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Cofre Lizama, L.E.; Pijnappels, M.A.G.M.; Rispens, S.M.; Reeves, N.P.; Verschueren, S.M.; van Dieen, J.H.

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Mediolateral balance and gait stability in older adults

L. Eduardo Cofré Lizama [a,b], Mirjam Pijnappels [a,**], Sietse M. Rispens [a], N. Peter Reeves [c], Sabine M. Verschueren [d], Jaap H. van Dieën [a,e,*]

[a] MOVE Research Institute Amsterdam, Faculty of Human Movement Sciences, VU University Amsterdam, The Netherlands
[b] Department of Medicine (Royal Melbourne Hospital), The University of Melbourne, Melbourne, Australia
[c] College of Osteopathic Medicine, Michigan State University, USA
[d] Department of Rehabilitation Sciences, Faculty of Kinesiology and Rehabilitation Sciences, Katholieke Universiteit Leuven, Leuven, Belgium
[e] King Abdulaziz University, Jeddah, Saudi Arabia

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ABSTRACT

Early detection of balance impairment is crucial to identify individuals who may benefit from interventions aimed to prevent falls, which is a major problem in aging societies. Since mediolateral balance deteriorates with aging, we proposed a mediolateral balance assessment (MELBA) tool that uses a CoM-tracking task of predictable sinusoidal and unpredictable multisine targets. This method has shown to be reliable and sensitive to aging effect, however, it is not known whether it can predict performance on common daily-life tasks such as walking. This study aimed to determine whether MELBA is an ecologically valid tool by correlating its outputs with a measure of mediolateral gait stability known to be predictive of falls.

Nineteen community-dwelling older adults (72 ± 5 years) tracked predictable and unpredictable target displacements at increasing frequencies with their CoM by shifting their weight sideward. Response delay (phase-shift) and amplitude difference (gain) between the CoM and target in the frequency domain were used to quantify performance. To assess gait stability, the local divergence exponent was calculated using mediolateral accelerations with an inertial sensor when walking on a treadmill (LDE_{TR}) and in daily-life (LDE_{DL}) for one week. Pearson product-moment correlation analyses were performed to determine correlations between performance on MELBA tasks and LDE.

Results show that phase-shift bandwidth for the predictable target (range above -90°) was significantly correlated with LDE_{TR} whereas phase-shift bandwidth for the unpredictable target was significantly correlated with LDE_{DL}. In conclusion MELBA is an ecologically valid tool for mediolateral balance assessment in community-dwelling older adults who exhibit subtle balance impairments.

1. Introduction

Falls have a high incidence in healthy elderly, with 30% of people over 65 falling at least once every year, and falls are even more common among elderly with chronic diseases and disabilities [1]. This poses a major health problem for our aging society in which more than 15% of the population worldwide will be over 65 years old by 2050 [2]. Most older people exhibit some degree of balance impairment, which can increase the risk of falling [3]. Therefore detecting balance impairments at early stages in this population is crucial to identify people at risk of falling and ultimately of paramount importance for healthy aging.

Balance impairment and its association to fall risk have been studied using clinical and laboratory measures of balance control. Several measures of postural sway (i.e. spontaneous sway of the center of pressure) have shown that impairment of balance in the mediolateral (ML) direction is predictive of falls [4]. Unfortunately, most of the current clinical balance tests do not emphasize ML balance capacities and were shown to exhibit ceiling effects. In line with this, Pardasaney and co-workers (2013) suggested that for the community-dwelling older adults, new balance assessment tools should be of greater complexity to improve sensitivity [5].

* Corresponding author at: MOVE Research Institute Amsterdam, Faculty of Human Movement Sciences, VU University Amsterdam, van der Boechorststraat 9, 1081 BT, The Netherlands. Tel.: +31 20 5988501.
** Corresponding author at: MOVE Research Institute Amsterdam, Faculty of Human Movement Sciences, VU University Amsterdam, van der Boechorststraat 9, 1081 BT Amsterdam, The Netherlands. Tel.: +31 20 5988501; fax: +31 20 59 88529.
E-mail addresses: m.pijnappels@vu.nl (M. Pijnappels), j.van.dieen@vu.nl (J.H. van Dieën).

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In this context, we recently proposed a ML balance assessment tool (MELBA) in which subjects track a visually presented target with ML movements of their Center of Mass (CoM) [6]. MELBA was shown to be reliable and sensitive to subtle balance impairments in healthy elderly not detected by conventional posturography and clinical measures of balance [6]. Responsiveness (bandwidth) of the balance control system is assessed in terms of the response delay (phase-shift) and amplitude difference (gain) between the CoM and the target along predictable and unpredictable ML trajectories. Impairments of ML balance control likely affect gait, which is the activity during which most falls occur [7]. However, the association between ML balance control, as assessed with MELBA, and stability of gait is as yet unknown.

Gait stability has been quantified using the maximum Lyapunov exponent, or more appropriately the local divergence exponent (LDE) [8,9]. The LDE quantifies the sensitivity of the gait kinematics to continuous small perturbations present due to external perturbations and neuromuscular noise with greater (positive) values indicating "less stable" kinematics [10]. The LDE has been suggested to be the most suitable measure of gait stability available at present [11]. Estimates of the LDE of gait kinematics obtained during walking on a treadmill and during walking in daily-life are both predictive of fall risk [9,12,13]. Although both walking contexts assess physical capacities, daily-life walking may also include behavioral and environmental determinants of fall risk [14]. Furthermore, the LDE has been shown to be sensitive to induced impairments of balance through galvanic stimulation of vestibular afferents [15] and through external mechanical perturbations [16].

Therefore, we hypothesized that measures of balance control obtained with MELBA are associated with measures of ML gait stability in walking on a treadmill and during daily-life. Such associations would demonstrate MELBA's predictive ability regarding gait stability and hence its ecological validity.

2. Methodology

2.1. Participants

Nineteen healthy older adults (7 women and 12 men, age: 72 ± 5 years; height: $1.73 \pm .09$ m; weight: 76.6 ± 15 kg) with no history of falls over the previous 12 months participated in this study. Participants were excluded if they presented any musculoskeletal or neurological condition or used medications that could affect balance. Participants had mini mental state examination scores $\geq$25 out of 30 [17] and clinical balance assessment that revealed maximum or close to the maximum scores above the cut-off scores for the highest category defined for each test [6].

This study was approved by the Ethical Committee of the Faculty of Human Movement Sciences, VU University (2011-48M) and the Medical Ethical Committee of the VU University Medical Center Amsterdam (2010/290), in accordance with the ethical standards of the declaration of Helsinki. All participants were informed of the experimental procedures and signed informed consent prior to the experiment.

2.2. Task and procedure

2.2.1. MELBA – mediolateral balance assessment

Each participant performed a series of ML-CoM tracking tasks, while standing barefoot and with the arms crossed in a quiet and low-intensity lit room (Fig. 1). Body CoM was calculated with a 9-markers frontal plane model (forehead, shoulder, anterior-superior iliac spines, knees and ankles) tracked with an Optotrak Certus system (NDI, Waterloo, Ontario, Canada). Gender specific CoM calculations were performed using scaling of anthropometric data and inertial parameters described by de Leva [18]. D-flow 3.10.0 software (Motek Medical, Amsterdam, The Netherlands) was used to produce target signals as well as to record (60 samples/s) and display target and CoM data on a screen 2.5 m in front of the

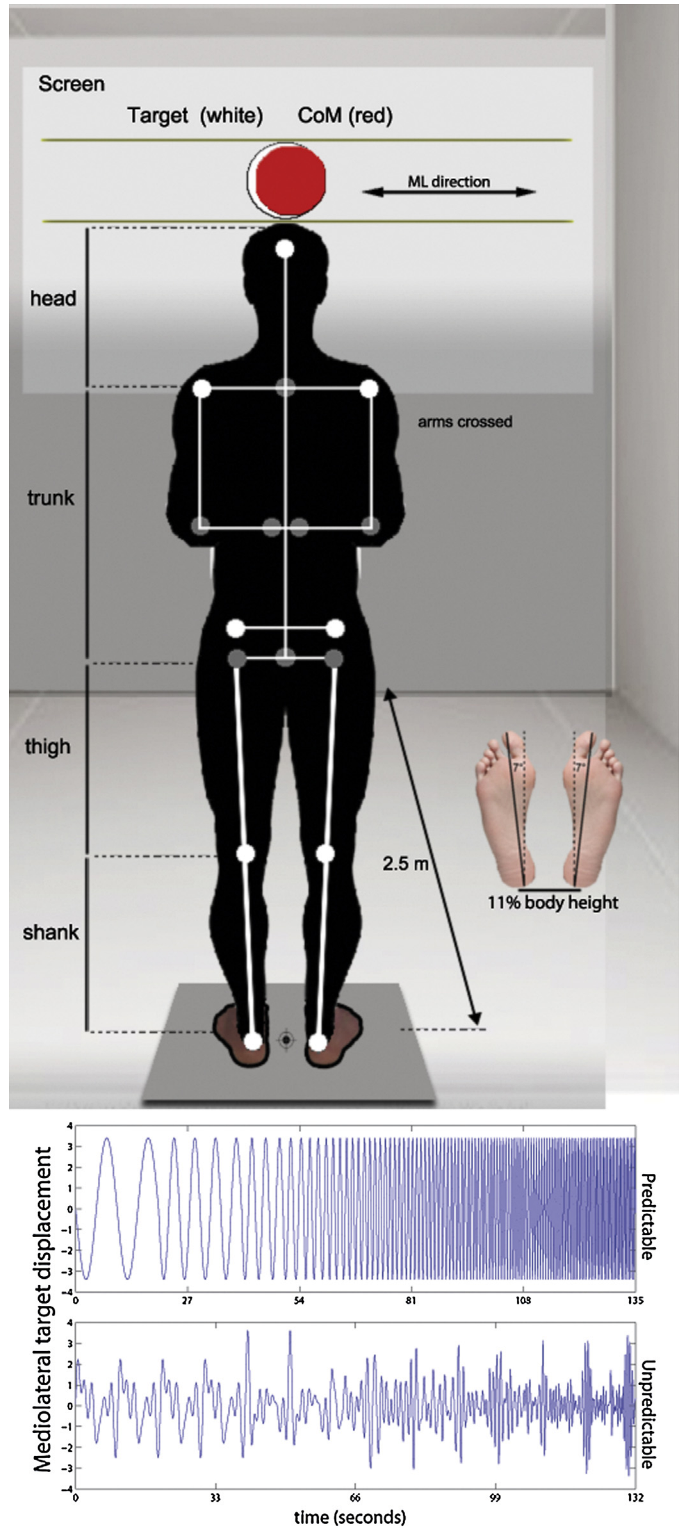

Fig. 1. Set-up and model for Center of Mass (CoM) calculation showing a silhouette with superimposed makers (white dots) and estimated joint centers (gray dots). The displays of the CoM feedback (red sphere) and the target (white sphere) are also presented. Insertion at the right bottom depicts stance width and angle. The target mediolateral (ML) displacement patterns (predictable and unpredictable) are shown at the bottom panel [7]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

participant. ML-CoM tracking consisted of tracking a predictable and an unpredictable target signal using the ML displacement of the CoM projected on the screen. The target signal and CoM were represented by white and red spheres of 11 and 9 cm diameter, respectively (Fig. 1).

The *predictable* target signal was constructed using 2 blocks of 20 s, 1 block of 10 s and 17 blocks of 5 s, each composed by one sine wave, which increased in frequency from 0.1 to 2.0 Hz in steps of 0.1 Hz. This information was enhanced using a metronome synchronized with the maximum displacement of the target to increase sensory input abundance. The total duration for this target signal was 135 s.

The *unpredictable* target signal was constructed using 15 blocks composed by the sum of 6 consecutive sine waves separated by 0.1 Hz. A pseudorandom phase-shift between sine waves between -1 to 1 period was introduced in order to avoid predictability. After each block the lowest frequency, which started at 0.1 Hz, was increased by 0.1 Hz until it reached 1.5 Hz. Duration was 40 s for block 1, 20 s for block 2, 10 s for block 3, 8 s for blocks 4 and 5, 6 s for blocks 6 and 7, and 4 s for blocks 8–15. Duration of the blocks was chosen to obtain a minimum of 2 cycles per frequency. The total duration for this target signal was 132 s.

Each participant performed 6 ML-CoM tracking trials: 3 with the predictable and 3 with the unpredictable target. Before performing the test, one practice trial was allowed for each of the conditions. Trials were performed with at least with 1 min of rest in between. Stance width was standardized by setting the heel distance to 11% of body height at a fixed 14° angle between the feet (Fig. 1). Rationale for the selection of the stance parameters are described elsewhere [6,19]. Target maximum side-to-side displacement for both conditions was normalized for each subject at 50% of stance width. On average, the participants stood on the force plate with $19.0x \pm 1.0$ cm distance between heels, which determined a maximum target displacement of $9.5x \pm 0.5$ cm.

2.3. ML gait stability

Accelerations (3D) in the ML direction were recorded using an inertial sensor (Dynaport Hybrid, McRoberts, The Hague, The Netherlands) placed at sacrum with an elastic band while walking on a treadmill at a fixed 1.2 m/s steady-state speed for 5 min. For daily life gait ML stability, accelerations at the sacrum level were recorded during one week with a tri-axial accelerometer (DynaPort MoveMonitor, McRoberts, The Hague, The Netherlands). Participants were instructed to wear this accelerometer at all times, except during activities that could cause damage to the instrument due to contact with water (e.g. showering). The median of estimates of separate walking episodes was used for further analysis [14].

2.4. Data analysis

2.4.1. MELBA – mediolateral balance assessment

All data analysis was performed using custom-made software in Matlab R2011a (Mathworks, Natick MA, USA). Balance performance over the frequency ranges in the target signal was described by the gain of the linear constant coefficient transfer function between CoM and target signal from which phase-shift (PS) and gain (G) and coherence (Coh) were calculated. A detailed explanation of the method can be found elsewhere [19]. Perfect tracking performance implies PS = 0° and G = 1 over all frequencies comprised in the target signal. Coh was used to corroborate the assumption of input (target)/output (CoM) linearity and therewith the validity of estimates of PS and G. Perfect linearity yields Coh = 1 over all frequencies comprising the target signal.

To characterize balance performance, 4 descriptors were calculated. First, the values at which PS dropped below 90 degrees and G dropped below 0.5 were determined as the cutoff frequencies (coined f_{PS} and f_G, respectively). Second, PS_{mean} and G_{mean} were computed as the averages of the G and PS values within the bandwidths determined by f_{PS} and f_G, respectively.

2.4.2. ML gait stability

Treadmill. The local divergence exponent in the ML direction (LDE_{TR}) was calculated using the method described by Wolf et al. [20] over the whole period of 5 min; For the embedding we followed previous papers [21,22] using an embedding of 7 dimensions with a delay of 10 samples (0.1 s); Normalization of the exponent to stride time was performed by multiplying with stride time.

Daily life. LDE in the ML direction (LDE_{DL}) was calculated using the median over multiple non-overlapping 10 s windows of walking episodes. The same embedding and normalization to stride time as described above was performed. All analyses were performed using custom-made Matlab functions (R2011a, Natick MA, USA).

2.5. Statistical analysis

A univariate ANOVA was performed to determine differences between predictable and unpredictable CoM-tracking performance as well differences between walking on a treadmill (LDE_{TR}) and during daily life (LDE_{DL}). Person product-moment correlation analyses were performed to determine correlations between MELBA descriptors (f_{PS}, PS_{mean}, f_G and G_{mean}) for both targets and LDE_{DL} and LDE_{TR}. For all analyses significance level was set at $p < 05$. Statistical analyses were performed using IBM SPSS (Statistics 21).

3. Results

Overall, performance on the predictable CoM tracking task was significantly ($p < .01$) better than on the unpredictable with PS values closer to 0 and G values closer to 1 (Fig. 2). Control bandwidth was wider when tracking the predictable target, with higher f_{PS} and f_G ($p < .01$) and higher PS_{mean} and G_{mean} within these bandwidths ($p < .01$) (Table 1).

Mean LDE values were significantly lower (more stable; $p < 01$) when walking on the treadmill than during daily life.

Results for all linear regression analyses are presented in Table 2 whereas Fig. 3 shows scatter-plots for the significant correlations found. Linear regression analyses revealed that f_{PS} for the predictable target was significantly correlated to LDE_{TR} ($r = -.48$, $p = .04$) whereas f_{PS} for the unpredictable target was significantly correlated to LDE_{DL} ($r = -.57$, $p = .01$). Other MELBA descriptors for both targets did not exhibit significant correlations either with LDE_{DL} nor with LDE_{TR}.

4. Discussion

Early detection of balance impairments is crucial to identify older adults at risk of falls and further impairments. Therefore, sensitivity to subtle changes in balance is imperative for assessment tools [5]. Besides sufficiently sensitive, a method must be ecologically valid and consider the main factors that challenge balance in daily-life activities. Since measures of gait stability appear to be predictive of falls, MELBA's association with gait stability during treadmill and daily-life indicates it is an ecologically valid tool. Significant associations between LDE_{TR} and f_{PS} (control bandwidth) for the predictable target and LDE_{DL} and f_{PS} for the unpredictable target were found, but not between LDE_{DL} and f_{PS} for the predictable and LDE_{TR} nor between LDE_{TR} and f_{PS} for the unpredictable.

When compared to gait stability in daily-life walking, a study showed that treadmill walking was more symmetric, less variable and more stable [14]. Since, in this experiment, unexpected challenges to the balance control did not occur during treadmill

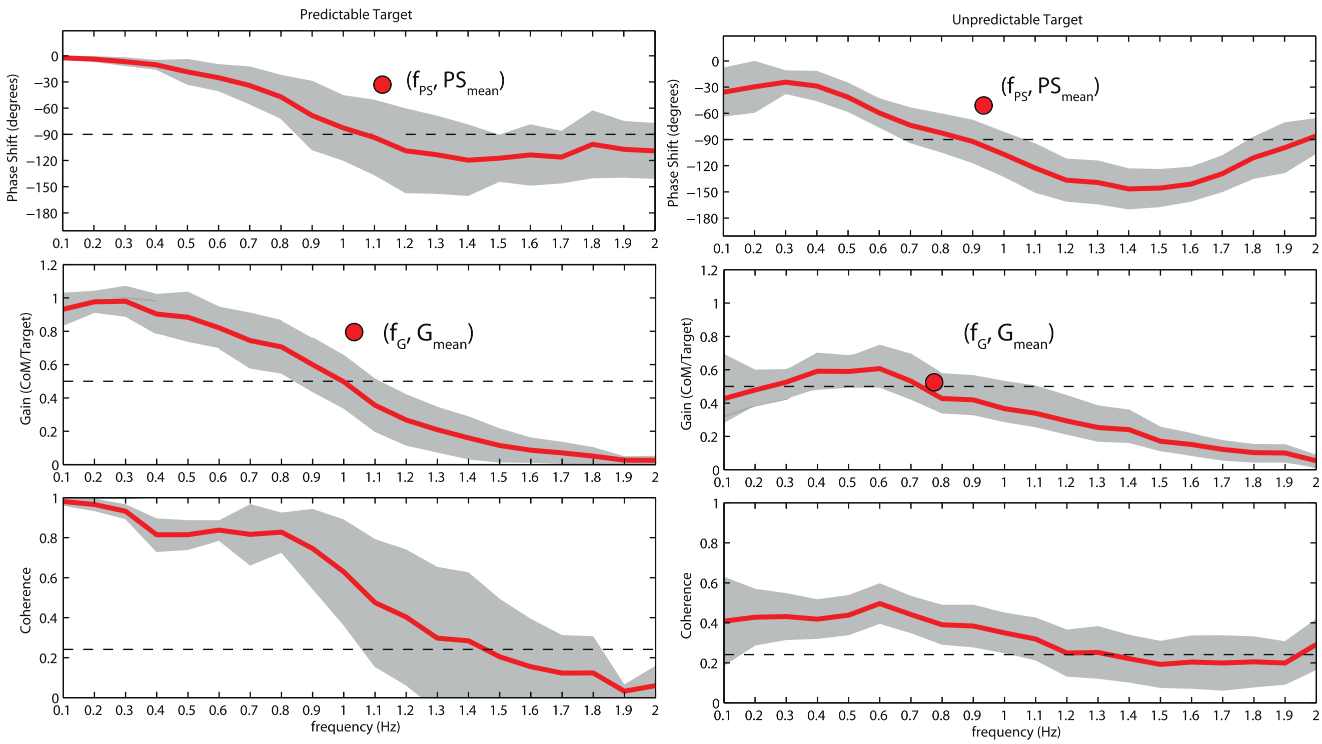

Fig. 2. Averaged curves (± sd) for phase shift (top panel), gain (mid panel) and coherence (bottom panel) measures using both, predictable target (left) and unpredictable (right) targets. Gray shading indicates the ± sd for all subjects and for all trials. Circular markers inserted in the plots indicate means for performance descriptors.

Table 1
Descriptive statistics for all MELBA descriptors (± sd) for both targets and ML gait stability measures (LDE) on both settings (treadmill and daily-life) are presented on the top and bottom part of the table, respectively. Right side of the table presents 95% confidence interval ranges and significant differences (*p*-values) when comparing performance descriptors between targets and measures of gait stability between settings.

			Mean	sd	95% confidence		*p*
Unpredictable	f_{PS}	(Hz)	.96	.19	0.86	1.05	<.01
	PS_{mean}	(°)	−49.91	6.54	−53.04	−46.40	
	f_G	(Hz)	.80	.21	0.70	0.91	
	G_{mean}		.53	.09	0.48	0.57	
Predictable	f_{PS}	(Hz)	1.13	.26	0.99	1.26	
	PS_{mean}	(°)	−32.81	5.32	−35.65	−30.24	
	f_G	(Hz)	1.04	.14	0.97	1.11	
	G_{mean}		.79	.05	0.77	0.82	
Stability	LDE_{TR}		1.43	.36	1.25	1.62	<.01
	LDE_{DL}		2.01	.39	1.82	2.21	

walking, stability in this task was likely determined mainly by physical capacities. MELBA's predictable task also assesses this aspect of balance, which may explain the association between LDE_{TR} and f_{PS} for the predictable target [19]. During treadmill walking as well as during predictable CoM-tracking, a fixed weight-shifting pattern is followed. However, whereas for treadmill walking this pattern is constant, in MELBA, physical capacities are progressively further challenged by increasing the frequency of the target to be tracked yet maintaining the amplitude of the ML displacement. Although not significant, the correlation found between LDE_{TR} and f_{PS} for the unpredictable target may indicate that similar resources are assessed by the two tracking tasks, however, a possible redundancy of these tasks when assessing balance control is yet to be explored.

Table 2
Results for the Pearson product-moment correlation analyses performed between MELBA performance descriptors for both targets and ML gait stability measures (LDE). Left side of the table shows *r*- and *p*-values for the treadmill walking (LDE_{TR}) whereas right side presents test statistics for the daily-life condition (LDE_{DL}). Significant correlations ($p < .05$) are highlighted in bold.

		LDE_{TR}		LDE_{DL}	
		r	*p*	*r*	*p*
Predictable	f_{PS}	**−.48**	**.04**	−.40	.10
	PS_{mean}	−.40	.09	−.27	.27
	f_G	−.31	.20	−.12	.64
	G_{mean}	−.29	.23	−.35	.16
Unpredictable	f_{PS}	−.46	.05	**−.57**	**.01**
	PS_{mean}	−.19	.43	−.25	.33
	f_G	−.15	.54	−.05	.84
	G_{mean}	−.08	.73	.06	.82

The significant associations between LDE_{DL} and f_{PS} (control bandwidth) for the unpredictable target may indicate that similar ML balance resources are utilized during CoM-tracking tasks and walking in daily life. The unpredictable nature of the context of daily-life walking, where environmental challenges such as uneven terrain or potential collisions with other people, require adjustments of the gait pattern may explain this association. Gait adjustments likely require fast sensory integration to control weight-shifts similar to those required during the unpredictable CoM-tracking task. It has been previously reported that incorrect weight-shifting accounts for 41% of falls in residential care

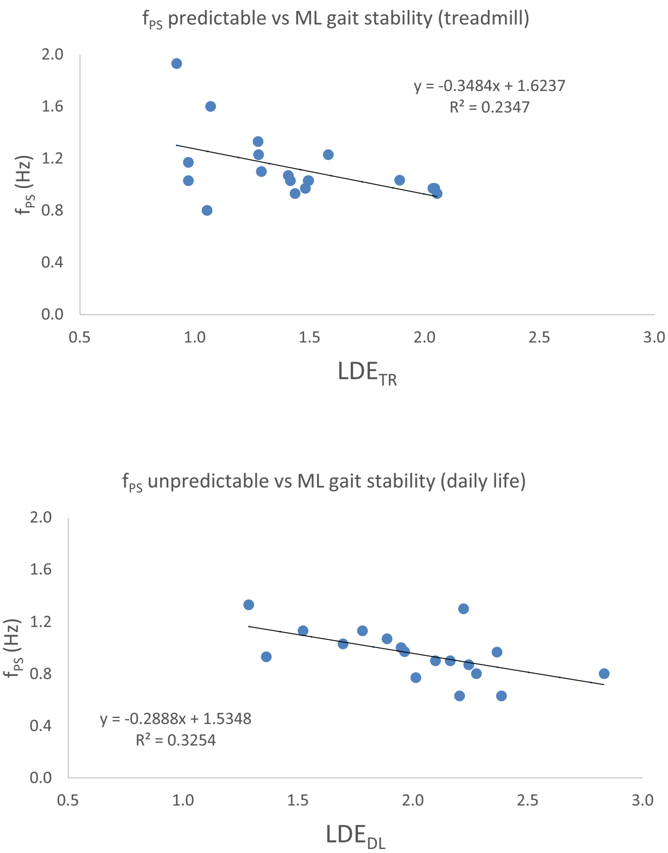

Fig. 3. Scatter-plots showing significant ($p < .05$) correlations found between f_{PS} for the predictable target and LDE_{TR} (top panel) as well as f_{PS} for the unpredictable target and LDE_{DL} (bottom panel). Regression equations as well as R^2 values are also presented within the figure.

facilities, which mainly occurred during walking [23]. Although we assessed community-dwelling older adults, MELBA's sensitivity to age [6] indicates that weight-shifting may also be an early sign of balance deterioration in healthy elderly.

According to literature, the ML CoM displacement at a velocity of 1.2 m/s as used in the our treadmill walking protocol is about 4.4 cm and has a frequency of 0.8 Hz [24]. ML CoM displacement at f_{PS} for the predictable target as we observed was around 5 cm, but occurred at a higher frequency (1.13 Hz). This suggests that ML balance control is greater challenged during the predictable task than during walking. The unpredictable task, on average, elicits smaller albeit unpredictable ML CoM amplitudes [25] which may be closer to the ML CoM displacements when walking in daily life. These differences in ML CoM amplitudes and frequency may explain the relatively weaker LDE_{tr} and predictable fps correlation compared to the LDE_{dl} and unpredictable f_{PS} correlation. Unlike f_{PS}, other performance descriptors showed poor correlations with LDE in both; treadmill walking and daily life conditions. However, considering that MELBA tasks appears to be more challenging for ML balance control than walking, performance descriptors may greater correlate with LDE under perturbed walking as in those situations potentially leading to a fall.

The characterization of gait stability using accelerometers during treadmill and daily-life walking has been shown to predict falls in the elderly population, hence offering an ecologically valid measure of balance performance [9,12,13]. However, since stability-threatening events do not necessarily occur on a regular basis, these measures may not reflect one's ability to cope with strong balance threats [11]. Challenging the balance system to its maximal capacities is crucial to determine subtle impairments that may hamper responses to external perturbations, especially in able-bodied older adults. In this respect, MELBA has shown to be challenging enough so as to observe CoM-tracking performance consistently dropping below PS and G thresholds even in healthy young subjects [6].

It has been reported that impairments of different systems contributing to balance control are affected by aging [3,26]. This is likely to affect performance during CoM-tracking tasks as well as stability during walking; however, sensory re-weighting and changes in motor strategies may occur to compensate for sensorimotor deficits and avoid instability during both MELBA and walking. Balance assessment measures should, therefore, aim to maximize the contribution of each system when assessing an older person's maximal capacities. When compared to clinical and posturographic measures, MELBA has shown to be more sensitive to aging and hence likely demands each balance sub-system's contribution to a greater extent [6]. In addition, the use of visual feedback is not likely to mask the impairment of other sensory systems [27].

While LDE_{DL} obtained over a full week [14] and MELBA performance descriptors [6] have been shown to have good reliability, LDE_{TR} over a single session has been shown to be less reliable [28]. This limited reliability may have affected associations between LDE_{TR} and MELBA descriptors. Although other measures of gait stability have also been shown to predict falls in the elderly [14], we only focus on the ML direction, since compelling evidence points to balance on this plane as the most affected by aging when standing and walking [4,13,23,29,30]. Further studies should explore whether the combination of MELBA and gait stability measures has added value for the prediction of falls in the older adults in prospective studies.

5. Conclusion

Significant correlations between mediolateral stability during treadmill and daily-life walking and ML balance as determined with MELBA, support the ecological validity of this tool for ML balance assessment in community-dwelling older adults, who exhibit subtle balance impairments.

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Conflicts of interest statement

No conflict of interest.

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