Elsevier Editorial System(tm) for Journal of Biomechanics Manuscript Draft

Manuscript Number: BM-D-14-00318R3

Title: CAN STABILITY REALLY PREDICT AN IMPENDING SLIP-RELATED FALL AMONG OLDER ADULTS?

Article Type: Full Length Article (max 3500 words)

Keywords: Fall prevention, Fall risk screening, Variability

Corresponding Author: Prof. Clive Pai, PhD

Corresponding Author's Institution: University of Illinois at Chicago

First Author: Feng Yang, PhD

Order of Authors: Feng Yang, PhD; Clive Pai, PhD

Abstract: The primary purpose of this study was to systematically evaluate and compare the predictive power of falls for a battery of stability indices, obtained during normal walking among communitydwelling older adults. One hundred and eighty seven community-dwelling older adults participated in the study. After walking regularly for 20 strides on a walkway, participants were subjected to an unannounced slip during gait under the protection of a safety harness. Full body kinematics and kinetics were monitored during walking using a motion capture system synchronized with force plates. Stability variables, including feasible-stability-region measurement, margin of stability, the maximum Floquet multiplier, the Lyapunov exponents (short- and long-term), and the variability of gait parameters (including the step length, step width, and step time) were calculated for each subject. Accuracy of predicting slip outcome (fall vs. recovery) was examined for each stability variable using logistic regression. Results showed that the feasible-stability-region measurement predicted fall incidence among these subjects with the highest accuracy (68.4%). Except for the step width (with an accuracy of 60.2%), no other stability variables could differentiate fallers from those who did not fall for the sample studied in this study. The findings from the present study could provide guidance to identify individuals at increased risk of falling using the feasible-stability-region measurement or variability of the step width.

Dear Dr. Cappozzo and Dr. Guilak:

We would like to thank you and the Reviewer for the effort spent on the review of our revised manuscript, entitled: "CAN STABILITY REALLY PREDICT AN IMPENDING SLIP-RELATED FALL AMONG OLDER ADULTS?" (BM-D-14-00318R2). By taking the Reviewer' comments seriously, we have carefully revised our manuscript. We believe that we now have thoroughly addressed each of the Reviewer's comments. Consequently, we believe that it has become an improved paper. We would like to resubmit the revised paper, together with a point-by-point response to Reviewer's comments (in Italic font).

Please note that both authors have made substantial contributions to all of the following: (1) the conception and design of the study, or acquisition of data, or analysis and interpretation of data; (2) drafting the article or revising it critically for important intellectual content; (3) final approval of the version to be submitted. All contributors who do not meet the criteria for authorship are listed in the acknowledge section. No writing assistance was provided to this manuscript.

Please also note that this paper has not been published previously, that it is not under consideration for publication elsewhere, and that if accepted it will not be published elsewhere in the same form, in English or in any other language, without the written consent of the publisher.

Should you have any questions, please do let us know.

Sincerely,

Clive Pai

The Referee List

#	Name	Address	Tel.	E-mail
1	James Ashton-Miller	Institute of Gerontology, University of Michigan, 3208 GG Brown, Ann Arbor, MI 48109-2125	734-763-2320	jaam@umich.edu
2	Cagdas Onal	Department of Mechanical Engineering, Worcester Polytechnical University	508-831-4857	cdonal@wpi.edu
3	Christopher Rhea	Department of Industrial and Systems Engineering, Virginia Tech, Virginia 24061	336-334-3023	ckrhea@uncg.edu
4	Martin Tanaka	Department of Engineering and Technology, Western Carolina University	828-227-2561	mtanaka@wcu.edu
5	M. Mahdi Agheli H	Department of Mechanical Engineering, Worcester Polytechnical University	508-831-5864	mmaghelih@wpi.edu

Dear Dr. Cappozzo and Dr. Guilak:

We would like to thank you and the Reviewer for the effort spent on the review of our revised manuscript, entitled: "*CAN STABILITY REALLY PREDICT AN IMPENDING SLIP-RELATED FALL AMONG OLDER ADULTS?*" (BM-D-14-00318R2). By taking the Reviewer' comments seriously, we have carefully revised our manuscript. We believe that we now have thoroughly addressed each of the Reviewer's comments. Consequently, we believe that it has become an improved paper. We would like to resubmit the revised paper, together with a point-by-point response to Reviewer's comments (*in Italic font*).

Reviewer's comments:

Reviewer #2:

1. Page 3 Line 4: There appears to be an incorrect word. Consider changing "It is important to identify individuals subject to an elevated risk" to "It is important to identify individuals subject at an elevated risk"

This sentence has been rewritten. It reads

"It is important to identify individuals at an elevated risk of falling before implementing effective fall prevention strategies." (Page 3, Lines 4-5)

2. Page 6 Line 3: The sentence is too long and awkward. Consider changed to two shorter sentences "The full-body harness, attached by shock-absorbing ropes, attaches to shoulders and waist to a low-friction linear bearing moving along a ceiling-mounted track, was employed for subjects' protection while imposing negligible resistance or constraint to their movement (Fig. 2)."

We are grateful for this comment. This sentence has been rephrased. It reads

"During walking, all subjects wore a full-body safety harness which was connected to a bearing by shock-absorbing ropes at the shoulders and waist. This low-friction linear bearing moved smoothly along a ceiling-mounted track. The harness system protected subjects from any potential injuries during falling while imposing negligible resistance or constraint to their walking movement (Fig. 2)." (Page 6, Lines 2-7)

3. Page 14 Line 17: The "literatures" should be "literature".

Sorry for the typo. This change has been made. (Page 14, Line 17)

TITLE PAGE

CAN STABILITY REALLY PREDICT AN IMPENDING SLIP-RELATED FALL AMONG OLDER ADULTS?

Feng Yang¹ and Yi-Chung Pai²

 ¹ Department of Kinesiology University of Texas at El Paso El Paso, TX 79968, USA
 ² Department of Physical Therapy University of Illinois at Chicago Chicago, IL 60612, USA

Corresponding author:

(Clive) Yi-Chung Pai, PhD Department of Physical Therapy University of Illinois at Chicago 1919 West Taylor St., Room 426 (M/C 898) Chicago, Illinois 60612, USA Tel: +1-312-996-1507 Fax: +1-312-996-4583 E-mail: cpai@uic.edu 1

ABSTRACT

2 The primary purpose of this study was to systematically evaluate and compare the 3 predictive power of falls for a battery of stability indices, obtained during normal walking 4 among community-dwelling older adults. One hundred and eighty seven community-5 dwelling older adults participated in the study. After walking regularly for 20 strides on a 6 walkway, participants were subjected to an unannounced slip during gait under the 7 protection of a safety harness. Full body kinematics and kinetics were monitored during 8 walking using a motion capture system synchronized with force plates. Stability 9 variables, including feasible-stability-region measurement, margin of stability, the 10 maximum Floquet multiplier, the Lyapunov exponents (short- and long-term), and the 11 variability of gait parameters (including the step length, step width, and step time) were 12 calculated for each subject. Accuracy of predicting slip outcome (fall vs. recovery) was 13 examined for each stability variable using logistic regression. Results showed that the 14 feasible-stability-region measurement predicted fall incidence among these subjects with 15 the highest accuracy (68.4%). Except for the step width (with an accuracy of 60.2%), no 16 other stability variables could differentiate fallers from those who did not fall for the 17 sample studied in this study. The findings from the present study could provide guidance 18 to identify individuals at increased risk of falling using the feasible-stability-region 19 measurement or variability of the step width.

20

21 Keywords: Fall prevention, Fall risk screening, Variability

INTRODUCTION

2	Falls can result in injury, institutionalization, and even death in older adults (Bieryla et
3	al., 2007). Slips during walking comprise 40% of outdoor falls among older adults
4	(Luukinen et al., 2000). It is important to identify individuals at an elevated risk of
5	falling before implementing effective fall prevention strategies. While it is logical to
6	postulate that a person's gait stability should yield useful clues as to the likelihood of
7	falls (Hamacher et al., 2011), there is little consensus on how gait stability should be
8	defined or measured. Though there are many measurements quantifying human gait
9	stability, little evidences support their capability of actually predicting an impending fall.
10	
11	The definition of a person's stability can be based on the kinematic relationship between
12	this person's center of mass (COM) and its base of support (BOS) (Borelli, 1680), as it
13	reflects a person's ability to restore or maintain COM balance in upright posture without
14	resorting to alter the existing BOS. Beyond the classical quantification of the limits of
15	stability (i.e. within the confine of the BOS) which only deals with the relative position of
16	COM to BOS, its extended conceptual framework measures the dynamic stability in
17	terms of the relative motion state (i.e. the position and velocity) between COM and its
18	BOS (Pai and Patton, 1997). Such conceptual framework has been used to estimate the
19	feasible stability region (FSR) in the COM-BOS-state space in walking (Fig. 1). Two
20	different methods: the 7-link model optimization (Yang et al., 2007) and a single-link
21	pendulum model with a linear approximation of the equation of motion (Hof et al., 2005),
22	have been used and different FSRs were established. The predictive measures
23	characterized by these two methods will be named in the present study as FSR

- 1 *measurement* and *margin of stability*, respectively.
- 2

3 Alternatively, gait variability has also been applied to quantify its stability. Based on the 4 nonlinear dynamics theory for cyclical movement, variability in kinematics is indicative 5 of stability (Dingwell et al., 2001; England and Granata, 2007; Hausdorff et al., 2001). 6 Indices, such as the maximum *Floquet multipliers* (Dingwell et al., 2007) and *Lyapunov* 7 *exponents* (Dingwell and Cusumano, 2000), have been employed to continuous joint or 8 trunk kinematics (Bruijn et al., 2010; Dingwell and Kang, 2007) to respectively evaluate 9 body orbital and local stability. During gait, perturbations can arise from internal (e.g. 10 neuromuscular) and external sources (e.g. slip). Thus, the likelihood of falls is dependent 11 not only on the individual's neuro-musculoskeletal capacity, but on external factors like 12 type and intensity of perturbations encountered in daily life. Indeed, some studies have 13 proposed that the local stability (Lockhart and Liu, 2008) and the orbital stability 14 (Grabiner et al., 2008; Hamacher et al., 2011) are able to differentiate fall-prone 15 individuals from their health counterpart. 16 17 Further, simpler yet, descriptive spatiotemporal *gait parameters* such as the standard

17 I detailed, simpler yet, descriptive spatiotemportal gate parameters such as the standard 18 deviation of step length, step width or step/stride time can also yield useful information 19 reflecting a person's control of gait stability (Hausdorff et al., 2001; Owings and 20 Grabiner, 2004; Woledge et al., 2005). It is unclear how well these methods can predict 21 an impending slip-related fall in walking among community-dwelling older adults, and 22 how well these approaches will fair relative to each other.

The purpose of this study was to evaluate the degree to which these stability measurements could predict an impending slip-related fall among community-dwelling older adults. We have been able to successfully induce inadvertent falls by initiating slips unknown to the walking older adults in a protective laboratory environment (Pai et al., 2014). The outcome from the gait-slip among older adults (fall vs. recovery) would be used to evaluate the capability of predicting slip-related falls for each one of these stability measurements.

8

METHODS

9 2.1 Subjects

One hundred and eighty seven community-dwelling older adults (age 71.9±5.1 years) participated in the gait-slip experiment (Table 1). All participants signed an informed consent form approved by the Institutional Research Board prior to participating in this study. They were free of any known neurological, musculoskeletal, or other systemic disorders that would have affected their postural control.

15

16 2.2 Experimental set-up

An unannounced slip was induced as subjects walked along a 7-m instrumented pathway in which a sliding device was embedded. The device consisted of a side-by-side pair of movable platforms, firmly locked in place when subjects walked along the walkway during regular walking (Fig. 2) (Yang and Pai, 2007). They had a low profile approximately 6 mm above the walkway, and were mounted on top of a low-friction metal frame embedded in the walkway. The locks were electronically released, unknown

to the person who stepped on the platform, to initiate a forward slip. The platforms were
free to slide ≥0.75 m forward after release. During walking, all subjects wore a full-body
safety harness which was connected to a bearing by shock-absorbing ropes at the
shoulders and waist. This low-friction linear bearing moved smoothly along a ceilingmounted track. The harness system protected subjects from any potential injuries during
falling while imposing negligible resistance or constraint to their walking movement (Fig.
2).

8

9 Subjects were instructed to walk in their preferred speed. Although they were informed 10 that a slip might occur later, they were not aware when, where, and how it would happen. 11 They were also instructed to try to recover their balance after slipping and continue 12 walking forward. After approximately 20 normal walking strides, the right platform was 13 released immediately after the right (slipping) foot contacted it. The left platform would 14 then be released once the subjects' left (recovery) foot landed on it during the slip trial. 15 The detection of foot contact was based on the measurement from four force plates 16 (AMTI, Newton, MA) installed beneath the metal frames.

17

18 2.3 Data reduction

19 Full body kinematics data from 28 retro-reflective markers placed on the subjects' body

20 and platforms were gathered using an 8-camera motion capture system (MAC, Santa

21 Rosa, CA) at 120Hz synchronized with the force plates and load cell at 600Hz.

22 Locations of joint centers, heels, and toes were computed from the filtered marker

23 positions. The body COM kinematics (including its position and velocity) was computed

using gender-dependent segmental inertial parameters (de Leva, 1996) based on a
distributed-mass human model. The trunk segment's position and orientation were
calculated from the joint centers of shoulders, hips and neck marker (C7) as well as
sacrum marker (Online Supplement). The vertical component of the ground reaction
force was used to identify the instants of touchdown in gait.

6

7 The outcome of slip was classified as a fall if the peak load cell force exceeded 30% body 8 weight (bw) (Yang and Pai, 2011). The falls were confirmed via visual inspection of 9 recorded video. A recovery occurred when the moving average of load cell force on the 10 harness did not exceed 4.5% bw over any one second period after slip onset (Yang and 11 Pai, 2011). If the average load cell force exceeded 4.5% bw over any one second period 12 after the slip occurred, but the load cell force never reached a peak of 30% bw, this trial 13 would be identified as harness assistance (Yang and Pai, 2011). The harness assistance 14 trials would be excluded from further analysis due to the uncertainty of determining the 15 slip outcome without the harness. No one was identified as harness-assistance trial in this 16 study.

17 2.4 FSR measurement

The FSR measurement (*s*, the length of the thin solid line in Fig. 1) indicates the magnitude of the instantaneous dynamic stability of the COM against backward falling. The stability is calculated as the shortest Euclidean distance from the COM motion state to the limits against backward falling (thick line in Fig. 1) (Yang et al., 2008a; Yang et al., 2008b). The two components of the COM motion state, i.e. its position (X_{COMBOS}) and velocity (\dot{X}_{COMBOS}) were calculated relative to the BOS and normalized by l_{BOS} and

1	$\sqrt{g \times bh}$ respectively, where l_{BOS} represents the foot length, g is the gravitational
2	acceleration and bh the body height (Fig. 1). The approaches to calculate the FSR
3	measurement and their Matlab codes can be found in the supplemental material of our
4	previous publication (Yang et al., 2008a). The FSR measurement was calculated at the
5	instant of right foot touchdown immediately prior to the slip onset upon the slip trial.
6	

7 2.5 Margin of stability

8 The margin of stability in the anteroposterior direction is calculated as the difference
9 between the anteroposterior boundary of the BOS and the extrapolated impending COM
10 location (*X*_{COM}) (Hof et al., 2005). The extrapolated COM can be calculated as

11
$$X_{\rm COM} = x + \frac{v}{\omega_0}$$

where *x* denoted the anteroposterior position of the body COM, *v* represented the anteroposterior velocity of body COM, and $\omega_0 = \sqrt{g/l}$; *l* was the equivalent pendulum length, which in this study was taken as the distance from the body COM to right ankle center. The margin of stability (*b*) was then defined as:

$$16 b = X_{\rm COM} - X_{\rm BOS}$$

17 where X_{BOS} was the backward boundary of the BOS (i.e. the right heel). The margin of 18 stability was also calculated at the instant of right foot touchdown prior to slip onset in 19 the slip trial.

20

21 2.6 Floquet multiplier

To assess the orbital (Floquet multiplier) and local (Lyapunov exponent) dynamic
stability during gait, the trunk segment kinematics over all 20 cycles (or strides, from a
touchdown to next touchdown of the same foot) during normal walking prior to the novel
slip trial were used. The 6-dimensional state space was built for the trunk's kinematics as
(Kang and Dingwell, 2006):

6
$$\mathbf{S}(t) = [x, y, z, \theta, \varphi, \psi] \in \mathfrak{R}^6$$

where *x/y/z* represented the anteroposterior/mediolateral/vertical position of the trunk
center; and θ/φ/ψ denoted the 3-dimensioal rotational movement of the trunk:
roll/pitch/yaw. The details of calculating trunk kinematics were provided in Online

10 Supplement.

11

The Floquet multiplier was estimated based on the well-developed method to characterize the orbital stability (Dingwell and Kang, 2007; Donelan et al., 2004; Hurmuzlu and Basdogan, 1994). First, the state space built above was partitioned into individual gait cycles and then each cycle was evenly divided into 100 intervals, corresponding to 0-160% of entire gait cycle (Dingwell and Kang, 2007). Poincare maps were then defined for each percent of the gait cycle as:

18
$$\mathbf{S}_{i+1} = \mathbf{F}(\mathbf{S}_i)$$

where \mathbf{S}_i is the state of the system at strike *i* at each given Poincare section (i.e. at each percent of the gait cycle). Fixed points for each Poincare map (\mathbf{S}^*) were defined from the average trajectory across all strides. Thus:

22 $\mathbf{S}^* = \mathbf{F}(\mathbf{S}^*)$

23 The Floquet multiplier of the system was then estimated from a linearized approximation

1 of the Poincare map:

2
$$\mathbf{S}_{i+1} - \mathbf{S}^* \approx \mathbf{J}(\mathbf{S}^*)(\mathbf{S}_i - \mathbf{S}^*)$$

where, the $\mathbf{J}(\mathbf{S}^*) \in \mathfrak{R}^{6\times 6}$ is the Jacobian matrix of the system for each Poincare section 3 4 (percent of the gait cycle). The Jacobian matrix was determined by solving above 5 equation using a least squares algorithm (Bruijn et al., 2009; Hurmuzlu and Basdogan, 1994). The first 5 eigenvalues of $\mathbf{J}(\mathbf{S}^*)$ defined the Floquet multiplier (Bruijn et al., 6 7 2009; Donelan et al., 2004; Hurmuzlu and Basdogan, 1994; Kang and Dingwell, 2008; Kuo, 1999). The last (i.e., the 6th) eigenvalue of $\mathbf{J}(\mathbf{S}^*)$ had a value of ~0 and was thus 8 9 false (Kang and Dingwell, 2008). The magnitude of the maximum Floquet multiplier of 10 each percent of the gait cycle was calculated. These Floquet multiplier values were then 11 averaged to obtain the maximum Floquet multiplier over all strides, which were used in 12 the present study.

13

14 2.7 Lyapunov exponents

Short-term and long-term Lyapunov exponents were calculated to quantify the local stability. From the constructed state spaces as mentioned above, Euclidean distances between neighboring trajectories in the state space were calculated as a function of time and averaged over all original nearest neighbor pairs to obtain the average exponential rate of divergence (Dingwell and Cusumano, 2000; Rosenstein et al., 1993):

20
$$y(i) = \frac{1}{\Delta t} \langle \ln[d_j(i)] \rangle = [\lambda^*] i + \ln[d_{0j}]$$

21 where $d_i(i)$ represents the Euclidean distance between the j^{th} pair of nearest neighbors

1	after <i>i</i> discrete time steps (i.e. $i\Delta t$); $\langle \cdot \rangle$ denotes the average over all values of <i>j</i>
2	(Rosenstein et al., 1993), and d_{0j} is the initial value of d_j . The slope of the mean
3	logarithmic divergence curve is used as a measure of the divergence (Dingwell and
4	Marin, 2006). Short-term exponents were calculated as the slopes of linear fits to the
5	divergence curves between 0 and 0.5 stride, while long-term exponents were taken as the
6	slopes between strides 4 and 10 (Bruijn et al., 2009; Dingwell and Cusumano, 2000).
7	

8 2.8 Gait parameters

9 We first computed the step length, step width, and step time for those 20 normal walking 10 strides (Owings and Grabiner, 2004; Woledge et al., 2005). The variability of these gait 11 parameters was then calculated as the standard deviation of the step length, step width, 12 and step time over all step cycles which started at the heel strike and finished at the next 13 heel strike of the contralateral foot. The step length/step width was the 14 anteroposterior/mediolateral distance between heels at touchdown. The step time was the 15 time elapsed between two consecutive touchdowns. These measurements were assessed 16 to evaluate the temporal and spatial aspects of the gait parameters.

17

18 2.9 Statistical analysis

19 Independent *t*-test and χ^2 test were used to examine whether the demographics and fall 20 history were different between groups (fall vs. recovery, Table 1). Independent *t*-tests 21 were also employed to identify if the eight predictors, including the FSR measurement, 22 the margin of stability, the Floquet multiplier, the short-term Lyapunov exponent, the

1 long-term Lyapunov exponent, and the variability in step length, step width, and step 2 time, demonstrated significant outcome-related difference (Table 2). Logistic regression 3 was then conducted to examine the prediction power of each variable with outcome (fall 4 vs. recovery) as the dependent variables (Table 3). Sensitivity, specificity, and likelihood 5 ratio analyses were performed for each predictive variable between fallers and those who 6 did not fall based on the cutoff score predicted from the logistic regression (which was 7 set at 0.5). Odds ratios were also calculated for each predictive variable based on the 8 logistic regression coefficient and its standard deviation (SD) across all subjects (Table 9 4). All statistics were performed using SPSS 19.0 (IBM Corp., Armonk, NY), and a 10 significance level of 0.05 was used throughout.

- 11
- 12

RESULTS

13 Ninety-eight people (52.4%) fell and 89 recovered successfully. The margin of stability, 14 the Floquet multiplier, and both short- and long-term Lyapunov exponents were not 15 significantly different between fallers and those who did not fall (Table 2, p > 0.05 for all). 16 Among the gait parameters, only the variability of the step width differed between falls 17 and recoveries: fallers had greater variability in step width than those who did not fall 18 (Table 2, p < 0.01). However, fallers and those who recovered exhibited similar variability 19 in step length and step time (Table 2, p > 0.05). The FSR measurement was significantly 20 different between the fall and recovery groups at touchdown during gait. Falls were more 21 instable in comparison with recoveries at touchdown (Table 2, p < 0.001). 22

23 The logistic regression model revealed the predictive ability of these variables (Table 3).

1	The variability in step width, and the FSR measurement achieved significance level
2	(p <0.01 for step width variability and p <0.001 for FSR measurement, Table 3) in
3	predicting slip outcomes. Between these two predictors, FSR measurement was the one
4	with the greater overall prediction accuracy (62.6%); followed by the variability in step
5	width (54.5%). None of other variables reached the significance criterion (p >0.05). A
6	decrease of 1SD (=0.048 across all subjects) in FSR measurement increased the
7	probability of falling by 1.74 (Table 4). An increase of 1SD of variability in step width
8	(=0.029m) increased the odds of falling by a factor of 1.50 (Table 4).
9	

10

DISCUSSION

The results indicated that the FSR measurement offers the best prediction of the slip outcome during gait among older adults, followed by the variability of the step width. Both appear to have reasonable ability (62.6% and 54.5%, respectively) to predict an impending recovery or fall from a slip in gait. Other measurements failed to differentiate falls from recoveries.

16

The FSR measurement reflects the simultaneous control of both COM position and velocity relative to the BOS (Pai, 2003). The latter is critically dependent upon how well a person executes a protective stepping to recover from a severe postural perturbation such as gait-slip. A balance loss is a precursor of a fall during an unannounced novel slip (Yang et al., 2007). One of the criteria to derive the FSR was to prevent the person from a loss of balance during gait (Yang et al., 2008a). Nonetheless, not all loss of balance has led to an actual fall. An effective protective step can quickly restore stability after the

slip, and this might explain why the FSR measurement only had a limited success
(62.6%) in predicting the outcome from an impending falls. Previous empirical findings
have demonstrated that together, FSR measurement and another measurement of a
person's limb support can nearly fully (~100%) account for the outcome following gaitslip among young adults (Yang et al., 2011).

6

The margin of stability was proposed based on a simplified inverted pendulum model
with linear approximation of the solution of its equation of motion (Hof et al., 2005).
While this approach is highly attractive due to its simplicity, the linearity may not quite
accurately characterize the limits of stability at a movement speed range like that during
walking (Hof et al., 2005). This might be why the margin of stability was not different
between fallers and those who did not fall in this study (Table 2).

13

14 Increased variability in gait parameters has been prospectively associated with an 15 increased risk of falls in elderly subjects (Hausdorff et al., 2001; Maki, 1997). Healthy 16 elderly also exhibit increased step width variability (Owings and Grabiner, 2004). 17 Consistent with the literature, the results from the present study indicated that gait 18 variability, particularly in step width, was another variable showing significantly group-19 related difference. The variability of step width was able to correctly predict 20 approximately 54.5% of the overall slip outcome in this study. The increased step width 21 variability may have implications for the placement of feet and further the lateral 22 instability during gait (Bauby and Kuo, 2000; Kuo, 1999). It has been proposed that 23 lateral instability plays a critical role in predicting falls among older adults (Maki, 1997).

Hence, the variability of step width in the current study shows evident predictive power
of slip outcome. Although the predictive power of step width is slightly (8%) less than
the FSR measurement, the variability in step width could still be an important predictor
of potential falls due to its remarkable simplicity.

5

6 Both the local stability (Lyapunov exponents) and orbital stability (Floquet multiplier) 7 failed to distinguish fallers from those who did not (Table 2). One potential reason could 8 be that both of them did not directly account for the dynamic mechanisms underlying the 9 variability (Beauchet et al., 2007). A dynamic system, especially a human body, can be 10 described as a complex neurocontroller coupled with a nonlinear biomechanical system. 11 Limit-cycle behavior generated by this system is influenced by input disturbances 12 causing output variance. Therefore, output variability is a product (convolution) of input 13 disturbances, neuromuscular control, and biomechanical dynamics. A basic assumption 14 of these approaches is that an increased variability in walking pattern is indicative of 15 impaired motor control. However, the extent to which this variability is equal to stability 16 is not clear (England and Granata, 2007); there might be a difference between variability 17 and instability (Beauchet et al., 2007). A person's successful recovery from a slip 18 perturbation was mainly controlled by the entire dynamic system. The probability of falls 19 after slip will not only depend upon gait variability, but also on the placement of 20 protective stepping after the onset of perturbation. It is possible that both FSR 21 measurement and the variability of the step width reflect the foot placement that is 22 associated with essential aspects of the impending stepping behavior (Bruijn et al., 2011; 23 Yang et al., 2009).

1

2 Another possible explanation could be that both orbital and local stability reflect the 3 response characteristics to a small external or internal disturbance of a dynamic system 4 (Dingwell and Cusumano, 2000; Dingwell and Kang, 2007; Hurmuzlu and Basdogan, 5 1994). However, slip perturbations encountered in the present study (the maximum slip 6 distance could reach 90cm) were considerably large in scale. Given such an intensive 7 external perturbation, the orbital or local stability may not be able to detect a system's 8 perturbation response correctly. Consequently, both of them did not exhibit any group-9 related difference and failed to differentiate fallers from those who recovered. Further, 10 due to its inherent cycle-to-cycle variability, human gait is neither strictly periodic (a 11 requirement of orbital stability calculation) nor strongly aperiodic (an assumption of local 12 stability computation) (McAndrew et al., 2011). These factors may also contribute to the 13 failure of these two in predicting slip outcome.

14

15 Contrary to the present findings, some studies proposed that the local stability (Lockhart 16 and Liu, 2008) and the orbital stability (Grabiner et al., 2008; Hamacher et al., 2011) are 17 able to differentiate fall-prone individuals from their health counterpart. Several factors 18 may contribute to such discrepancy. First, the subject selections were different between 19 studies. The fall-prone older adults in previous studies (Grabiner et al., 2008; Lockhart 20 and Liu, 2008) were identified by their history of falls (at least one fall within 6 months). 21 Among our study participants, past fall incidence did not correlate with their immediate 22 lab reproduced falls as evidenced by nearly equal past fall rates in both the fall and 23 recovery groups (36.1% vs. 38.8%, Table 1). Although approximately 37% of our

participants reported having had one fall in the past year; this would not be sufficient to
classify them as being fall-prone. Further, the investigated falls were different between
studies. The causes of falls for fall-prone people in previous studies could be any
possible factors, not limited to slip (Grabiner et al., 2008; Lockhart and Liu, 2008).

5

6 Since over-ground walking is more natural, we collected the gait-slip date during over 7 ground walking rather than on treadmill. However, this set-up limited our ability to 8 collect sufficiently long data set because the person would "walk out" of the motion 9 capture area. The limited data may not lead to accurate calculation of Floquet multipliers 10 and Lyapunov exponents. This may further affect the predictive capability of slip-related 11 falls for both orbital and local dynamic stabilities. To our best knowledge, there is no 12 guideline or consensus on the minimal length of data series required to yield acceptable 13 estimates (Bruijn et al., 2009). As the first attempt of its kind, the present study still shed 14 light on the relative predictive power across various contemporary methods. To examine 15 the predictive capability of falls for various stability indices based on huge amount of 16 continuous strides would merit our further effort.

17

In summary, the study has indicated the FSR measurement provides the best prediction on falls or slip-recovery. On the other hand, the variability of the step width may be the most practical measurement due to its simplicity. The findings from the present study could provide guidance to identify individuals at raised fall risk using these two measurements of stability, especially among a seemingly non-symptomatic population (e.g. community-living older adults) before they actually experience an injurious fall,

- 1 which would be essential for fall prevention.
- 2

3 ACKNOWLEDGEMENTS

- 4 This work was funded by NIH RO1-AG16727 and AG029616. The authors would like
- 5 to thank Dr. Debbie Espy for assisting in data collection and processing.

6

7 CONFLICT OF INTEREST STATEMENT

8 None declared.

REFERENCES

2	Anderson, F. C., Pandy, M. G., 1999. A dynamic optimization solution for vertical iumping in three dimensions. Computer Methods in Biomechanics and Biomedical
5 1	Engineering 2, 201-231
т 5	Bauby C. E. Kuo, A. D. 2000. Active control of lateral balance in human walking
6	Journal of Biomechanics 33, 1433-1440.
7	Beauchet, O., Allali, G., Berrut, G., Dubost, V., 2007. Is low lower-limb kinematic
8	variability always an index of stability? Gait and Posture 26, 327-328.
9	Bieryla, K. A., Madigan, M. L., Nussbaum, M. A., 2007. Practicing recovery from a
10	simulated trip improves recovery kinematics after an actual trip. Gait and Posture 26,
11	208-213.
12	Borelli, G. A., 1680. De Motu Animalium (On the Movement of Animals). NY:
13	Springer-Verlag, Berlin.
14	Bruijn, S. M., Bregman, D. J. J., Meijer, O. G., Beek, P. J., van Dieen, J. H., 2011. The
15	validity of stability measures: A modelling approach. Journal of Biomechanics 44,
16	2401-2408.
17	Bruijn, S. M., Kate, W. R., Faber, G. S., Meijer, O. G., Beek, P. J., van Dieen, J. H.,
18	2010. Estimating dynamic gait stability using data from non-aligned inertial sensors.
19	Annals of Biomedical Engineering 38, 2588-2593.
20	Bruijn, S. M., van Dieen, J. H., Meijer, O. G., Beek, P. J., 2009. Statistical precision and
21	sensitivity of measures of dynamic gait stability. Journal of Neuroscience Methods
22	178, 327-333.
23	de Leva, P., 1996. Adjustments to Zatsiorsky-Seluyanov's segment inertia parameters.
24	Journal of Biomechanics 29, 1223-1230.
25	Dingwell, J. B., Cusumano, J., Cavanagh, P., Sternad, D., 2001. Local dynamic stability
26	versus kinematic variability of continuous overground and treadmill walking. Journal
27	of Biomechanical Engineering 123, 27-32.
28	Dingwell, J. B., Cusumano, J. P., 2000. Nonlinear time series analysis of normal and
29	pathological human walking. Chaos 10, 848-863.
30	Dingwell, J. B., Gu, K. H., Marin, L. C., 2007. The effects of sensory loss and walking
31	speed on the orbital dynamic stability of human walking. Journal of Biomechanics 40,
32	1723-1730.
33	Dingwell, J. B., Kang, H. G., 2007. Differences between local and orbital dynamic
34	stability during human walking. Journal of Biomechanical Engineering 129, 586-593.
35	Dingwell, J. B., Marin, L. C., 2006. Kinematic variability and local dynamic stability of
36	upper body motions when walking at different speeds. Journal of Biomechanics 39,
37	444-452.
38	Donelan, J. M., Shipman, D. W., Kram, R., Kuo, A. D., 2004. Mechanical and metabolic
39	requirements for active lateral stabilization in human walking. Journal of
40	Biomechanics 37, 827-835.
41	England, S. A., Granata, K. P., 2007. The influence of gait speed on local dynamic
42	stability of walking. Gait and Posture 25, 172-178.
43	Goldstein, H., Poole, C. P., Safko, J. L., 2001. Classical mechanics. Addion-Wesley,
44	Boston, MA.

1	Grabiner, M. D., Donovan, S., Bareither, M. L., Marone, J. R., Hamstra-Wright, K.,
2	Gatts, S., Troy, K. L., 2008. Trunk kinematics and fall risk of older adults:
3	Translating biomechanical results to the clinic. Journal of Electromyography and
4	Kinesiology 18, 197-204.
5	Greenwood, D. T., 1988. Principles of dynamics. Prentice Hall, Englewood Cliffs, NJ.
6	Hamacher, D., Singh, N. B., Van Dieen, J. H., Heller, M. O., Taylor, W. R., 2011.
7	Kinematic measures for assessing gait stability in elderly individuals: a systematic
8	review. Journal of The Royal Society Interface 8, 1682-1698.
9	Hausdorff, J. M., Rios, D. A., Edelberg, H. K., 2001. Gait variability and fall risk in
10	community-living older adults: a 1-year prospective study. Archives of Physical
11	Medicine & Rehabilitation 82, 1050-1056.
12	Hof, A. L., Gazendam, M. G., Sinke, W. E., 2005. The condition for dynamic stability.
13	Journal of Biomechanics 38, 1-8.
14	Hurmuzlu, Y., Basdogan, C., 1994. On the measurement of dynamic stability of human
15	locomotion. Journal of Biomechanical Engineering 116, 30-36.
16	Kang, H. G., Dingwell, J. B., 2006. A direct comparison of local dynamic stability during
17	unperturbed standing and walking. Experimental Brain Research 172, 35-48.
18	Kang, H. G., Dingwell, J. B., 2008. Separating the effects of age and walking speed on
19	gait variability. Gait and Posture 27, 572-577.
20	Kuo, A. D., 1999. Stabilization of lateral motion in passive dynamic walking.
21	International Journal of Robotics Research 18, 917-930.
22	Lockhart, T. E., Liu, J., 2008. Differentiating fall-prone and healthy adults using local
23	dynamic stability. Ergonomics 51, 1860-1872.
24	Luukinen, H., Herala, M., Koski, K., Honkanen, R., Laippala, P., Kivela, S. L., 2000.
25	Fracture risk associated with a fall according to type of fall among the elderly.
26	Osteoporosis International 11, 631-634.
27	Maki, B. E., 1997. Gait changes in older adults: predictors of falls or indicators of fear.
28	Journal of American Geriatrics Society 45, 313-320.
29	McAndrew, P. M., Wilken, J. M., Dingwell, J. B., 2011. Dynamic stability of human
30	walking in visually and mechanically destabilizing environments. Journal of
31	Biomechanics 44, 644-649.
32	Owings, T. M., Grabiner, M. D., 2004. Step width variability, but not step length
33	variability or step time variability, discriminates gait of healthy young and older
34	adults during treadmill locomotion. Journal of Biomechanics 37, 935-938.
35	Pai, YC., 2003. Movement termination and stability in standing. Exercise and Sport
36	Sciences Reviews 31, 19-25.
37	Pai, YC., Patton, J. L., 1997. Center of mass velocity-position predictions for balance
38	control. Journal of Biomechanics 30, 347-354.
39	Pai, YC., Yang, F., Bhatt, T., Wang, E., 2014. Learning from falling: Long-term motor
40	retention among older adults. AGE 36, 1367-1376.
41	Pandy, M. G., Anderson, F. C., Hull, D. G., 1992. A parameter optimization approach for
42	the optimal control of large-scale musculoskeletal systems. Journal of Biomechanical
43	Engineering 114, 450-460.
44 45	Kosenstein, N. 1., Collins, J. J., DeLuca, C. J., 1993. A practical method for calculating
45	largest Lyapunov exponents from small data sets. Physica D: Nonlinear Phenomena
40	03, 11/-134.

- Woledge, R. C., Birtles, D. B., Newham, D. J., 2005. The variable component of lateral
 body sway during walking in young and older humans. Journal of Gerontology Series
 A: Biological Sciences and Medical Sciences 60, 1463-1468.
- Yang, F., Anderson, F. C., Pai, Y.-C., 2007. Predicted threshold against backward
 balance loss in gait. Journal of Biomechanics 40, 804-811.
- Yang, F., Anderson, F. C., Pai, Y.-C., 2008a. Predicted threshold against backward
 balance loss following a slip in gait. Journal of Biomechanics 41, 1823-1831.
- 8 Yang, F., Bhatt, T., Pai, Y.-C., 2009. Role of stability and limb support in recovery
 9 against a fall following a novel slip induced in different daily activities. Journal of
 10 Biomechanics 42, 1903-1908.
- Yang, F., Bhatt, T., Pai, Y.-C., 2011. Limits of recovery against slip-induced falls while
 walking. Journal of Biomechanics 44, 2607-2613.
- Yang, F., Pai, Y.-C., 2007. Correction of the inertial effect resulting from a plate moving
 under low-friction conditions. Journal of Biomechanics 40, 2723-2730.
- Yang, F., Pai, Y.-C., 2011. Automatic recognition of falls in gait-slip training: Harness
 load cell based criteria. Journal of Biomechanics 44, 2243-2249.
- 17 Yang, F., Passariello, F., Pai, Y.-C., 2008b. Determination of instantaneous stability
- against backward balance loss: Two computational approaches. Journal of
 Biomechanics 41, 1818-1822.

1 **TABLES**

- 2 Table 1 The demographics in mean \pm SD and history of fall for both groups (fall
- 3 vs. recovery).
- 4

Groups	Fall	Recovery	<i>p</i> value	Pooled	
	(<i>n</i> = 98)	(<i>n</i> = 89)		(<i>n</i> = 187)	
Age (years)	71.8 ± 5.5	71.9 ± 4.8	0.969	71.9 ± 5.1	
Gender (female)	77 (78.6%)	52 (58.4%)	0.003 *	129 (69.0%)	
Height (cm)	164.1 ± 7.5	168.8 ± 9.2	0.001	166.2 ± 8.6	
Mass (kg)	75.8 ± 13.7	77.1 ± 14.0	0.515	76.4 ± 13.8	
Fall history (%)	36.1	38.8	0.749 *	37.4	

5

6 *: the χ^2 test was used.

- 1 Table 2 Comparisons of all predictive variables organized by slip outcome (fall vs.
- 2 recovery).
- 3

Variables		Fall $(n = 98)$	Recovery $(n = 89)$	<i>p</i> value
Feasible-stabi	lity-region			
		-0.181 ± 0.048	-0.156 ± 0.047	< 0.001
measurement				
Margin of stal	bility	0.039 ± 0.058	0.051 ± 0.052	0.162
Floquet multi	plier	0.422 ± 0.044	0.432 ± 0.044	0.121
Lyapunov	Short-term	0.671 ± 0.442	0.737 ± 0.587	0.383
exponent	Long-term	0.034 ± 0.036	0.026 ± 0.045	0.205
Gait	Step length (m)	0.070 ± 0.040	0.062 ± 0.035	0.113
parameters	Step width (m)	0.031 ± 0.013	0.027 ± 0.010	0.009
variability	Step time (sec)	$0.0\overline{44\pm0.020}$	0.041 ± 0.019	0.460

1 Table 3 Prediction sensitivity, specificity, and likelihood ratios of slip outcomes (fall vs. recovery) from logistic regression

2 analysis based on each predictive variable.

Predictive variables		Sens	itivity	Specif	icity	Overall	Likel	ihood ratio	<i>p</i> value	Threshold
		Value	95% CI	Value	95% CI	prediction	Value	95% CI		
		(% fall)		(% recovery)		(%)				
Feasible-sta	bility-region	<u>(9,4</u>	59 (7(7	56.0	45.9.66.0	(2)(150	1 10 2 05	< 0.001	0.160
measurement		08.4	58.0-70.7	56.2	45.8-00.0	62.0	1.50	1.19-2.05	< 0.001	-0.160
Margin of stability		71.4	61.8-79.4	36.0	26.8-46.3	54.5	1.12	0.91-1.36	0.166	
Floquet mul	ltiplier	71.4	61.8-79.4	43.8	34.0-54.2	58.3	1.27	1.02-1.59	0.121	
Lyapunov	Short-term	84.7	76.3-90.5	15.7	9.61-24.7	51.9	1.01	0.89-1.14	0.383	
exponent	Long-term	65.3	55.5-74.0	48.3	38.2-58.6	57.2	1.26	0.99-1.62	0.205	
Gait	Step length	63.3	53.4-72.1	47.2	37.2-57.5	55.6	1.20	0.94-1.54	0.116	
parameters	Step width	60.2	50.3-69.3	48.3	38.2-58.6	54.5	1.17	0.90-1.51	0.011	0.026
variability	Step time	84.7	76.3-90.5	18.0	11.4-27.2	52.9	1.03	0.91-1.17	0.459	

3 CI: confidence interval.

1 Table 4 Odds ratio for slip-related falls for all predictive variables of slip outcome

2

Predictive v	ariables	SD	Odds ratio	95% CI
Feasible-sta	bility-region	0.048	1.74	0.96-3.16
measuremen	nt			
Margin of s	tability	0.055	1.22	0.66-2.26
Floquet multiplier		0.044	1.26	0.69-2.32
Lyapunov	Short-term	0.516	1.14	0.52-2.51
exponent	Long-term	0.041	1.22	0.68-2.20
Gait	Step length (m)	0.066	1.27	0.71-2.28
parameters	Step width (m)	0.029	1.50	0.92-2.93
*	Step time (sec)	0.019	1.11	0.52-2.41

3

*: The odds ratio indicates the factor by which the fall probability increases with an
increase (for Lyapunov exponents and gait parameters) or decrease (for the feasiblestability-region measurement, margin of stability, and Floquet multiplier) of 1SD in the
variable across all subjects.

8 CI: confidence interval.

CAPTIONS 1

2

Fig. 1 Schematic illustration of the feasible-stability-region (FSR) measurement (s). The 3 thin solid line indicates the magnitude of the FSR measurement against backward balance 4 loss, which was defined as the shortest distance from the given center of mass (COM) 5 motion state (i.e., the combination of the COM anteroposterior position and forward 6 velocity) to the limits against backward balance loss (the thick solid line). When the 7 COM motion state is below/above the limits, the FSR measurement value is 8 negative/positive, respectively. Also shown is the computer predicted FSR in the COM 9 motion state space. The FSR is enclosed by two boundaries: the limits against backward 10 balance loss and the one against forward balance loss (the thick dashed line). Position $(X_{\text{COM/BOS}})$ and velocity $(\dot{X}_{\text{COM/BOS}})$ of the COM relative to the base of support (BOS) are 11 dimensionless variables expressed as a fraction of $l_{\rm BOS}$ and $\sqrt{g \times bh}$, respectively, where 12 l_{BOS} depicts the foot length, g is gravitational acceleration, and bh the body height. 13 14 15 Fig. 2 The diagrammatic representation of the experimental setup for inducing slip in 16 gait. A slip is induced by releasing two low-friction movable platforms. Each of the two 17 platforms is mounted on a frame with four linear bearings, and the frame was bolted to 18 two force plates to measure the ground reaction force. The movable platforms were 19 embedded in a 7-m walkway and made less noticeable to the subject by surrounding 20 stationary decoy platforms. A set of 28 light-reflective markers were placed on bilateral 21 upper and lower extremities, torso, and platforms. Their spatial positions were captured 22 by an 8-camera motion capture system. The subjects were required to wear a safety

- 1 harness which is individually adjusted to prevent a fall to the ground. A load cell was
- 2 used to measure the force exerted on the harness.

ONLINE SUPPLEMENT 1

2 1. Derivation of the Feasible Stability Region (FSR) using a 7-link Model

3 To derive the FSR under dynamic situation (like walking), a sagittal-plane bipedal model 4 comprised of seven rigid body segments was developed (Yang et al., 2007). The 5 segments included a lumped head, arms, and trunk segment (HAT) as well as feet, both 6 shanks and thighs. Each segment possessed its own anthropometric and inertial 7 properties which were adopted from Anderson and Pandy (1999). Each anatomical joint 8 in the model was actuated by a single resultant joint moment with peak flexion and 9 extension limits set based on published values (Anderson and Pandy, 1999). Specifically, 10 the resultant joint moment was computed using the following relationship:

11
$$\tau_{i} = \begin{cases} a_{i}(t) T_{i}^{E} & a_{i}(t) \ge 0 \\ a_{i}(t) T_{i}^{F} & a_{i}(t) < 0 \end{cases}$$
(S1)

12 where τ_i , a_i , and T_i are the torque, activation level, and the physiological moment range 13 of the *i*-th joint, respectively. The superscripts E and F represent extension and flexion, 14 or plantar flexion and dorsiflexion for the ankle, respectively. A first order differential equation governed the rise ($\tau_{\rm rise}$) and decay ($\tau_{\rm fall}$) of activation level in response to a net 15 16 muscle excitation (Pandy et al., 1992).

17

,

$$\dot{a} = (1/\tau_{rise})(u^2 - ua) + (1/\tau_{fall})(u - a)$$

$$u = u(t) \in [-1, 1]$$

$$a = a(t) \in [-1, 1]$$
(S2)

Each muscle excitation-time history, u(t), was defined by a set of independent linearly 18 19 interpolated variables or control nodes. Contact of each foot with the ground was

modeled using a set of 16 visco-elastic elements uniformly distributed beneath the foot
 (Anderson and Pandy, 1999).

3

4 Dynamic optimization technique was used to establish the FSR. The optimization 5 (Simulated Annealing Approach) entailed a cyclic process of movement simulation, 6 evaluation of the cost function from the simulation results, an update of the model inputs 7 based on a balance recovery and termination of movement, which were quantified 8 through a cost function. The cost function incorporated mathematical expressions 9 representing the desired final stable state of the model, the anatomical (e.g., joint range of 10 motion), physiological (e.g., joint moment) limitations, and the environmental constraints 11 (e.g., characteristics of the ground reaction force). Specifically, the cost function 12 consisted of the following terms:

13
$$\min f = f_0(\text{initial COM velocity}) + \sum k_i(\text{movement stability criteria}) + \sum g_i(\text{constraint functions})$$
(S3)

14 where, the first term of the cost function was to determine the optimal initial center of 15 mass (COM) velocity for a given initial COM position. The second term represented the 16 balance equilibrium and movement termination criteria. In detail, it required the COM's 17 projection to lie within the base of support (BOS) with the swing foot forward of the 18 slipping foot at termination of the simulation. This term also ensured the relative velocity 19 and acceleration between the COM and BOS diminish forming the static and stable 20 equilibrium at the termination of the simulation. The third term guaranteed that all 21 constraint functions were met, like the ground reaction forces presented under the 22 slipping foot but not beneath the swing foot; the joint angles and angular velocities to be

remained within physical limits determined by experimental data; and the joint moments
 being within their physiological limitations.

3

4 **2.** Calculation of the Trunk Kinematics

5 The method developed by Kang et al. (Kang and Dingwell, 2006) was used to calculate 6 the trunk's kinematics during walking. Briefly, linear motions of the trunk were defined 7 from the translational excursions of a virtual center marker (VCM) within the trunk in the 8 XYZ space (Kang and Dingwell, 2006), calculated as the mean location of the six torso 9 markers including the shoulders, hips, neck, and sacrum. This minimized the effects of 10 measurement noise and non-rigid behavior of the trunk.

11

12 The rotations of the trunk were described from Cardan angles using the yaw-pitch-roll 13 (Z-y'-x") conversion (Goldstein et al., 2001; Greenwood, 1988; Kang and Dingwell, 14 2006), where the first rotation (yaw) occurred around the global Z (vertical) axis, the 15 second rotation (pitch) was taken about the new y' (mediolateral) axis, and the third rotation (roll) was about the new x" (anteroposterior) axis. Rotational motions were 16 17 computed with respect to the initial position of the trunk at time zero for each trial. Rotation matrices, $\Re(t)^{3\times3}$, were computed from the movements of the six markers with 18 19 respect to the VCM, using the Moore-Penrose pseudo-inverse of the marker positions at t 20 = 0:

21
$$\Re(t) = [\mathbf{M}(t)] \cdot [\mathbf{M}(t=0)]^{-1}$$
(S4)

where $\mathbf{M}(t)$ defined a 3 × 6 matrix containing the x, y, and z positions of all six markers relative to the VCM at time t, and

$$1 \qquad \qquad \Re(t) = \begin{bmatrix} C_{\theta}C_{\psi} & C_{\theta}S_{\psi} & -S_{\theta} \\ S_{\phi}S_{\theta}C_{\psi} - C_{\phi}C_{\psi} & S_{\phi}S_{\theta}S_{\psi} + C_{\phi}C_{\psi} & C_{\theta}S_{\phi} \\ C_{\phi}S_{\theta}C_{\psi} + S_{\phi}S_{\psi} & C_{\phi}S_{\theta}S_{\psi} - S_{\phi}C_{\psi} & C_{\theta}C_{\phi} \end{bmatrix}$$
(S5)

2 where C_{α}/S_{α} represents $\cos \alpha/\sin \alpha$. The Cardan angles were then calculated as 3 (Greenwood, 1988):

4 Pitch:
$$\theta(t) = \sin^{-1}(-\mathfrak{R}_{13})$$

5 Roll:
$$\varphi(t) = \tan^{-1}\left(\frac{\Re_{23}}{\Re_{33}}\right)$$

6 Yaw:
$$\psi(t) = \tan^{-1}\left(\frac{\Re_{12}}{\Re_{11}}\right)$$

7 To eliminate the effects of different units and magnitudes of these variables, they were

8 demeaned and normalized to unit variance.



Fig. 1 [Yang & Pai, 2014]



Fig. 2 [Yang & Pai, 2014]

Conflict of interest statement

None.