Influences of Frailty Syndrome on Open-Loop and Closed-Loop Postural Control Strategy

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Key Words

Frailty · Balance · Statistical mechanics · Stabilogram · Muscle strength · Body worn sensor

Abstract

Background: As the population of older adults quickly increases, the incidence of frailty syndrome, a reduction in physiological reserve across multiple physiological systems, likewise increases. To date, impaired balance has been associated with frailty; however, the underlying frailty-related postural balance mechanisms remain unclear. **Objective:** The aim of the current study was to use open-loop (OL; postural muscles) and closed-loop (CL; postural muscles plus sensory feedback) mechanisms to explore differences in postural balance mechanisms between nonfrail ($n = 44$), prefrail ($n = 59$) and frail individuals ($n = 19$). **Methods:** One hundred and twenty-two older adults (age ≥ 65 years) without major mobility disorders were recruited, and frailty was measured using Fried's criteria. Each participant performed two 15-second trials of Romberg balance assessment, once with their eyes open and once with their eyes closed. Body-worn sensors were used to estimate center of gravity (COG) plots. Body-sway (traditional stabilogram analysis) and OLCL (stab-

ilogram diffusion analysis) parameters were derived using COG plots and compared between groups using ANOVA. Frailty and prefrailty were estimated using a multiple variable logistic regression while controlling for age, body mass index, body-sway and OLCL parameters. **Results:** Between-group differences in the parameters of interest were more pronounced during the eyes-closed condition, for which OL duration was approximately 33 and 22% shorter, respectively, in the frail and prefrail groups when compared to nonfrail controls (mean = 1.9 ± 1.1 s, $p = 0.01$). The average rate of sway during the OL was 164 and 66% higher, respectively, in frail and prefrail when compared to nonfrail subjects (0.03 ± 0.02 cm²/s, $p < 0.001$). Results also suggest that OLCL parameters can predict frail and prefrail categories when compared to nonfrail controls. Using this method, frailty was identified with a sensitivity and specificity of 97 and 88% (as compared to nonfrail), and prefrailty with 82 and 92%, respectively. **Conclusions:** This study suggested an innovative method to differentiate between frailty status using sensory dependency characteristics of postural control. Results suggest that postural muscle deconditioning may compromise balance in frail elders, leading to dependency on somatosensory feedback to compensate for errors and stabilize the system.

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Introduction

By 2050, the number of adults aged 65 and older is projected to be 88.5 million in the USA, more than double the population in 2010 [1]. Not only are elders increasing in proportion, but they are likewise living longer [1]. With these changes comes a need to concomitantly improve their health span. The common geriatric syndrome of 'frailty' is used to identify older adults at higher risk of falls, disability, institutionalization and death [2, 3]. Frailty is characterized by low physiological reserves and vulnerability to illness and other stressors [2]. An estimated 10% of community-dwelling older adults are frail and another 41.6% are prefrail, with increasing prevalence with age [4].

To identify frailty, several assessment approaches have been developed to separate categories of frailty (i.e. nonfrail, prefrail and frail). The most common approach is the Fried frailty index, which is based on three to five of the following: unintentional weight loss, exhaustion, muscle strength, walking speed and physical activity [2]. Studies have suggested that compromised human balance is also an indicator of frailty [5–7], which is subsequently associated with the outcomes of falling and increased morbidity [8]. Accordingly, a few studies have aimed to determine differences in postural balance behaviors in categories of frailty [9–11].

To this end, significant differences in balance parameters have been obtained from multiscale entropy [10] and wavelet [11] approaches between nonfrail and prefrail/frail groups, but not between nonfrail and prefrail or between prefrail and frail categories [10, 11]. Furthermore, traditional balance parameters were found to be different only between nonfrail and frail samples [9]. Although these approaches have provided evidence of inherent differences in balance between frailty groups, the underlying neuromuscular mechanism, especially differences in using postural muscle strength and sensory feedback in maintaining balance, have not yet been investigated.

One method that has recently gained more popularity in measuring postural balance is open-loop (OL)/closed-loop (CL) analysis (i.e. stabilogram diffusion analysis). In a study by Collins and De Luca [12], OLCL analysis was used to understand dynamic characteristics of body sway. In this approach, the trajectory of body center of mass on the ground surface (center of gravity; COG) was estimated and then used to derive the temporal displacement between adjacent data points to generate an OLCL plot (see Methods section for more details; center of mass is the

equivalent point of the total body mass in the global reference system [13]).

The OLCL plot can, to some extent, reflect the performance of neuromuscular postural control mechanisms; the plot is divided into short-term 'OL' and long-term 'CL' control mechanisms of balance. The OL region is known as a controlling mechanism that works without recruiting sensory feedback (such as visual, vestibular and/or somatosensory systems) [14, 15]. This mechanism is assumed to operate by setting a steady-state activity level for the postural muscles to control the short-term fluctuations of COG. On the other hand, the CL mechanism may be called into play in long intervals of COG displacement, using sensory feedback to control balance [12, 14, 15]. The level of body sway is defined for each region as the OL and CL slopes.

The goal of the current study was to use OLCL analysis to first identify OL and CL strategies, and then to further explore whether postural behavior during OL and CL conditions differ between nonfrail and prefrail, and prefrail and frail individuals. We hypothesized that with increasing frailty level, the transition between OL and CL would occur more quickly. In addition, we expected that those who were frail would manifest a higher increase in magnitude of body sway, with increasing time intervals during the balance period. As a secondary hypothesis, we expected to observe better sensitivity and specificity in frailty prediction when using OLCL compared to traditional COG plots.

Methods

Participants

One hundred and twenty-two older adults participated in the study, among which 44 were nonfrail (36%), 59 (48%) were prefrail and 19 (16%) were frail based on Fried's frailty classification (see table 1 for demographic information of participants). A community-dwelling convenience sample of older adults (age ≥ 65 years) with no major mobility disorders was recruited from geriatric clinics in a southwestern tertiary academic medical center, after completing informed consent (as approved by the University of Arizona Institutional Review Board). Participants were screened using the Mini-Mental State Examination (MMSE) exam [16] and participants with total scores less than 24 were excluded from the study. Sensor-monitored gait, daily physical activity and balance parameters were collected in addition to foot pain, fall status and fear of falling (the results of this paper are limited to balance and Fried frailty category).

Frailty Evaluation

Standard Fried frailty criteria [2] were used as the 'gold standard' to stratify participants to frail, prefrail and nonfrail categories [based on unintentional weight loss, self-reported exhaustion,

Table 1. Mean (SD or percentage) values of participant demographic information and frailty criteria

	Nonfrail	Prefrail	Frail	p value
Participants, n	44 (36%)	59 (48%)	19 (16%)	–
Male, n	7 (16%)	14 (23%)	3 (16%)	0.61
Age, years	74.6 (6.5)	80.0 (8.6)	83.3 (8.9)	<0.001*
Stature, cm	159.1 (6.8)	158.8 (9.1)	158.1 (10.4)	0.92
Body mass, kg	66.1 (15.8)	75.8 (18.5)	75.8 (18.6)	0.02*
BMI	25.7 (4.5)	29.4 (6.7)	29.9 (6.2)	<0.01*
MMSE score	29.2 (1.1)	29.2 (1.4)	28.7 (1.8)	0.18
Foot pain (0–10 scale ¹)	0.7 (1.1)	0.8 (1.5)	2.8 (3.0)	<0.0001*
Fallers, n	14 (32%)	28 (47%)	10 (53%)	0.19
Fear of falling (7–49 scale ²)	20.8 (4.2)	27.8 (8.7)	38.4 (11.6)	<0.0001*
Walking time/15 ft, s	5.0 (0.9)	7.4 (2.6)	13.7 (9.9)	<0.0001*
Observed frailty criteria, n				
Weight loss	–	3 (5%)	6 (32%)	<0.001*
Weakness	–	22 (37%)	15 (79%)	<0.0001*
Slowness	–	39 (66%)	15 (79%)	<0.0001*
Exhaustion	–	11 (19%)	18 (95%)	<0.0001*
Low activity	–	8 (14%)	13 (68%)	<0.0001*

Values in parentheses are SD, unless otherwise indicated. Percentage values relate to the group total, with the exception of the participants data, for which the percentage of the whole study is indicated. Asterisk (*) indicates a significant effect. Participants' classification was based on Fried frailty criteria.

¹ Visual analog scale.

² Short falls efficacy scale international (FES-I) [30].

weakness (grip strength), slow walking speed and low physical activity]. Data were entered into the Johns Hopkins frailty calculator and compared to population norms. Individuals with three or more positive frailty criteria were considered 'frail', those with one or two frailty criteria were considered 'prefrail', and those with none of the above criteria were considered 'nonfrail'.

Balance Test Procedure and COG Estimation

Each participant performed two 15-second trials of balance assessment, within which participants stood upright with their feet together as close as possible without touching each other, and with their arms crossed across their chest. Participants were instructed to keep their eyes open (no target was specified) in the first trial, and to keep their eyes closed in the subsequent trial. Two sensors (fig. 1), each including a triaxial accelerometer, triaxial gyroscope and a triaxial magnetometer, were used to estimate three-dimensional angles of the ankle and hip joints (BalanSens™, BioSensics LLC, Brookline, Mass., USA). The COG was estimated for each trial following identical procedures reported in our earlier studies [17]. Briefly, each sensor provided real-time quaternions (sample frequency = 100 Hz) that were converted to Euler angles, which were used to estimate the trajectories of the participant's ankle and hip rotations. A two-link inverted pendulum model of the human body was then used to calculate the COG from anterior-posterior (AP) and medial-lateral (ML) angles during body movements [18]. The COG was used to derive several outcome measures.

Stabilogram Traditional Analysis

Traditional outcome measures from stabilogram analysis include body-sway parameters: COG_{AP} sway, COG_{ML} sway and COG sway. The ranges of sway in the AP and ML directions were defined as COG_{AP} sway and COG_{ML} sway, respectively, after excluding outliers as described in a previous study [17]. The COG sway (i.e. total sway) was then calculated by multiplying the range of motion in AP and ML directions (i.e. COG sway = COG_{AP} sway × COG_{ML} sway) [17].

Open-Loop/Closed-Loop Analysis

To identify OL and CL strategies, we used an OLCL method as described by Collins and De Luca [12, 14]. In summary, the square of displacement $(\Delta r_i)^2$ between successive COG data points separated in time by a specified time interval (Δt) were calculated. The squared displacements $(\Delta r_i)^2$ were then averaged over the specified time interval (Δt) , ranging from 0 to 10 s ($0 \leq \Delta t \leq 10$ s) to provide a plot of mean square COG displacement (Δr^2) versus Δt according to the following formula:

$$\langle \Delta r^2 \rangle_{\Delta t} = \frac{\sum_{i=1}^{N-m} (\Delta r_i)^2}{(N-m)}, \quad (1)$$

where N is the number of data points for the first 10 s of the COG data series and, for a given Δt , m is the number of data intervals. Using this approach, an OLCL plot is developed (fig. 2) which represents square value of COG displacement (Δr^2) as a function of time interval (Δt) . Two distinguishable regions exist in the OLCL

Fig. 1. Two sensors are attached to the shank and trunk to provide three-dimensional angles of the ankle and hip joints, and ultimately estimate COG.

Fig. 2. Sample of an OLCL plot from a nonfrail participant illustrating the two separate OL and CL regions. Fitted-line slopes in each region (OL_{slope} and CL_{slope}) indicate the rate of change in magnitude of sway as a function of time interval. The critical point ($OL_{\Delta t}$, CL_{sway}) is the intersection of these two lines.

plot, named as short-term (OL) and long-term (CL) regions, which are separated by identifying the critical time interval ($OL_{\Delta t}$: critical time interval Δt_c). $OL_{\Delta t}$ is estimated by identifying two best linear fits, which represent, respectively, the short-term linear fit (fitted on short time interval data points) and long-term linear fit (fitted on long time interval data points) of the OLCL plot, as illustrated in figure 2. The slope of these two fits were then calculated to represent estimations of the rate of sway change as a function of time interval during OL (OL_{slope}) and CL (CL_{slope}) conditions [19]. It has been hypothesized that $OL_{\Delta t}$ represents the maximum time interval in which the CL controlling mechanism is added to the OL, and the squared magnitude of sway for this time interval is denoted as OL_{sway} ($OL_{sway} = < \Delta r^2 >_{\Delta t_c}$) [20]. Following an identical approach, COG AP and COG ML data series were used to calculate OL_{slope} , CL_{slope} , $OL_{\Delta t}$ and OL_{sway} in AP and ML directions.

Statistics

Previous studies reported high within-subject variability when using OLCL plots to derive outcome measures [12, 20]. To improve the reliability of our analysis, outliers were identified and removed following a similar procedure, as in previous work [20]. For this purpose, OLCL plots were compared in AP and ML directions within each frailty group, and trials were removed if they had a mean square displacement more than 3.5 standard deviations (SD) at any time interval from the average of mean square displacement. The 3.5 SD was chosen to detect outliers that could have been visually identified as suboptimal when plotting OLCL graphs for each frailty group. Such trials likely occur due to deviation from the protocol, inappropriate installations of sensors, or other problems with data collection. Furthermore, outliers can occur due to limitations in COG estimation using wearable sensors; when sway magnitudes exceed beyond a certain threshold, the two-link model might not be accurate enough for COG estimation [17].

Body-sway and OLCL parameters were compared between the three frailty groups, for eyes-open and eyes-closed conditions using separate analyses of variance (ANOVAs); post hoc Tukey's honestly significant difference tests were performed for three pairwise comparison between the frailty groups. ANOVAs and χ^2 tests were performed to evaluate the differences in demographic parameters between the groups. Independent associations between balance parameters and frailty were assessed using a multivariate ordinal logistic regression model, considering frailty as the dependent variable, and age and body mass index (BMI) as the covariates. Of note, only age and BMI were considered as demographic covariates because they had the strongest association with frailty. Although not the primary focus of the current study, nominal logistic regression models were used to estimate the sensitivity and specificity of balance parameters in predicting the prefrail and frail groups. Regression models were employed to compare prediction quality of the prefrail and frail groups using OLCL versus body-sway parameters. Three models were developed: 'model 1' only consisted of age and BMI; 'model 2' consisted of age, BMI and body-sway parameters, and finally 'model 3' included age, BMI and OLCL parameters as predictor variables. Parameters with an association with frailty ($p < 0.2$) were entered into each model. All analyses were performed using JMP™ (version 10; SAS Institute Inc., Cary, N.C., USA), with a significance level of $p < 0.05$. Summary results are presented as means with SD and standard errors (SE).

Table 2. Mean, SD and ANOVA results for body-sway and OLCL parameters in the eyes-open condition for the nonfrail, prefrail and frail groups

Parameter	Group	Mean	SD	p value (ES)	Groups	Pairwise p value (ES)	95% confidence intervals
COG, cm ²	N	0.66	0.58	0.10 (0.16)	N and P	0.10 (0.35)	-0.04 to 0.62
	P	0.90	0.82		N and F	0.53 (0.21)	-0.25 to 0.66
	F	0.78	0.62		P and F	0.84 (0.17)	-0.29 to 0.49
COG _{AP} , cm	N	1.14	0.60	0.04 (0.19)*	N and P	0.12 (0.34)	-0.06 to 0.51
	P	1.35	0.63		N and F	0.06 (0.49)	0.00 to 0.72
	F	1.44	0.63		P and F	0.64 (0.14)	-0.21 to 0.45
OL _{slope} , ×10 ⁻² cm ² /s	N	1.30	0.84	0.10 (0.25)	N and P	0.51 (0.37)	-0.48 to 1.31
	P	2.13	3.09		N and F	0.09 (0.47)	-0.11 to 2.23
	F	3.41	6.28		P and F	0.37 (0.26)	-0.48 to 1.76
OL _{slope-AP} , ×10 ⁻² cm ² /s	N	1.80	1.42	0.04 (0.30)*	N and P	0.31 (0.56)	-0.35 to 1.47
	P	2.93	2.49		N and F	0.04 (0.49)*	0.06 to 2.47
	F	4.34	7.16		P and F	0.31 (0.26)	-0.44 to 1.85
CL _{slope} , ×10 ⁻² cm ² /s	N	0.42	0.41	0.10 (0.23)	N and P	0.86 (0.16)	-0.15 to 0.23
	P	0.50	0.56		N and F	0.09 (0.45)	-0.03 to 0.46
	F	0.85	1.30		P and F	0.18 (0.35)	-0.06 to 0.41
CL _{slope-AP} , ×10 ⁻² cm ² /s	N	0.72	0.77	0.02 (0.31)*	N and P	0.95 (0.11)	-0.26 to 0.35
	P	0.81	0.81		N and F	0.03 (0.55)*	0.05 to 0.85
	F	1.62	2.20		P and F	0.04 (0.49)*	0.02 to 0.79
OL _{Δt} , s	N	2.10	0.97	0.02 (0.29)*	N and P	0.01 (0.64)*	0.10 to 0.98
	P	1.56	0.68		N and F	0.33 (0.34)	-0.23 to 0.94
	F	1.75	1.07		P and F	0.72 (0.21)	-0.38 to 0.75
OL _{Δt-AP} , s	N	2.09	0.99	0.23 (0.16)	N and P	0.91 (0.09)	-0.41 to 0.58
	P	2.18	1.04		N and F	0.38 (0.41)	-0.29 to 1.04
	F	1.72	0.80		P and F	0.20 (0.50)	-0.18 to 1.10
OL _{sway} , ×10 ⁻³ cm ²	N	0.26	0.21	0.02 (0.19)*	N and P	0.70 (0.24)	-0.14 to 0.29
	P	0.33	0.35		N and F	0.18 (0.38)	-0.07 to 0.50
	F	0.47	0.76		P and F	0.43 (0.24)	-0.13 to 0.41
OL _{sway-AP} , ×10 ⁻³ cm ²	N	0.23	0.17	<0.01 (0.37)*	N and P	0.01 (0.84)*	0.06 to 0.60
	P	0.56	0.53		N and F	0.05 (0.64)	-0.01 to 0.69
	F	0.57	0.73		P and F	0.99 (0.02)	-0.31 to 0.34

Asterisk (*) indicates a significant effect. ML results were not presented here, since no significant result or specific trend was observed. N = Nonfrail; P = prefrail; F = frail; ES = effect size.

Results

Participants

Mean age was significantly different between the three frailty groups, with a greater age among frail participants. Mean MMSE scores were not significantly different between groups. As expected, the number of fallers was higher in the prefrail compared to nonfrail, and in frail compared to prefrail groups.

Differences in Postural Balance Parameters among Frailty Categories

The most discriminating by-group body-sway parameter was COG_{AP} sway in the eyes-open condition (table 2). COG_{AP} sway was greater in frail individuals, although no significant difference was observed between the nonfrail and prefrail, or prefrail and frail groups. Averaged OLCL plots for the nonfrail, prefrail and frail groups are illustrated in figure 3 and reported in tables 2 and 3. Five eyes-

Fig. 3. OLCL plots of balance for nonfrail, prefrail and frail participants in the eyes-open (**a**) and eyes-closed (**b**) condition. Mean values and SE are illustrated.

closed trials (two nonfrail, two prefrail and one frail) and one eyes-open trial (one prefrail) were removed as outliers. For these trials, OLCL plots and derived parameters were beyond the physiological range of previously reported values [21]. Results from Tukey's honestly significant difference tests indicated that, unlike body sway, parameters from OLCL analysis were significantly different between nonfrail and prefrail ($OL_{\Delta t}$), and prefrail and frail groups (OL_{slope} and CL_{slope} ; fig. 4; tables 2, 3). The between-group differences in OLCL parameters were more pronounced during the eyes-closed condition. In the eyes-open condition, $OL_{\Delta t}$ was 17 and 26% smaller in the frail and prefrail groups, respectively, compared to nonfrail controls. The rate of sway change in the frail and prefrail groups compared to nonfrail group were 162 and 64% larger for OL_{slope} and 102 and 19% larger for CL_{slope} , respectively. In the eyes-closed condition, $OL_{\Delta t}$ was significantly smaller by 33% in the frail and 22% in prefrail groups, compared to nonfrail controls. OL_{slope} was 164% greater in the frail and 66% greater in prefrail groups

compared to nonfrail participants; corresponding differences in CL_{slope} were 325% higher values in frail and 130% higher values in prefrail compared to nonfrail individuals (see tables 2, 3 for more details).

Sensitivity and Specificity of Frailty Prediction Using Balance Parameters

Frailty prediction results from the logistic regression model revealed a sensitivity and specificity of 78 and 90% on average in eyes-open and eyes-closed conditions when body-sway parameters were used as independent variables; corresponding values for prefrailty prediction were 65 and 85% (table 4). Overall, the prediction quality using body-sway parameters (model 2) was comparable to the condition when only age and BMI were considered as predictors (table 4).

Using OLCL parameters as independent variables in the logistic regression model, a sensitivity and specificity of 97 and 88% was achieved in predicting frailty on average among conditions (table 4). Similarly, in predicting prefrailty, the respective values of sensitivity and specificity were 82 and 92%. These results suggest an improved prediction of frailty and prefrailty compared to the condition when body-sway parameters were used as predictors (model 2).

Discussion

Physiological Interpretation of the OLCL Parameters

Our results suggest that rate of sway change versus time interval increases with frailty level in both OL (represented by larger OL_{slope} values) and CL (represented by larger CL_{slope} values) conditions (fig. 4; tables 2, 3). The difference between OL and CL balance control mechanisms is known to be in using sensory feedback. In short-term time intervals of OLCL plots, OL control has the main contribution in balance, and the activity level of postural muscles likely has the main role of maintaining balance [12, 14]. The increased OL postural sway that was observed among frail participants might be related to inability of lower extremity and trunk muscles to provide sufficient activity level and joint stiffness. This reduction in muscle strength can result from 'weakness' and 'exhaustion', which are the markers of frailty.

We also observed an increase in CL rate of sway change (CL_{slope}) with the level of frailty. It should be noted that values of CL_{slope} depend on OL behaviors; an increased level of OL_{slope} inherently increases CL_{slope} [12]. As such, within the current experimental setup, it was impossible

Table 3. Mean, SD and ANOVA results for body-sway and OLCL parameters in the eyes-closed condition for the nonfrail, prefrail and frail groups

Parameter	Group	Mean	SD	p value (ES)	Groups	Pairwise p value (ES)	95% confidence intervals
COG, cm ²	N	1.11	0.78	0.11 (0.25)	N and P	0.21 (0.48)	-0.16 to 0.99
	P	1.85	2.01		N and F	0.25 (0.62)	-2.88 to 1.36
	F	2.10	2.10		P and F	0.91 (0.12)	-0.62 to 0.90
COG _{AP} , cm	N	1.50	0.69	0.13 (0.25)	N and P	0.67 (0.45)	-0.27 to 0.54
	P	1.89	1.02		N and F	0.14 (0.70)	-0.12 to 0.84
	F	2.13	1.08		P and F	0.34 (0.23)	-0.49 to 1.02
OL _{slope} , ×10 ⁻² cm ² /s	N	2.87	2.20	<0.001 (0.40)*	N and P	0.07 (0.57)	-0.06 to 1.94
	P	4.75	4.11		N and F	<0.001 (0.91)*	0.95 to 3.72
	F	7.53	6.87		P and F	0.04* (0.49)	0.06 to 2.72
OL _{slope-AP} , ×10 ⁻² cm ² /s	N	3.91	3.24	<0.001 (0.39)*	N and P	0.21 (0.43)	-0.33 to 1.96
	P	5.55	4.29		N and F	<0.001 (0.89)*	1.08 to 4.22
	F	9.21	7.77		P and F	0.01* (0.58)	0.32 to 3.34
CL _{slope} , ×10 ⁻² cm ² /s	N	0.53	0.52	<0.01 (0.41)*	N and P	0.15 (0.63)	-0.09 to 0.78
	P	1.22	1.45		N and F	<0.01 (0.71)*	0.28 to 1.45
	F	2.26	3.42		P and F	0.07 (0.40)	-0.04 to 1.08
CL _{slope-AP} , ×10 ⁻² cm ² /s	N	1.18	1.20	0.04 (0.30)*	N and P	0.59 (0.37)	-0.44 to 1.05
	P	1.80	2.06		N and F	0.03 (0.47)*	0.10 to 2.15
	F	3.44	6.72		P and F	0.12 (0.33)	-0.17 to 1.81
OL _{Δt} , s	N	1.90	1.11	0.01 (0.30)*	N and P	<0.05 (0.45)*	0.00 to 0.83
	P	1.49	0.65		N and F	0.03 (0.71)*	0.05 to 1.20
	F	1.28	0.54		P and F	0.66 (0.35)	-0.36 to 0.77
OL _{Δt-AP} , s	N	1.85	1.02	0.36 (0.14)	N and P	0.47 (0.22)	-0.20 to 0.59
	P	1.65	0.74		N and F	0.44 (0.38)	-0.26 to 0.83
	F	1.56	0.39		P and F	0.92 (0.15)	-0.45 to 0.62
OL _{sway} , ×10 ⁻³ cm ²	N	0.43	0.40	0.01 (0.31)*	N and P	0.07 (0.57)	-0.02 to 0.62
	P	0.74	0.65		N and F	0.02 (0.69)*	0.08 to 0.96
	F	0.95	0.98		P and F	0.43 (0.25)	-0.20 to 0.63
OL _{sway-AP} , ×10 ⁻³ cm ²	N	0.67	0.68	0.01 (0.29)*	N and P	0.19 (0.39)	-0.10 to 0.66
	P	0.95	0.75		N and F	<0.01 (0.77)*	0.14 to 1.17
	F	1.32	0.99		P and F	0.17 (0.42)	-0.12 to 0.87

Asterisk (*) indicates a significant effect. ML results were not presented here, since no significant result or specific trend was observed. N = Nonfrail; P = prefrail; F = frail; ES = effect size.

to make any direct conclusion regarding differences between the CL control mechanism among nonfrail, prefrail and frail individuals. Overall, frailty increases both the OL and CL rate of sway change versus time interval.

Previous work suggested that the OL_{Δt} magnitude represents the time interval that sensory feedback and CL control add to the simple OL mechanism to help maintain balance [12]. OL_{Δt} was smaller here in frail compared to prefrail and in prefrail compared to nonfrail participants

(fig. 4; tables 2, 3). We believe that the reduction in time interval for adding the CL controlling mechanism to the OL is related to a higher magnitude of sway during the OL controlling mechanism. Postural muscle deconditioning in frail elders might lead to a higher magnitude of sway in the short-term region; therefore, additional CL control should be added sooner to minimize excessive sway and to prevent falling. This was also observable from larger values of OL_{sway} among frail people. Basically, OL_{sway}

Table 4. Sensitivity and specificity of prefrailty and frailty prediction using balance parameters and demographic variables

	Prefrailty prediction, %				Frailty prediction, %			
	eyes open		eyes closed		eyes open		eyes closed	
	sensitivity	specificity	sensitivity	specificity	sensitivity	specificity	sensitivity	specificity
Model 1	69	78	69	78	74	93	74	83
Model 2	74	76	56	93	79	85	77	94
Model 3	89	96	74	89	94	98	100	83

Predictor variables: model 1 = age and BMI; model 2 = age, BMI and body-sway parameters; model 3 = age, BMI and OLCL parameters.

Fig. 4. Sample of OLCL parameter changes in nonfrail, prefrail and frail participants during the eyes-closed condition. **a** Rate of change in magnitude of sway as a function of time interval during the OL controlling mechanism. **b** Rate of change in magnitude of sway as a function of time interval during the CL controlling mechanism. **c** Time interval in which the CL controlling mechanism is added to the OL. **d** Squared magnitude of sway at $OL_{\Delta t}$. Asterisk (*) indicates a significant difference between groups. Mean values and SE are illustrated.

shows the squared magnitude of sway at the time interval when the CL controlling mechanism is added to the OL mechanism (fig. 2). Interestingly, although this switching between the OL and CL mechanism happened in smaller time intervals, the values of OL_{sway} were still larger among frail participants; on average, respective ~ 49 and $\sim 36\%$ increases in OL_{sway} were noticeable from nonfrail to prefrail, and from prefrail to frail participants.

Older adults become more sedentary with increasing levels of frailty and are more likely to have shorter durations of upright standing. Therefore, in addition to inevitable muscle strength loss with aging, lack of practice may also cause more dependency on the CL controlling mechanism in frail adults, especially for long time intervals of upright standing [22]. According to motor control theory, practicing can enhance the dynamics of interaction with the environment by building and adapting an 'internal model' for the central nervous system [23, 24]. To develop this internal model, the balance controlling mechanism may use feedforward and feedback components in the OL and CL mechanisms [22]. As such, impairment in the feedforward mechanism, due to a lack of practice or postural muscle strength can potentially compromise balance in frail individuals. The observed higher dependency on the feedback mechanism here might have happened to compensate for errors and stabilize the system because of deconditioning of the feedforward mechanism. However, it should be noted that these are hypothetical conclusions and need to be assessed in future research. Specifically, more investigations are required to understand whether the impaired balance in frail individuals is related to lack of practice or muscle strength.

Frailty Identification Using Balance Data

Our results confirmed our hypothesis regarding the precisions of OLCL over traditional approaches in dis-

criminating nonfrail and prefrail, and prefrail and frail elders. Comparing the OLCL and traditional analyses, on average sensitivity and specificity of prefrailty and frailty prediction were improved by 23 and 6%, respectively, using the former method. Once older adults develop frailty, rehabilitation may become more difficult [25, 26] and, therefore, accurate and objective early identification of prefrailty and frailty is critical. Despite frailty being increasingly recognized in the literature, there are limited objective clinimetrically sensitive and easily performed frailty assessment methods able to separate frailty categories. In addition, there is limited evidence to guide interventions to reduce the negative outcomes associated with frailty, such as poor balance. OLCL balance assessment using wearable sensors is an objective method, which can be used for both diagnosis and to assist with measurement of change with rehabilitation.

Our results here suggest that body sway in the AP direction is better associated with frailty than ML sway. Accordingly, there is also previous evidence showing that AP sway can best distinguish young from adult participants [27], and a low-risk faller and healthy elders [20]. Because of the hinge-like structure of the ankle and tibiotarsal joints, to control body sway in the AP direction, muscle groups in both legs provide movements in similar directions [12, 13]. In contrast, invertor/evertor muscles of the ankle and abductor/adductor muscles of the hip work in opposite directions in the left and right sides for balancing the body [13]. Therefore, due to the larger flexibility in the AP direction and the inherent controlling mechanism, maintaining balance in the AP direction may require more muscle strength compared to the ML direction. As such, balance behavior in the AP direction may be more related to ‘weakness’ and ‘exhaustion’.

Limitations and Future Direction

One limitation of the current study was the number of balance trials that were used for each participant. According to previous studies, high within-subject variability exists when deriving OLCL plots, and the average of a few repeated trials was therefore used to improve the reliability of measurements [12, 20]. However, our experimental design prohibited us from measuring more than two trials of balance from each participant, since the balance test was part of a more general study for measuring several frailty markers. Thus, a limited duration of balance test was considered here to minimize participants’ exhaustion. However, to improve the reliability of statistical conclusions, outliers were indicated and removed. In our future study, we aim to collect a series of balance trials from

each participant in order to improve the reliability of the modeling procedures.

A key challenge in using wearable sensors to estimate COG is that, unlike a camera motion analysis system or force platform that uses a fixed landmark reference (i.e. room reference axis), the axis of the sensor is highly dependent on how it is attached to the body and how it rotates during body motion. To address this challenge, we used a quaternion model, as described earlier [17], to better estimate rotations and correct the change in landmark reference of wearable sensors. Another limitation of this study is using a two-link inverted-pendulum model to estimate COG, assuming that motions around other body joints during the balance test are negligible compared to motions around the hip and ankle joints. In our previous study [28], we demonstrated that this assumption produces an acceptable agreement ($r > 0.8$) for estimation of COG trajectory compared to a full biomechanical model of the human body as estimated by a camera motion analysis system.

It should be acknowledged that some limitations exist in using the OLCL approach, which have been recognized by previous research. One limitation of OLCL approaches, as claimed by Winter [13], is related to using similar controlling approaches for both AP and ML directions. More specifically, as discussed above, a loading/unloading balance mechanism exists for the ML direction that perhaps requires more sensory feedback compared to AP balance control. In the OLCL model, similar controlling approaches are considered for both directions, which is a limitation of these models. However, all conclusions here were drawn from parameters in the AP direction or total sway (that was dominantly affected by sway in the AP direction). Moreover, in the OLCL approach, two distinct regions – OL and CL – are considered, which means that at one specific time interval sensory feedback is added to control the balance. However, Newell et al. [19] criticized that the different sources of sensory feedback work continuously at different time intervals. Overall, due to these limitations, results of the current study should be interpreted cautiously; the results suggest (instead of directly support) differences in the underlying balance mechanism among frailty categories.

Conclusion and Clinical Implications

In contrast to previous methods, we were able to analyze the frailty syndrome in more detail based on OL and CL controlling mechanisms. We observed compromised OL balance control in frail individuals, which was ob-

served as a higher rate of sway change during OL control, probably due to deconditioning of postural muscles. A higher rate of OL sway change may consequently result in a faster transition to the CL controlling mechanism in frail people compared to the healthy sample. In contrast to traditional balance parameters, differences in OLCL balance behaviors were distinguishable, not only between nonfrail and prefrail/frail (combined), but also between the nonfrail and prefrail, and prefrail and frail groups. Based on previous research, early frailty identification may slow its progression with structured exercise, or even an active lifestyle [5, 29]. Overall, the knowledge from the current study provides us with a potential target for the rehabilitation of frail elders with poor balance control, and exploration of interventions to sustain and/or improve rate of sway during OL strategies.

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Disclosure Statement

None.

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