector (**θ**) was calculated at each percent of stance by averaging the local joint-coordinate sagittal foot-to-floor, and ankle and knee intersegmental angles across trials. A forward kinematic model linked changes in elemental variables (sagittal plane foot-to-floor, and ankle and knee intersegmental angles) to the task-level variable of vertical limb length (Fig. 1). Custom MATLAB code was used to compute the Jacobian matrix (**J**(**θ**)) for each 1% of stance. **J**(**θ**) determines how small deviations in the angles from the average configuration influence the vertical limb length. A consistent time-dependent vertical limb length was considered stable performance. The null space of **J**(**θ**) is the linear approximation of the UCM subspace; variance within the UCM subspace is performance-irrelevant variability (V_{UCM}). Variance within the subspace orthogonal to the UCM is the performance-destabilizing variability (V_{ORT}). The index of motor abundance (IMA) was computed as the normalized difference between V_{UCM} and V_{ORT}. IMA is also commonly referred to as the index of synergy (ΔV) in the UCM literature. J(**θ**), V_{UCM}, V_{ORT} and IMA were calculated at every 1% of the stance phase. The stance phase integral of each measure was then computed.

Vertical limb length standard deviation magnitude (VLL_{SD}), was computed for comparison to uncontrolled manifold analysis. Vertical limb length was considered the distance from the floor to the hip joint center throughout stance. VLL_{SD} was calculated for each 1% of the stance phase, and then the stance phase integral was calculated.

Limb stiffness was calculated as the absolute value of the slope of the regression line fitted to the scatter plot of vertical ground reaction force (multiples of bodyweight, BW) vs. center of mass height (estimated by L_5S_1 marker position) during the absorption sub-phase of stance (touchdown to center of mass minimum) [6]. Since the spring-mass model predicts linear limb stiffness, we quantified deviation from spring-mass model-type behavior in terms of deviation from linear limb stiffness ($Stiff_{\mathrm{Dev}}$) for both hopping rates (Fig. 2). Since there is no established method for quantifying such deviation, we calculated $Stiff_{\mathrm{Dev}}$ as a single percentage according to Eq. (1). The larger the negative ratio, the greater the deviation from spring-mass model-type behavior. Specifically, a larger negative ratio represents a greater decrement in limb stiffness late in the absorption sub-phase, compared to the initial limb stiffness following touchdown.

$$Stiff_{\mathrm{Dev}} = \frac{Stiffness_{\text{100\% absorption sub-phase}} - Stiffness_{\text{First 50\% absorption sub-phase}}}{Stiffness_{\text{First 50\% absorption sub-phase}}} \quad (1)$$

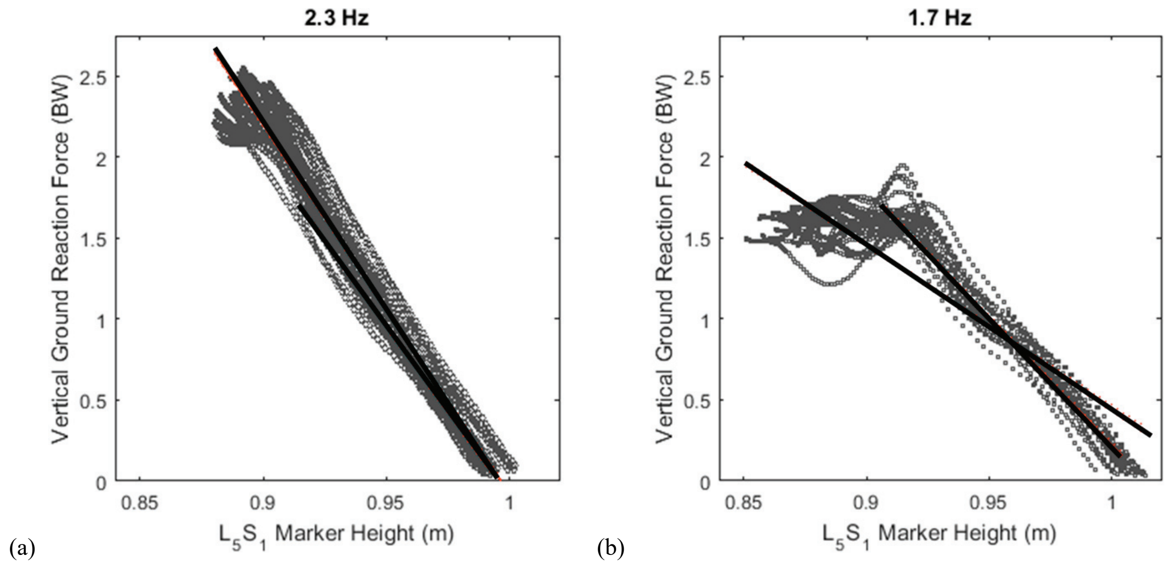


Fig. 2. Single-participant example $Stiff_{\mathrm{Dev}}$ calculation. The selected participant demonstrated a notable increase in $Stiff_{\mathrm{Dev}}$ when shifting from 2.3 to 1.7 Hz hopping. Limb stiffness was calculated as the absolute value of the slope of the regression line fitted to the scatter plot of bodyweight-normalized vertical ground reaction force vs. L_5S_1 marker position. Lines overlaying the scatter plot represent stiffness during the first 50%, and throughout 100%, of the absorption subphase at 2.3 Hz (a) and 1.7 Hz (b)

Statistical analyses

SPSS Statistics 22.0 software (IBM Corp.; Armonk NY, USA) was used for all statistical analyses. Differences for each measure between 2.3 Hz and 1.7 Hz hopping conditions were determined with paired-samples *t*-tests. Data were reported as mean ± standard deviation. Cohen's D effect sizes were calculated for all paired *t*-test results. Pearson correlations were used to examine the relationship between the change scores ($\text{Value}_{1.7\text{ Hz}} - \text{Value}_{2.3\text{ Hz}}$) for $Stiff_{\text{Dev}}$ and the two variability measures (total stance phase IMA and total stance phase VLL_{SD}). Significance was set at $\alpha = 0.05$.

3. Results

Limb stiffness was greater during 2.3 Hz than 1.7 Hz hopping (Table 1, Fig. 3). All participants demonstrated decreased stiffness when switching from typical (2.3 Hz) to slow (1.7 Hz) hopping (95% CI: decrease of 12.20–13.56 BW/m). Deviation from spring-mass model-type behavior was greater during 1.7 Hz than 2.3 Hz hopping; this is represented by a more negative $Stiff_{\text{Dev}}$ (Table 1, Fig. 4). All participants demonstrated increased $\text{Stiff}_{\text{Dev}}$ when switching from typical to slow hopping (95% CI: more negative by 0.25–0.33).

Total stance phase standard deviation of vertical limb length (VLL_{SD}) was greater during 1.7 Hz than 2.3 Hz hopping (Table 1, Fig. 5). Most participants (85%) demonstrated increased VLL_{SD} when switching from typical to slow hopping (95% CI: increase of 0.11–0.27 m).

Total stance phase index of motor abundance regarding limb length stabilization (IMA) was greater during 2.3 Hz than 1.7 Hz hopping (Table 1, Fig. 6a). IMA quantifies the degree to which a greater or lesser proportion of the total variability is channeled into the performance-irrelevant (V_{UCM}) vs. the performance-destabilizing (V_{ORT}) subspace. A larger positive IMA

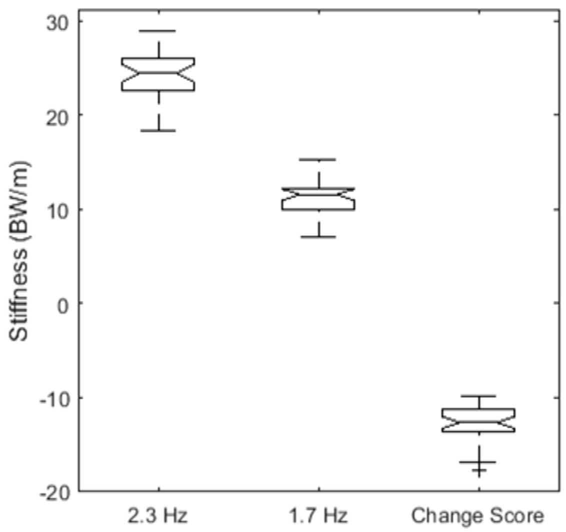


Fig. 3. Limb stiffness. Limb stiffness decreased with the shift from 2.3 to 1.7 Hz hopping

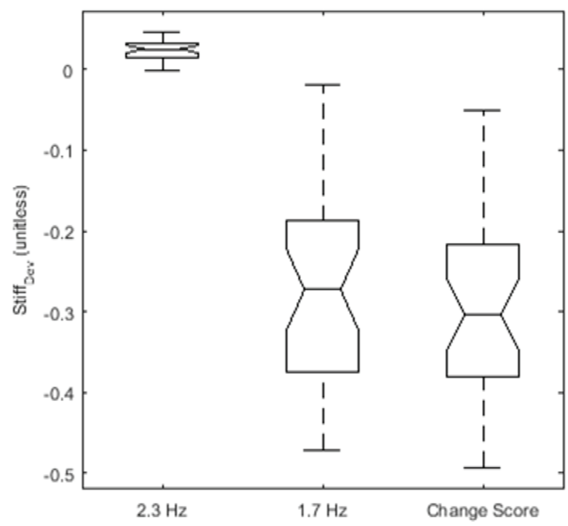


Fig. 4. Deviation from spring-mass model-type behavior. $\text{Stiff}_{\text{Dev}}$ became more negative with the shift from 2.3 to 1.7 Hz hopping

Table 1. Results of paired *t*-tests for the difference between hopping at 2.3 Hz and 1.7 Hz

	2.3 Hz	1.7 Hz	Difference between 2.3 and 1.7 Hz	
	Average (SD)	Average (SD)	*p*-value	Effect size
Limb Stiffness [BW/m]	24.17 (2.51)	11.29 (1.58)	<0.001	6.639
$Stiff_{\text{Dev}}$ [%]	0.02 (0.01)	–0.26 (0.13)	<0.001	2.355
VLL_{SD} [m]	0.87 (0.24)	1.06 (0.24)	<0.001	0.863
IMA [–]	60.15 (19.30)	54.64 (16.04)	0.35	0.377
V_{UCM} [rad^2/DOF]	0.24 (0.07)	0.30 (0.14)	0.003	0.551
V_{ORT} [rad^2/DOF]	0.14 (0.06)	0.19 (0.12)	0.005	0.517

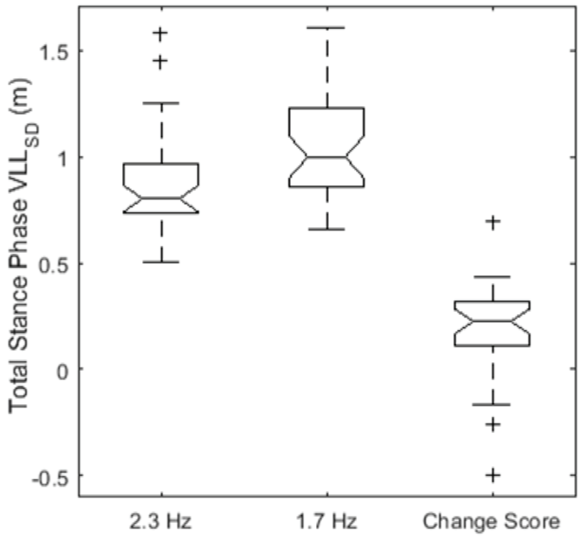


Fig. 5. Total stance phase variability in vertical limb length (VLL_{SD}). VLL_{SD} increased with the shift from 2.3 to 1.7 Hz hopping

value at a given time-point indicates $V_{UCM} > V_{ORT}$, so that most of the variability that occurs still allows a consistent vertical limb length across hopping repetitions. An IMA value near zero indicates that $V_{UCM} \approx V_{ORT}$, so that vertical limb length is not particularly consistent across hopping repetitions. The majority of participants (68%) decreased IMA when switching from typical to slow hopping (95% CI: decrease of 0.41–10.59).

Change in IMA is dictated by changes in its determinants (V_{UCM} and V_{ORT}). Both V_{UCM} and V_{ORT} were greater during 1.7 Hz than 2.3 Hz hopping (Table 1, Figs. 6b and 6c). Most participants (74%) increased V_{UCM} when switching from typical to slow hopping (95% CI: increase of 0.03–0.11 rad^2/DOF). Most participants (74%) also increased V_{ORT} when switching from typical to slow hopping (95% CI: increase of 0.02–0.08 rad^2/DOF).

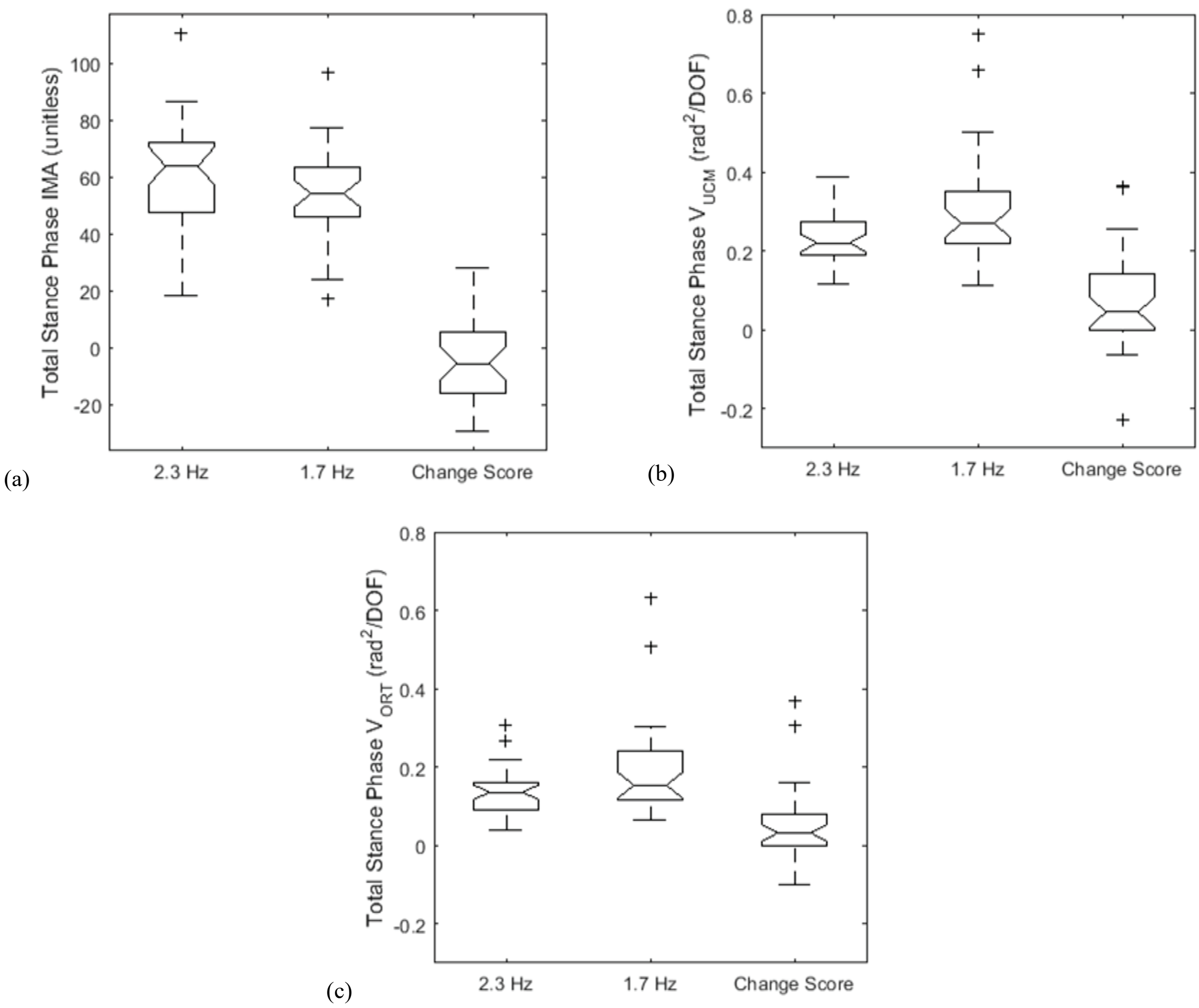
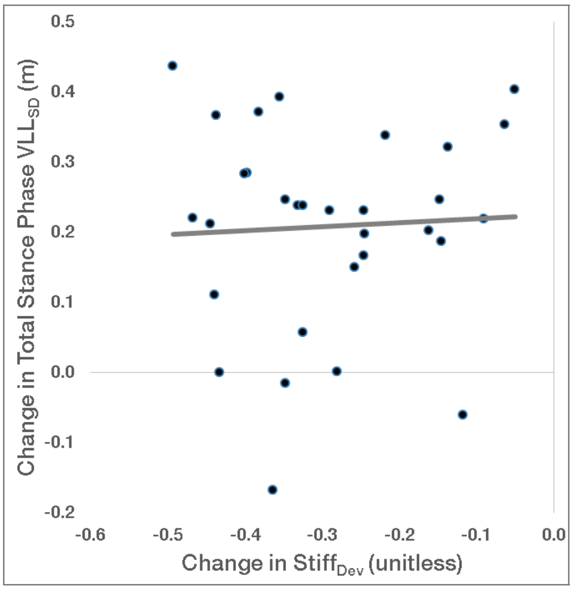
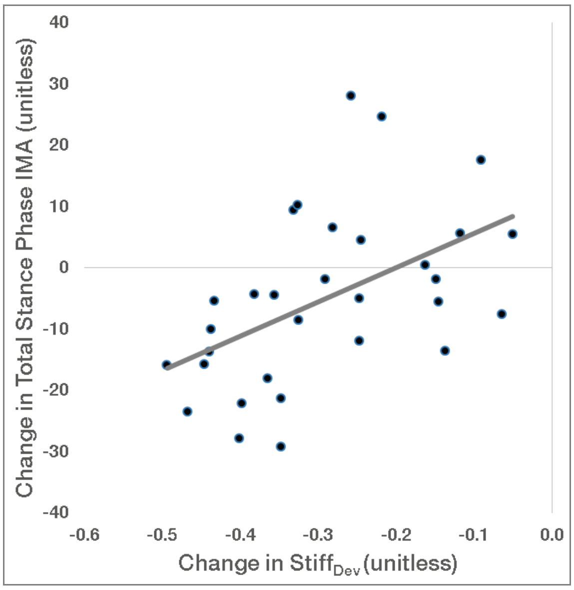


Fig. 6. Total stance phase index of motor abundance regarding limb length control (IMA) and its determinants (V_{UCM} and V_{ORT}): (a) IMA decreased with the shift from 2.3 to 1.7 Hz hopping, (b) V_{UCM} increased with the shift from 2.3 to 1.7 Hz hopping, (c) V_{ORT} increased with the shift from 2.3 to 1.7 Hz hopping



(a)



(b)

Fig. 7. Correlation between deviation from spring-mass model-type behavior and variability measures: (a) there was no significant relationship between change scores for $Stiff_{Dev}$ and VLL_{SD}, (b) there was a moderate correlation between change scores for $Stiff_{Dev}$ and IMA

Change scores for $Stiff_{Dev}$ and VLL_{SD} did not correlate ($p = 0.755$, $R = -0.056$). The lack of relationship held when the 3 outlier participants' data was removed ($p = 0.784$, $R = 0.051$, Fig. 7a). In contrast, the change scores for StiffDev and IMA were moderately correlated ($p = 0.003$, $R = 0.489$). This relationship improved in strength when the 3 outlier participants' data was removed ($p = 0.004$, $R = 0.502$, Fig. 7b).

4. Discussion

Two different methods of measuring movement variability that provide limb length (task level) control information, within the same data set, were compared. The first method was the basic movement variability measure of VLL_{SD}. The second method was UCM analysis of the degree to which coordination between variability in foot, shank and thigh positioning contributed to stabilization of vertical limb length (IMA). The capacity of VLL_{SD} and IMA to illuminate the neuromotor control system's response ($Stiff_{Dev}$) to the perturbation of switching from typical (2.3 Hz) to challengingly slow (1.7 Hz) hopping was determined. Correlations between change scores for VLL_{SD} and IMA with change in $Stiff_{Dev}$ were examined. Change scores for IMA and $Stiff_{Dev}$ were moderately correlated, but no relationship was found between VLL_{SD} and $Stiff_{Dev}$ change scores (Fig. 7).

Limb stiffness is closely related to the control of limb length, and decreased limb stiffness with the 2.3 to 1.7 Hz shift found in this study (Fig. 3) corroborates previous findings [5]. Previous studies show that hopping at rates slower than typically self-selected challenges spring-mass model-type behavior (particularly linearity of limb stiffness) [5]. For all participants, limb stiffness was nearly linear throughout all of stance at 2.3 Hz. Similarly, for all participants, limb stiffness was linear throughout the majority of stance at 1.7 Hz, likely indicating an attempt to maintain spring-mass model-type behavior even in this challengingly slow condition, which could have warranted a very different control strategy. Deviation from linearity occurred only near mid-stance, where participants demonstrated relatively lesser stiffness. The greater deviation from spring-mass model-type behavior (more negative $Stiff_{Dev}$) with the shift from 2.3 to 1.7 Hz found in this study (Fig. 4) matches these previous findings.

UCM analysis considers variability at two levels to address both magnitude and quality of movement variability. We examined how variability in lower extremity segmental postures either contributed to (V_{ORT}) or minimized (V_{UCM}) variability of overall vertical limb length across hopping trials. The index of motor abundance (IMA) expresses the degree to which a greater or lesser proportion of the total variability is shunted into the vertical limb length-irrelevant (V_{UCM}) type, as opposed to vertical limb length-destabilizing (V_{ORT}) type. In the present study, 68% of participants decreased IMA with increasing task difficulty, while 32% increased IMA (Fig. 6). Previous studies have demonstrated alterations in IMA with perturbations or changes in task difficulty [1], [22]. Despite small sample sizes ($6 \leq n \leq 11$), neither of these studies discussed individual IMA-responses to the task changes probed.

To understand what drives changes in IMA, individual changes in V_{UCM} and V_{ORT} variability types must be examined. This need is underscored by the fact that participants in this study who decreased IMA with increasing task difficulty were not the exact same subset of participants who decreased VLL_{SD}. Of the 23 participants who decreased IMA with the shift from 2.3 to 1.7 Hz, 74% did so by increasing total variability (V_{ORT} more than V_{UCM}), 13% by decreasing total variability (V_{UCM} more than V_{ORT}), and 13% by increasing V_{ORT} while decreasing V_{UCM}. Increased total variability matches with some previous UCM studies, as well as several non-UCM variability studies that demonstrated increasing variability with increasing task difficulty [2], [9], [21], [22], [24]. The 18% of participants who responded to the hopping rate shift with decreased total variability match previous non-UCM variability studies demonstrating decreasing variability with increasing task difficulty [9], [24].

Vertical limb length standard deviation (VLL_{SD}) is a typical task-level movement variability measure that quantifies between-hop "error" in the control system. A larger VLL_{SD} value may indicate poor limb length control. In this study, 85% of participants increased VLL_{SD} with the shift from 2.3 to 1.7 Hz hopping (Fig. 5); this finding is consistent with previous literature demonstrating increased error-associated variability with increasing task difficulty [1], [12], [18].

This study illustrates the capacity of UCM analysis to illuminate the neuromotor control system's response ($Stiff_{Dev}$) to the perturbation of switching from typical (2.3 Hz) to challengingly slow (1.7 Hz) hopping condition. Limb stiffness is closely related to limb length control, which is captured in different manners by VLL_{SD} and IMA. A significant large correlation was found between change scores for IMA and $Stiff_{Dev}$, but no relationship was found between VLL_{SD} and Stiff_{Dev} (Fig. 7). The UCM method's consideration of how the neuromotor control system is shunting movement variability into performance-irrelevant and performance-destabilizing subspaces rather than strictly error-based movement variability likely underlies this finding. As such, UCM-based movement variability analysis may be better at illuminating more global control aspects than the typical types of movement variability measures (e.g., VLL_{SD}).

This study was limited by participant age skewing toward the younger end of the age range tested (68% under the average age of 30 yr., 26% > 30 yr.). However, it has been shown that young and elderly adults display similar spring-mass model-type behavior and limb stiffness across multiple hopping rates [13]. The vertical limb length control measured in this study is closely related to limb stiffness, and thus could be expected to be reasonably similar across age groups as well.

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