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Local dynamic stability and variability of gait are associated with fall history in elderly subjects

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ABSTRACT

Gait parameters that can be measured with simple instrumentation may hold promise for identifying individuals at risk of falling. Increased variability of gait is associated with increased risk of falling, but research on additional parameters indicates that local dynamic stability (LDS) of gait may also be a predictor of fall risk. The objective of the present study was to assess the association between gait variability, LDS of gait and fall history in a large sample of elderly subjects.

Subjects were recruited and tested at a large national fair. One hundred and thirty four elderly, aged 50–75, who were able to walk without aids on a treadmill, agreed to participate.

After subjects walked on a treadmill, LDS (higher values indicate more instability) and variability parameters were calculated from accelerometer signals (trunk worn). Fall history was obtained by self-report of falls in the past 12 months.

Gait variability and short-term LDS were, individually and combined, positively associated with fall history.

In conclusion, both increased gait variability and increased short-term LDS are possible risk factors for falling in the elderly.

1. Introduction

Aging is associated with fall risk. Falls can result in severe injuries resulting in loss of independence, institutionalization and even death [1]. As most falls occur during walking [2,3], assessing fall risk based on gait parameters may be a promising approach for selecting subjects for preventive measures. This paper focuses on gait variability and gait stability parameters.

Variability of gait can be defined as the variance of the gait parameter around the mean, and a broad range of variability measures has been reported in literature [2,4–7]. Generally, increased spatial and temporal variability is associated with increased fall risk [2,4,7]. However, other studies found that high variability was associated with decreased fall risk [8] and that low variability was associated with increased fall risk [4], which raises the question if gait variability might be non-linearly related to fall risk [9,10]. In addition, it has been established that strides are related to each other in time [6]. The measure gait variability assumes that each stride is unrelated to strides in the past, and that inter-stride variations are random [5]. The above indicates that the debate on which variability measures to use for assessing fall risk, and how to use them, is unresolved. Therefore, it could be useful to investigate the association of other gait measures with fall risk. The present study will focus, in addition to variability, on local dynamic stability of gait.

In the present study, stability of gait is defined as the resilience of the walking subject to infinitesimal, i.e. local, perturbations during walking [11], which are the result of naturally occurring internal and external influences. Local dynamic stability (LDS), quantified by the maximum time-finite Lyapunov exponent, is a measure of the ability of the walking subject to attenuate the effects of these local perturbations and is not related to gait variability [5]. LDS might be related to fall risk [12–17] as it predicts falls of a walking computer model [12,16]. In people, assessment of LDS indicate that elderly subjects are generally more unstable during gait than young subjects which is in accordance with the association between age and fall risk [13,14]. A recent study showed that a combination of LDS and variability could correctly classify 83% of all trials as normal walking or walking with a balance impairment, induced by galvanic vestibular stimulation [17]. LDS successfully differentiated elderly fallers from elderly non-fallers and young subjects [15]. However, this

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was a small study ($N = 13$), and the results may be confounded by differences in walking speed between groups [18]. Furthermore, in this study [15] fallers were defined as subjects who fell after an induced slip in an earlier experimental study, not necessarily predictive of real-life fall risk. In conclusion, several studies indicate that LDS might be associated with fall risk, but this has not yet been investigated within a large sample of elderly.

Literature shows that both variability and stability of gait are quantified using many measures, often with subtle differences. The first aim of the present study is to explore the collinearity of these measures using a factor analysis to determine whether these measures can be clustered in variability and stability as different properties of an individual's gait pattern. The results of this analysis will be used to answer the main research question, whether variability and stability of gait are associated with fall history in a large sample of elderly subjects.

2. Methods

2.1. Participants

Subjects were recruited and tested at a national fair aimed at people of 50 years and older. Subjects were included if they were aged between 50 and 75 years and able to walk on a treadmill without aids. Subjects older than 75 years were excluded given the short time to reconsider their decision to participate and given an estimated increase in injury risk in relation to a part of the experimental protocol (not described in this paper). All subjects gave informed written consent. The ethics committee of the Faculty of Human Movement Sciences, VU University Amsterdam approved the experimental protocol.

2.2. Experimental protocol

Subjects walked for 12–17 minutes on a treadmill at 4 km h^{-1}. The first 5–10 minutes were used to become familiar with treadmill walking. The final 7 minutes of treadmill walking were used to collect trunk accelerations and angular velocities using a small device (Dynaport Hybrid, McRoberts B.V., The Hague, The Netherlands). The device was strapped to the back, just below the shoulder blades, as trunk control is critical for gait stability [19].

Fall history was obtained by self-report of number of falls and fall cause in the past 12 months. A subject was classified as a faller if at least one fall had occurred in the past 12 months. Subjects were classified as experienced treadmill walkers if they had walked on a treadmill at least twice before the fair visit.

2.3. Gait parameters

3D linear accelerations and 3D angular velocities of the trunk were measured with the Dynaport Hybrid during treadmill walking, resulting in 6 time-series to calculate gait parameters. The data were analyzed in the sensor coordinate system which was approximately aligned with the global coordinate system [17]. Because of clipping of the vertical acceleration time-series in 35% of the subjects, only the other 5 time-series were used. In subjects with clipping, on average 0.34% of the measured signal was affected. The final 150 strides were used to calculate gait parameters. Foot contacts were detected based on the anterior-posterior acceleration signal for all gait parameters [20].

For the variability parameters the data were low pass filtered (20 Hz, 4th order Butterworth) before further processing. In total, 7 gait variability parameters were calculated. Stride-time variability (STV), was calculated as the standard deviation of 150 stride times. The other parameters were stride-to-stride variability of the 5 analyzed time-series and the stride-to-stride variability of the Euclidean norm of the three angular velocity time-series. To calculate stride-to-stride variability, each stride of 150 strides of the 6 time-series was time normalized (0–100%). The mean over the stride-cycle of the standard deviation across strides at each increment of normalized time was used as a measure of stride-to-stride variability of gait [5].

Stability of gait was quantified by LDS. Since there is no consensus on which time-series to use for calculation, LDS was calculated for each of the 5 time-series and 2 combinations of the angular velocity time-series [21–23]. The method for calculating LDS has been described extensively in other studies [21,22]. Briefly, LDS describes how a subject responds to small initial differences in kinematics over the course of 10 strides. Following several other studies, the dynamics of gait were analyzed in a 5-dimensional state-space [13,15,18,21,22] that was reconstructed from each of the individual time-series using the method of time-delayed embedded dimensions (delay of 10 samples) [15,18,21]. The state-spaces from combined signals were a 15-dimensional state-space from the combination of 5-dimensional state-spaces of the three angular velocities and a 6-dimensional state-space consisting of 2-dimensional (1 embedded dimension) of the three angular velocities. For each time point in state-space, a nearest neighbor was found and the Euclidean distance between these points in state-space was tracked for 10 strides. The divergence curve was calculated as the mean of the log of the time-distance curves. Short-term LDS (LDS_S) was calculated as the linear fit through the 1st step of the divergence curve [18]. Thus, LDS_S indicates the rate of divergence as a result of differences in initial conditions during the time needed for 1 step. Long-term LDS (LDS_L) was calculated as the linear fit through strides 4 till 10 in the divergence curve. LDS_L indicates the rate of divergence after small differences in initial conditions between the 4th and the 10th stride. A positive LDS_S or LDS_L indicates instability, a larger positive value indicates more instability.

In summary, 7 variability, 7 LDS_S, and 7 LDS_L parameters were calculated to quantify gait parameters (Table 1). All calculations were performed by custom made Matlab 7.6 (The MathWorks, Inc., Natick, MA) scripts.

2.4. Statistical analysis

The Mann–Whitney *U*-test, the independent samples *t*-test, and the chi-square test were used to test differences in demographics, and treadmill experience between fallers and non-fallers. PASW Statistics 18.0 (SPSS, Inc., Chicago, IL) was used and statistical significance was declared if $p < 0.05$.

To answer the first research question, whether the calculated measures of gait parameters can indeed be clustered in concepts of variability and stability, all variability and stability parameters were first log transformed to correct non-normality. Factor analysis was used to extract the underlying grouping, i.e. factors, of intercorrelated clusters of gait parameters. Therefore, all variability and stability of gait parameters were used as input in the factor analysis. However, one gait parameter ($LDS_{LS\omega}$, see Table 1 for abbreviation) was excluded after the individual Kaiser–Meyer–Olkin test resulted in a value <0.5 (indicating unsuitability for factor analysis [24]) leaving 20 gait parameters for the development of the factor structure. The scree plot was used to determine the number of extracted factors. VariMax rotation was used to optimize the loading of variables onto factors.

To answer the main research question, whether variability and stability of gait are associated with fall risk, the gait parameter with the highest factor score for each factor, that resulted from the factor analysis, was selected to study its association with fall history using logistic regression. Univariate regressions with

Table 1
Time-series per class of parameters and abbreviations for variables used in text and tables. Note that all directions are in the local coordinate system, which was roughly aligned with the global (Cartesian) coordinate system.

Time-series	Variability	LDS_S	LDS_L
ML acceleration	VAR_{ML}	LDS_{SML}	LDS_{LML}
AP acceleration	VAR_{AP} STV	LDS_{SAP}	LDS_{LAP}
V acceleration	–[a]	–[a]	–[a]
F angular velocity	$VAR_{F\omega}$	$LDS_{SF\omega}$	$LDS_{LF\omega}$
S angular velocity	$VAR_{S\omega}$	$LDS_{SS\omega}$	$LDS_{LS\omega}$
T angular velocity	$VAR_{T\omega}$	$LDS_{ST\omega}$	$LDS_{LT\omega}$
Angular velocities combined	$VAR_{Full\omega}$	$LDS_{SFull\omega15D}$ $LDS_{SFull\omega6D}$	$LDS_{LFull\omega15D}$ $LDS_{SFull\omega6D}$

VAR: variability of gait; LDS_S: short-term local dynamic stability; LDS_L: long-term local dynamic stability and STV: stride-time variability. ML: medio-lateral; AP: anterior-posterior; V: vertical; ω: angular velocity; F: frontal plane; S: sagittal plane and T: transverse plane.
[a] V acceleration time-series discarded due to clipping of the signal.

individual gait parameters were followed by a forward stepwise regression, which tested the change in the −2-log-likelihood (chi-square test) for inclusion of gait parameters in the final model. The overall model fit of all models was quantified by Nagelkerke's R^2_N which can be interpreted as R^2 of linear regression [25]. The resulting regression model was checked for confounders (demographic variables and treadmill experience). A variable was considered a confounder if it changed a coefficient of any of the included gait variables by >10%.

3. Results

In total, 134 subjects participated in this study. The mean age was 62.4 (SD 6.2) years. There were no significant differences between fallers and non-fallers in demographic variables, physical activity score, and treadmill experience (Table 2). 44 subjects (32.8%) fell in the previous year. The majority of falls occurred during locomotion (tripping = 27, slipping = 3), while other causes were less common (lost consciousness = 3, vestibular disorders = 3, cannot remember cause = 4).

There were substantial inter-correlations between gait parameters ($-0.36 <$ Pearson $r < 0.87$). The factor analysis on log transformed gait parameters resulted in three uncorrelated ($-0.003 <$ Pearson $r < 0.02$) factors, "gait variability", "short-term gait *in*stability", and "long-term gait *in*stability", that accounted for 71% (38%, 20%, and 13%, respectively), of the total variance (all eigenvalues >1.5). The factor loadings of the gait parameters can be interpreted as the correlation of the gait parameter with the factor (Table 3). Generally, the absolute factor loadings were >0.6 with the exception of $LDS_{SF\omega}$, $LDS_{LF\omega}$, and LDS_{LAP}. LDS_{LAP} had substantial loading on 2 factors and was considered non-specific to a factor.

The most representative gait parameters, i.e. having the highest factor loadings for the three factors, selected to study the association with fall history, were VAR_{ML} (gait variability), $LDS_{SFull\omega6D}$ (short-term gait *in*stability) and $LDS_{LFull\omega6D}$ (long-term gait *in*stability). Univariate logistic regression analyses revealed that VAR_{ML} ($p < 0.001$, $R^2_N = 0.20$) and $LDS_{SFull\omega6D}$ ($p = 0.006$, $R^2_N = 0.12$) were significantly and positively associated with fall history while $LDS_{LFull\omega6D}$ was not significantly associated with fall history ($p = 0.361$, $R^2_N = 0.01$, Table 4).

In the multivariate analysis, both VAR_{ML} and $LDS_{SFull\omega6D}$ had a significant contribution (Table 5). Adding $LDS_{LFull\omega6D}$ did not further improve the regression model ($p = 0.827$). The model with VAR_{ML} and $LDS_{LFull\omega6D}$ ($R^2_N = 0.24$) was checked for confounding by adding demographics and treadmill experience individually. None of the added variables changed the coefficients by >10%. The regression coefficients revealed that subjects with higher VAR_{ML} and higher $LDS_{LFull\omega6D}$ were more likely to have experienced a fall in the previous year (Table 5).

Table 3
Loading of log transformed variables after factor analysis with VariMax rotation. Only absolute loadings >0.30 are shown.

Variable name	Factor 1	Factor 2	Factor 3	Factor name
VAR_{ML}	0.95			Gait variability
$VAR_{Full\omega}$	0.95			
$VAR_{T\omega}$	0.90			
$VAR_{S\omega}$	0.90			
$VAR_{F\omega}$	0.89			
VAR_{AP}	0.89			
STV	0.77			
LDS_{LAP}	−0.60[a]		0.32[a]	
$LDS_{SFull\omega6D}$		0.90		Short-term gait *in*stability
$LDS_{SFull\omega15D}$		0.81		
LDS_{SAP}		0.75		
LDS_{SML}		0.72		
$LDS_{ST\omega}$		0.71		
$LDS_{SS\omega}$		0.67		
$LDS_{SF\omega}$		0.45		
$LDS_{LFull\omega6D}$			0.96	Long-term gait *in*stability
$LDS_{LFull\omega15D}$			0.96	
$LDS_{LT\omega}$			0.83	
LDS_{LML}			0.69	
$LDS_{LF\omega}$			0.43	
$LDS_{LS\omega}$	Excluded during factor analysis			

[a] Indicates high loadings of a gait parameter that shares substantial loadings with other factors. For abbreviations see Table 1.

4. Discussion

Before addressing the main aim of this paper, i.e. to assess the association between gait variability and LDS and fall history, a factor analysis was used to determine whether the gait parameters could be clustered in gait variability and gait stability parameters and to select the strongest parameters within these clusters. Interestingly, gait variability parameters were clearly distinguishable from short-term and long-term gait *in*stability parameters. This is in line with earlier results where variability, short-term and long-term local dynamic *in*stability showed different patterns of

Table 2
Subject characteristics of fallers and non-fallers. All differences between fallers and non-fallers were non-significant. Data are presented as mean (SD), median (interquartile range) or percentages.

	Fallers	Non-fallers	*N* total
N	44	90	134
Age (years)	63.3 (6.4)	62.0 (6.1)	134
Gender (male/female)	16/28 (36.4%/63.6%)	33/57 (36.7%/63.3%)	134
Height (m)	1.71 (0.07)	1.71 (0.09)	134
Body mass (kg)	72.0 (67.0–80.0)	73.0 (67.0–80.0)	134
Treadmill experience (yes/no)	21/22 (47.7%/50.0%)	35/53 (38.9%/58.9%)	131

Table 4
Results of univariate logistic regression analyses for each log transformed gait variable that had the highest factor score.

Variable	β[a]	95% CI_β[b]	p[c]	R^2_N[d]
VAR_{ML}	6.53	3.39–9.67	<0.001	0.20
$LDS_{SFull\omega6D}$	13.62	5.25–21.99	0.001	0.12
$LDS_{LFull\omega6D}$	−1.08	−3.49–1.33	0.378	0.01

[a] β: unstandardized regression coefficient.
[b] 95% CI_β: 95% confidence interval of β.
[c] p: p-value.
[d] Model fit statistic Nagelkerke's R^2_N.

Table 5
Result of the final multivariate logistic regression analysis with log transformed VAR_{ML} and $LDS_{SFull\omega 6D}$.

Variable	β[a]	95% CI_{β}[b]	p[c]	R_N^2[d]
VARML	1.25	0.53–1.98	0.010	0.24
$LDS_{SFull\omega 6D}$	1.04	0.06–2.02	0.038	

[a] β: unstandardized regression coefficient.
[b] 95% CI_{β}: 95% confidence interval of β.
[c] p: p-value.
[d] Model fit statistic Nagelkerke's R_N^2.

change with increasing walking speed [26]. These results indicate that the three factors quantify different aspects of gait that could each provide important information about gait performance.

This is the first study, as far as we know, that showed that VAR_{ML} and $LDS_{SFull\omega 6D}$ were associated, individually and combined, with fall history while $LDS_{LFull\omega 6D}$ was not. This result is in line with several studies that showed the plausibility of an association between short-term gait *in*stability and factors related to gait stability (fall risk, age, and induced balance impairments) [10,12–15,17], while long-term gait *in*stability was not in most of these studies [12,15–17]. The results in this study do substantiate that short-term *in*stability and variability of gait are important sources of information, while long-term gait *in*stability is not, when assessing fall risk.

While the addition of $LDS_{SFull\omega 6D}$ to VAR_{ML} was statistically significant, the increase of the explained variance of the statistical model was small (change of $R_N^2 = 0.04$). Nevertheless, this implies that the association between gait parameters and fall history can be improved without extra measurement effort since LDS is calculated from the same data as gait variability.

We suggest that the higher relevance of short-term gait *in*stability compared to long-term gait *in*stability when assessing fall risk might be related to the time span of the parameters. Several studies indicate that whether a subject will fall as a result of trips or slips, i.e. global perturbations, is largely dependent on the reaction during the first step [27,28]. In contrast, long-term gait *in*stability quantifies the divergence of the gait pattern between 4 and 10 strides after a local perturbation, when most of the relevant reactions to global perturbations are completed. Indeed, it appears that short-term gait *in*stability is positively associated to the initial response phase during the first step after a global perturbation, while long-term gait *in*stability is not [19]. Long-term gait *in*stability might quantify some other characteristic of gait. However, strong hypotheses are lacking in the literature and the current results do not provide new hypotheses.

The results of this study indicate that gait variability is more strongly associated with fall history than short-term gait *in*stability. The association between variability of gait and falls has been found by several authors [2,4,5,7], while the association with falls had barely been investigated for short-term gait *in*stability [15]. Still, the best fit to the data is achieved when both variability and short-term *in*stability of gait are included in the regression model. In the past, increased variability has been associated with errors introduced by a suboptimal performance of the neuromuscular system in controlling movement execution [29]. Interestingly, variability of standing balance tasks is better understood when interpreted in relation to a boundary beyond which global stability is compromised [30]. Indeed, there is evidence that large variability during standing balance tasks can be associated with flexibility in movement execution [30]. Short-term gait *in*stability quantifies how fast gait patterns diverge after an infinitesimal perturbation irrespective of the distance to the boundary of stability. Fast divergence close to the boundary of stability could be unfavorable, while fast divergence well within the boundary of stability of gait could be unimportant. The combination of high variability, which may reflect the probability of approaching the boundary of stability, and high short-term *in*stability could therefore be a good predictor of the propensity to fall.

It is remarkable that in this relatively young group of elderly subjects, the association between fall history and variability and short-term *in*stability of gait was found. The age of the subjects was low compared to other studies investigating the relation between gait variability and falls (62.4 years vs 79–82 years) [2,4,7]. Despite this difference in age, other characteristics were similar. The percentage of fallers in this study was comparable with previous studies (32.8% vs 13–57%) [2,3,7], as was the percentage of falls during locomotion (68.2% vs 39–75%) [2,3,7]. The relatively high percentage of fallers in this young group of elderly subjects might be caused by the setting (a fair) where it was clear that the research was about stability of gait and to falls. Subjects with fall history were perhaps more inclined to participate than non-fallers. If the results of this paper are verified prospectively, assessment of variability and stability of gait may contribute to selection of elderly people for fall prevention programs.

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Conflict of interest statement

The authors declare that there are no conflicts of interest.

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