Trunk Angular Kinematics During Slip-Induced Backward Falls and Activities of Daily Living

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Prior to developing any specific fall detection algorithm, it is critical to distinguish the unique motion features associated with fall accidents. The current study aimed to investigate the upper trunk angular kinematics during slip-induced backward falls and activities of daily living (ADLs). Ten healthy older adults (age = 75 ± 6 yr (mean ± SD)) were involved in a laboratory study. Sagittal trunk angular kinematics were measured using optical motion analysis system during normal walking, slip-induced backward falls, lying down, bending over, and various types of sitting down (SN). Trunk angular phase-plane plots were generated to reveal the motion features of falls. It was found that backward falls were characterized by a simultaneous occurrence of a slight trunk extension and an extremely high trunk extension velocity (peak average = 139.7 deg/s), as compared to ADLs (peak average = 84.1 deg/s). It was concluded that the trunk extension angular kinematics of falls were clearly distinguishable from those of ADLs from the perspective of angular phase-plane plot. Such motion features can be utilized in future studies to develop a new prior-to-impact fall detection algorithm. [DOI: 10.1115/1.4028033]

Keywords: fall detection, fall intervention, slips and falls, trunk kinematics

Introduction

Falls are a major threat to the health of older adults. Recent statistics indicates that in United States, 21,600 older adults died from falling in 2007 alone [1], and about 1.7×10^6 older adults fall at least once a year [2]. Although much research on fall prevention has been performed (see review, Refs. [3] and [4]), the existing strategies are far from effective. More importantly, even the most effective programs cannot prevent fall accidents from happening altogether. Therefore, in the case of unavoidable fall accidents, it is critical to employ effective strategies not only for injury prevention but also for timely medical rescue.

As part of the injury prevention strategies, automatic fall event detection has been receiving research attentions over the years (see review, Refs. [5] and [6]). The idea of fall event detection is to detect the occurrence of a fall event through human motion characteristics prior to impact [7], during impact [8], or post impact [9]. Traditionally, fall detection as an alarming device is beneficial to ensure the timely arrival of remote medical assistance without or with minimal human intervention, thereby reducing injury-related complications and mortalities. It has been shown that 38.9% of fall victims were unable to get up without help and 3.2% had to lie on the floor for more than 20 min [10].

In addition, a prior-to-impact detection algorithm is the critical component for active wearable fall injury prevention systems (e.g., Ref. [11]), which may directly prevent the physical injury associated with fall accidents. However, existing research on fall detection, especially prior-to-impact detection, is limited and scarce. Much of this literature is not on older adults unexpectedly falling, but rather in younger adults who are often instructed to "simulate a fall" (e.g., Refs. [7] and [11]). Moreover, insufficient detection performance (i.e., misdetection and false alarms) hinders its practical implementation into a comprehensive fall intervention solution, and calls for further development in this area. For example, one fall detection study [7] achieved a perfect detection sensitivity (100%). But frequent false alarms (on average, 5 out of 20 ADL trials) were also evident.

Prior to developing any specific fall detection algorithm, it is critical to establish the theoretical foundation of the presence of a unique motion feature or a combination of motion features associated with fall accidents. Previous slips and falls research have concluded that during backward falls, abnormally high backward trunk angular velocity is always accompanied by a backward trunk orientation [7]. Therefore, the current study aimed to investigate the upper trunk angular kinematics during slip-induced backward falls and ADLs using laboratory-based motion analysis system. It is hypothesized that peak upper trunk angular kinematics during backward falls will be significantly different than those during ADLs.

Methods

Participants. Ten older adults (age = 75 ± 6 yr (mean ± SD), body mass = 74.1 ± 9.1 kg, height = 174 ± 7.5 cm, equal gender) were recruited from the local community for this study. They were required to be free from major musculoskeletal disorders or injuries and deemed suitable by the study physician. A sample size calculation based on pilot test results suggested that the sample size of 10 is able to achieve a statistical power of 0.84 while controlling the Type I error < 0.05. The pilot test simulated the performance of a fall detection algorithm from the literature [7] in differentiating slip-induced falls from normal walking (previously collected data [12]). The simulated fall detection time, as a primary parameter of interest in fall detection research, was used to calculate the statistical power for this study. The study was approved by the local Institutional Review Board. Informed consent was obtained from the participants prior to any data collection.

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Apparatus and Procedures

Normal Walking and Slip-Induced Backward Falls. A detailed description of walking and inducing slips and falls (Fig. 1) has been published previously [12,13]. Briefly, participants were instructed to walk at a self-selected speed on a linear walkway (1.5 m × 15.5 m) with the protection of an overhead harness system. Individual self-selected speed in the laboratory appeared to be consistent with the walking speed observed when participants were instructed to walk naturally in the hallway outside the laboratory before the start of the experiment. The harness was designed to allow the subjects' body center of mass (COM) to drop approximately 20 cm vertically. Such design would not only leave sufficient room for an individual's reactive responses to unexpected slips but also ensure the older adults' safety by preventing fall impact of any body parts other than feet [12]. Unexpected slips were induced by changing the dry floor surface into a slippery surface (covered with 3:1 K-Y Jelly and water mixture) without participants' awareness. Each participant was exposed to unexpected slips three times. Between subsequent slip exposures, a gait normalization procedure [14] was taken to minimize possible expectation effect. No significant fall kinematic changes were observed in the current study. Two force-plates (Type 4550-08, Bertec Corporation, Columbus, OH) and a six-camera optical motion analysis system (ProReflex, Qualysis AB, Gothenburg, Sweden) were synchronized to collect kinetic and kinematic data at a sampling rate of 100 Hz. A whole-body biomechanical model using 26 marker-set [14] plus one additional marker on the sternum was adopted in the current study. Briefly, there were seven markers on each leg, four markers on each arm, two markers on the head, and three markers (i.e., left and right acromions, and sternum) on the upper trunk. The rules for categorizing a perturbation trial as a fall were described in literature [12]. Briefly, a trial can be identified a fall when slip distance exceeds 10 cm, peaking sliding heel velocity exceeds whole body COM velocity, and the subject's body drop was arrested by the harness (through visual inspection).

ADLs. The same motion analysis system and biomechanical model were adopted in this session as described above. A gait analysis laboratory with regular living furniture (bed, chair, desk, etc.) was used as the experimental setting to represent seminaturalistic living environment. Participants were instructed to perform five types of daily activities (Table 1, Figs. 2 and 3) as naturally as possible at their own pace. The major difference between SN normally (i.e., SN) and sitting into a rocking chair (i.e., SR) was whether the participants were allowed to move after sitting. During SN, the participant was instructed to sit on a normal chair about knee height and then stand up. During SR, however, afterSR, the participant was free to move his/her body in a relaxed way as allowed by the rocking chair, and then stand up. They were instructed to remain stationery at the start and end of each trial. These activities were chosen for two reasons. First, they are representative of the activities that an older adult would perform on a daily basis. Second, several of these ADLs (e.g., bending over and SN) have been considered challenging for an effective fall detection algorithm in the literature [7]. Each activity was repeated three times. The sequence of the activities was randomized to minimize any order effect.

Data Analysis. Kinematics data from the motion analysis system was low-pass filtered using a zero-phase fourth order Butterworth filter with a cut-off frequency of 6 Hz. The upper trunk sagittal angle and angular velocity was calculated using the kinematics data of reflective markers placed on the acromions and sternum. The reference of zero was set as the vertical direction when participants took anatomical starting position, with positive indicating extension and negative indicating flexion.

The trunk segment was selected as the focus of the current study based on the practical consideration that trunk segment is an ideal site of ambulatory sensor attachment due to its proximity to the body's COM and acceptable user compliance [15,16].

To facilitate the description of the fall dynamics (Fig. 1), the following events were defined:

- fall initiation: an event same as the definition of slip start [14] when the forward heel velocity occurs after heel contact
- fall completion: the event when the trunk COM reaches its lowest vertical position

To facilitate the description of the ADL activity, the start and end point of each trial of the activity were determined as the following. First, the mean and standard deviation (SD) of trunk angular velocity during the initial 1 s of each trial of activity were analyzed. Then, the start point of an activity was defined as whenever the trunk angular velocity deviates over 2 SD from the mean

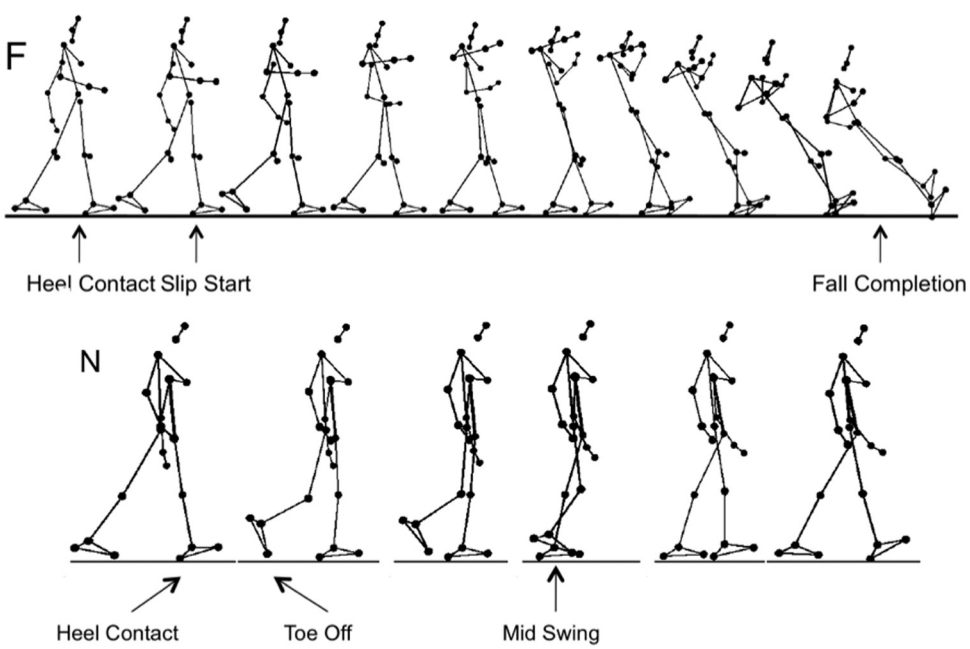

Fig. 1 Illustration of slip-induced backward falls (F) and normal walking (N)

Table 1 Summary of walking activities and ADL

Session	Code	Description
Walking (Fig. 1)	F	Slip-induced backward fall
	N	Normal walking
ADL (Figs. 2 and 3)	SN	Sit on a normal chair which is about knee height, then stand up
	SR	After SR, the participant was free to move his/her body in a relaxed way as allowed by the rocking chair. Then stand up.
	SB	Sit into a bucket seat about half knee height to simulate the sitting motion of getting into a car, then stand up
	LD	Lie down on his/her back from a sitting posture on a medical bed
	BO	Bend over from a standing posture to pick up an umbrella about one foot in the front, and rise up

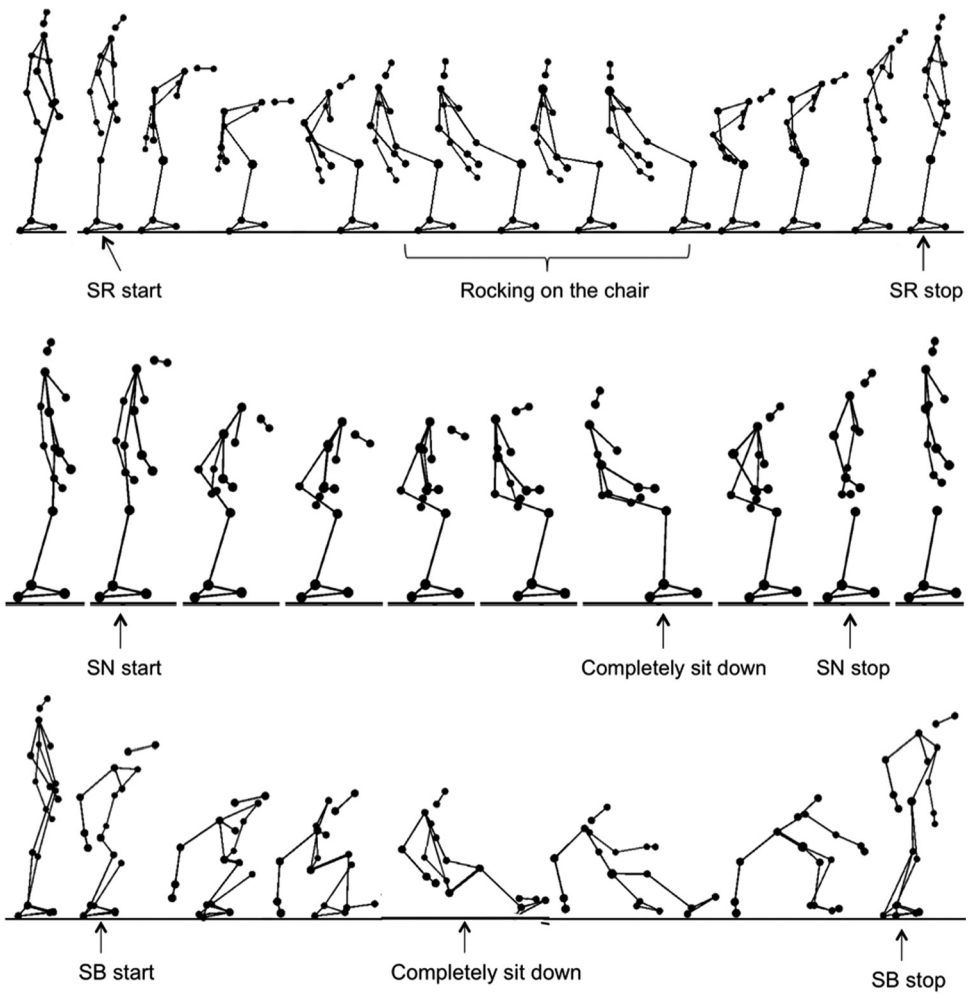

Fig. 2 Illustration of SN, SR, and SB

during the initial 1 s [17]. Similarly, the end point for that activity was defined as whenever the trunk angular velocity deviates more than 2 SD from the mean during the last 1 s.

Phase-plane plots of upper trunk angular kinematics were generated with trunk angle as the X-axis and trunk angular velocity as the Y-axis for each trial. During normal walking, the phase-plane plots were generated during one stance phase. During falling, the phase-plane plots were generated from fall initiation to fall completion. During ADLs, the phase-plane plots were generated between the activity start and end points. All of the data analyses were performed using a custom-designed MATLAB program (R2007b, MathWorks, Natrick, MA).

The dependent variables included maximum trunk flexion, maximum extension, maximum flexion velocity, and maximum extension velocity. Peak angular kinematics were analyzed because if proven capable to distinguish falls from ADLs, peak angular kinematics can be readily incorporated into a threshold-based fall detection algorithm. There was one independent variable (i.e., activity) with two levels: Fall or ADLs (including normal walking). A one-way within-subject analysis of variance was performed in JMP 7.0 (SAS Institute, Inc., Cary, NC), with the significant level being $\alpha = 0.05$.

Results

Upper Trunk Angular Kinematics During Normal Walking and Slip-Induced Backward Falls. As shown in Fig. 4(*a*), participants always walked with a slight trunk flexion (mean = 5.6 deg, SD = 2.9 deg) during normal walking, with peak extension and peak flexion occurring approximately at 30% and 70% of stance,

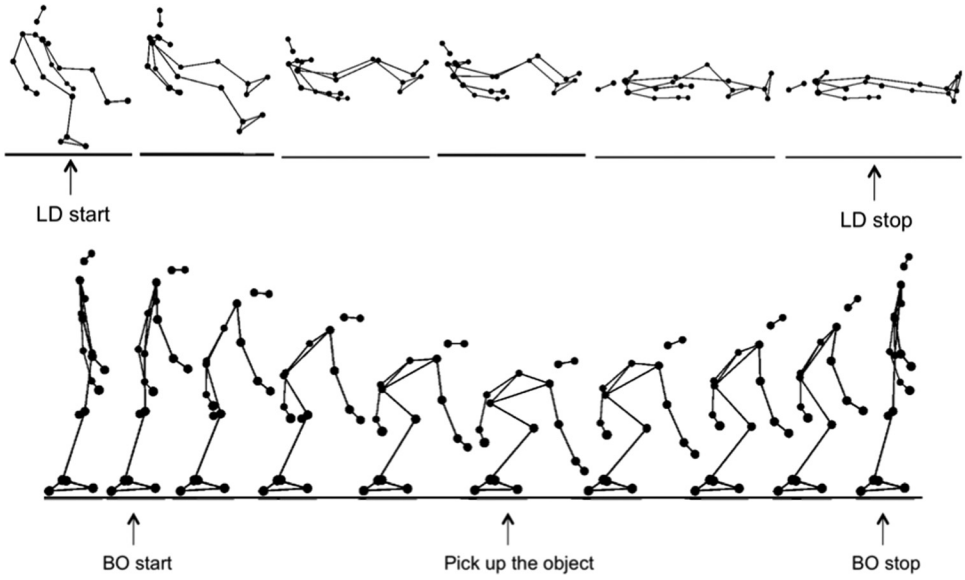

Fig. 3 Illustration of LD and BO

respectively. The peak trunk sagittal angular velocity has a limited range in extension (Fig. 4(*b*): N).

In total, 30 perturbation trials were collected; including 13 backward falls, 15 successful recovery trials, one forward fall, and one sideway fall. The forward fall was resulted from a slip perturbation occurred during toe-off instead of heel contact. The sideway fall was from a participant who showed a gait pattern with considerable large lateral ground reaction force during heel contact. For the purpose of the current study, only the 13 backward fall trials were analyzed.

Backward falls are characterized by a simultaneous rapid increase of both trunk extension (Fig. 4(*a*): F) and trunk extension velocity (Fig. 4(*b*): F). The corresponding phase-plane plot (Fig. 4(*c*): F) toward the end of the falling motion exhibits a parabolic shape, which is partially similar with the elliptical pattern observed during normal walking. From the temporal perspective, the duration from fall initiation to fall end (mean: 420 ms, SD: 166 ms) during fall trials was found to be less than the stance duration from normal gait (mean: 671 ms, SD: 50 ms).

Upper Trunk Angular Kinematics During ADLs. The bending over activity can be divided into two phases: an initial phase characterized by trunk flexion velocity and increasing trunk flexion, and a subsequent phase characterized by trunk extension velocity and decreasing trunk flexion (Figs.4(*a*)/4(*b*): BO). The trunk flexion peaks approximately in the middle of the activity. The peak trunk flexion and extension velocities are comparable. Bending over activity has the highest trunk flexion and flexion velocity among all the activities in the current study (Fig. 5).

The trunk angular kinematics during lying down (Figs. 4(*a*)/1(*b*): LD) is characterized by a dramatically increasing trunk extension and an extension-dominant velocity. The peak trunk extension occurs at the end of lying down while the peak extension velocity reaches an average of 90 deg/s. Distinctive from phase-plane plots of other ADLs in this study, the phase-plane plot of lying down (Fig. 4(*c*): LD) is characterized by a flattened, parabolic pattern, which is mainly located within the first quadrant of the phase-plane plot diagram.

Similar to that of bending over, the trunk angular kinematics of the SN activity can be divided into two phases: an initial phase characterized by trunk flexion velocity and increasing trunk flexion, and a later phase characterized by extension velocity and decreasing flexion. Sitting in a rocking chair (Figs. 4(*a*)/4(*b*): SR) and sitting in a bucket seat (Figs. 4(*a*)/4(*b*): SB) have similar trunk angular kinematics patterns as SN normally (Figs. 4(*a*)/4(*b*): SN).

From the temporal perspective, the mean and SD of the duration from start to stop was found to be 439(38) ms, 1289(309) ms, 534(48) ms, 516(31) ms, and 451(25) ms for SN, SR, SB, LD, and BO, respectively.

Comparison Between ADLs and Slip-Induced Backward Falls. In terms of trunk sagittal angular velocity (Fig. 4(*b*)), backward falls were distinguishable by an extremely high peak extension velocity towards the end of a fall.

From the perspective of ensemble averaged angular phase-plane plots, backward falls were clearly distinguishable from ADLs (Fig. 4(*c*)). Trunk angular kinematics of all the ADLs, except lying down, was mainly located within the second and third quadrants of the phase-plane plot diagram. In contrast, trunk kinematics during backward falls was uniquely located in a narrow region close to the positive vertical axis and within the first quadrant of the phase-plane plot.

There was a significant activity effect ($p < 0.0001$) on peak extension velocity, which indicates that the peak trunk extension velocity during falls was significantly different from those during ADLs (Fig. 5). No significant activity effect was found on peak flexion ($p = 0.7538$), peak extension ($p = 0.0960$), and peak flexion velocity ($p = 0.1202$).

Discussions

Various fall event detection algorithms have been proposed over the years [7,8,18]. However, to the authors' knowledge, the current study is the first attempt to investigate the distinguishable motion features of falls during motion, which constitutes 57% of falling [2]. In addition, very limited research [19] has been conducted on the characteristics of fall activities that differ from ADLs from a biomechanics perspective. In the authors' opinion, it is beneficial to build knowledge regarding unique motion features of falls before designing new fall detection algorithms. Meanwhile, the potential motion features should be easily measurable by the current ambulatory sensors. With these considerations, the current study investigated the possibility of differentiating falls from ADLs utilizing trunk angle and angular velocities, which can be derived or directly measured by an inertial measurement unit [20].

As expected, the slip-induced backward falls show a unique motion feature compared to ADLs. As illustrated in Fig. 4, the

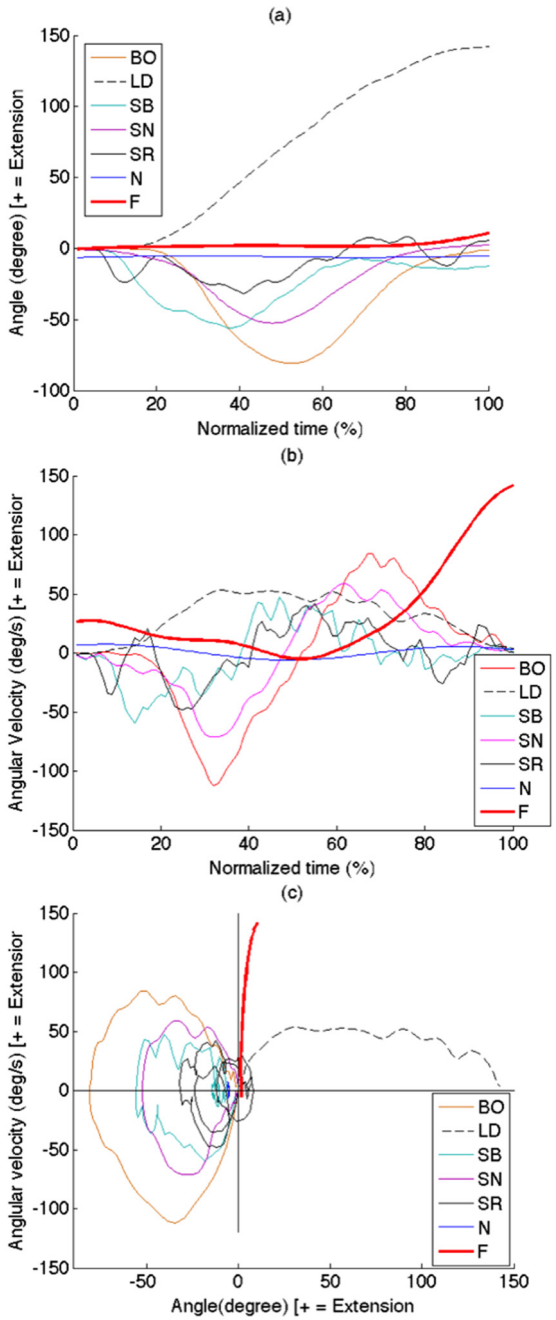

Fig. 4 Trunk angular kinematics during ADL and falls; (*a*) and (*b*) show ensemble average profiles; normalized time scale: 0% indicates activity start (ADLs), heel contact (normal walking), or fall initiation (fall trials), 100% indicates activity end (ADLs), toe-off (normal walking), or fall end (fall trials). (*c*) Shows ensemble average angular phase-plane plots; (BO: bending over and rising up; LD: lying down; SB: sitting into a bucket seat; SN: sitting down; SR: sitting into a rocking chair; N: normal walking; F: slip-induced backward falls).

trunk kinematics of backward falls is clearly distinguishable from those of ADLs in an angular phase-plane plot, with the simultaneous occurrence of trunk extension and trunk angular peak extension velocity. Such distinguishable distributions of falls and ADLs in an angular phase-plane plot could form the foundation for developing a novel detection algorithm.

Trunk angular kinematics obtained from the current study was generally comparable to the findings in the literature. During normal walking, profiles of trunk angle and angular velocity were consistent with those reported previously [21,22]. Quantitatively, the average peak trunk angular velocity and flexion were found to be 7–9.5 deg/s and 5.6 deg in the current study. As a comparison, Syczewska et al. [22] found a forward leaning of the whole spine of 4–5 deg. McGibbon and Krebs [21] found that for healthy young adults, the range of trunk angular velocity was within 34 deg/s. During ADLs, in the current study, the average peak angular velocity was 118.7 deg/s for bending over and 84.7–112.1 deg/s for three types of SN. Similarly, Nyan et al. [7] found the peak angular velocities being ~125 deg/s for bending over, and ~100 deg/s for SN. Dubost et al. [23] observed the range of trunk flexion to be 28.4 deg–51.8 deg during sit-to-stand motion.

During backward falls, however, the results from the current study were substantially different from those in literature. Nyan et al. [7] observed an average peak extension velocity to be ~450 deg/s, which was much higher than that 139.7 deg/s measured in the current study. Such discrepancy in peak extension velocity could be due to several factors. First major factor to consider is that the subjects in Nyan's study were young and healthy, rather than the older subjects tested in the current study. Second, the knowledge of the soft landing surface [7] could have contributed to different fall kinematics. Third, the active motion of the perturbation platform [7] would have contributed angular momentum and potentially increased the angular velocity through this mechanism. In addition, differences in how trunk angular kinematics was measured could also contribute to such discrepancy in peak extension velocity.

The current study had several limitations. First of all, only slip-induced backward falls were investigated. However, slipping was found to be a major contributor (40–50%) to fall-related injuries [24] and was considered as the most frequent unforeseen trigger event leading to the majority (55%) of same-level falls [25]. Second, the fall dynamics of the backward falls measured in the current study was not complete due to the concern of subject safety. In other words, the backward falls were always stopped by the overhead harness prior to the impact on the floor. Such protection was necessary to induce falls during walking, especially for elderly subjects. In addition, due to limited sample size and the unequal number of fall trials from each participant, the study findings should be generalized with caution.

Admittedly, it is an on-going quest to search for the suitable body part that offers the distinctive motion features of falls. Results from the current study showed that the upper trunk could be a possible solution for attaching a fall detector. Presumably, however, an individual could lie down or fall backward with the trunk being flat on the floor but the head being lifted up. This posture may lead to the upper trunk less extended than the rest of the trunk. A natural follow-up study would be to investigate whether the motion features of the rest of the trunk could compliment that of the upper trunk in fall detection. Consequently, a precise measurement of actual impact time is not available in the current study. Even in studies that include complete fall dynamics due to active perturbation (e.g., Ref. [7]), the thickness of the soft landing surfaces could also affect the actual fall distance and fall time. Nevertheless, it is feasible and desirable to evaluate a fall detector in terms of fall detection latency (e.g., from fall initiation to detection).

As stated in the Introduction section, one potential application of fall detection technology is to trigger wearable airbag. Though fall detection latency information was not available, the current results did find that the average duration from fall initiation to fall end was 420.8 ms. Considering the typical time requirement to inflate an airbag was merely 50 ms [26], the findings from the current study has great potential to be developed into a practical fall detection system.

In conclusion, the slip-induced backward falls were characterized by a simultaneous occurrence of an extremely high trunk extension velocity and a slight trunk extension. Such motion features of falls were found to be clearly distinguishable from those of ADLs and established a possible foundation for developing a new prior-to-impact fall detection algorithm.

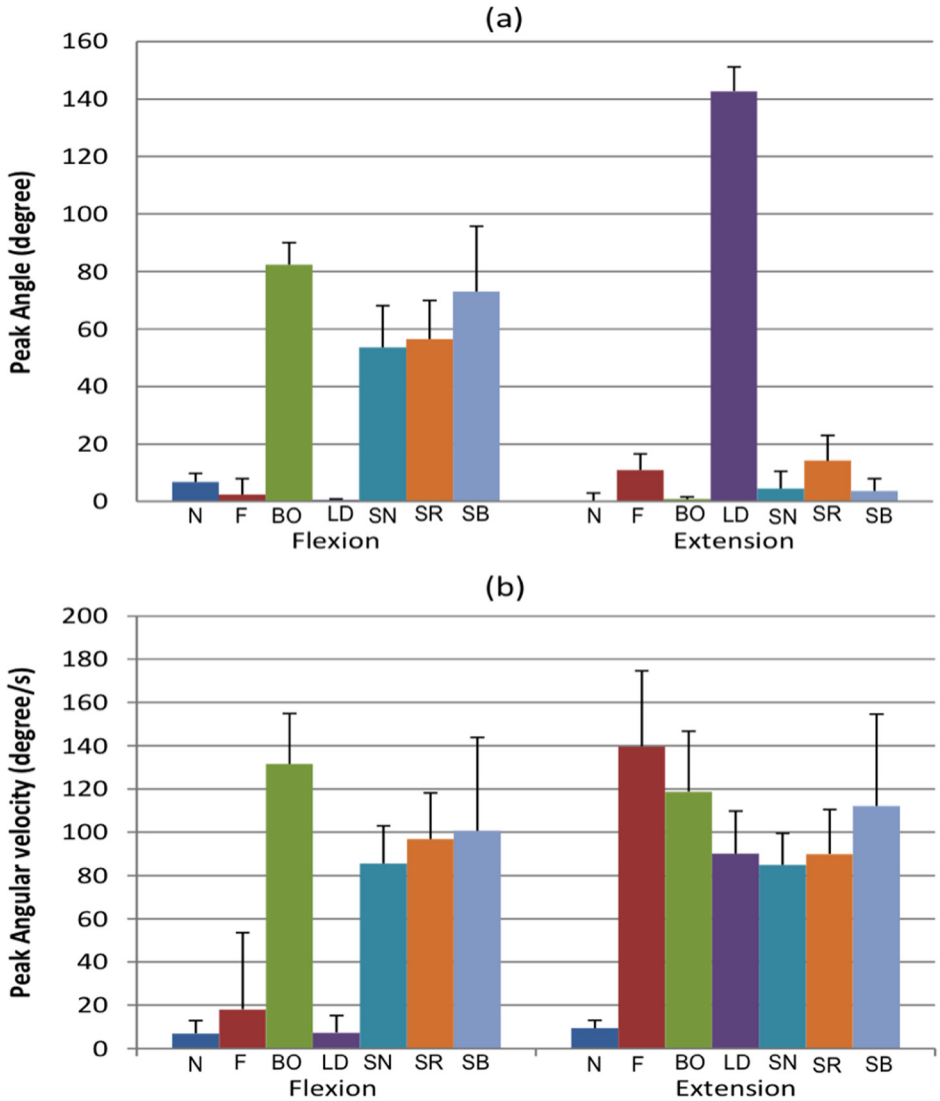

Fig. 5 Comparison of peak trunk angular kinematics ((*a*)—angle; (*b*)—angular velocity) during ADL and slip-induced backward falls (error bar indicates 1SD); (BO: bending over and rising up; LD: lying down; SB: sitting into a bucket seat; SN: sitting down; SR: sitting into a rocking chair; N: normal walking; F: slip-induced backward falls)

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