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Estimating fall risk with inertial sensors using gait stability measures that do not require step detection

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ABSTRACT

Falls have major consequences both at societal (health-care and economy) and individual (physical and psychological) levels. Questionnaires to assess fall risk are commonly used in the clinic, but their predictive value is limited. Objective methods, suitable for clinical application, are hence needed to obtain a quantitative assessment of individual fall risk. Falls in older adults often occur during walking and trunk position is known to play a critical role in balance control. Therefore, analysis of trunk kinematics during gait could present a viable approach to the development of such methods. In this study, nonlinear measures such as harmonic ratio (HR), index of harmonicity (IH), multiscale entropy (MSE) and recurrence quantification analysis (RQA) of trunk accelerations were calculated. These measures are not dependent on step detection, a potentially critical source of error. The aim of the present study was to investigate the association between the aforementioned measures and fall history in a large sample of subjects (42 fallers and 89 non-fallers) aged 50 or older. Univariate associations with fall history were found for MSE and RQA parameters in the AP direction; the best classification results were obtained for MSE with scale factor $\tau = 2$ and for maximum length of diagonals in RQA (72.5% and 71% correct classifications, respectively). MSE and RQA were found to be positively associated with fall history and could hence represent useful tools in the identification of subjects for fall prevention programs.

1. Introduction

Falls in the elderly have adverse physical and psychological consequences for the individuals, as well as substantial consequences for health-care and economy [1]. In older adults, falls often occur during walking [2]. The analysis of gait stability may allow identification of subjects at risk. However, the definition of gait stability is still not entirely clear, and many direct and indirect measures aiming to quantify this feature have been suggested in the literature [3]. Measures of trunk accelerations are crucial in the assessment of gait stability [4–6], as the trunk segment is known to play a critical role in regulating gait-related oscillations in all directions [7].

Many gait stability measures proposed in the literature are based on the identification of gait cycles [2,8–11]. Several methods for step detection have been presented in the literature [12–14], based on different techniques and sensor positioning. Errors in step detection can, however, critically affect stability outcomes, making step detection a possible intrinsic source of error. Examples are present in the literature of inability in the detection of gait events due to irregular acceleration patterns [15] and incorrect identification of acceleration peaks [16]. Gait characteristics or anomalies typical of certain pathologies (e.g. shuffling, crouched, toe gait) can result in atypical acceleration signals, determining unreliable step-detection. Assuming that such deviations are more common among people with a high fall risk, such errors may cause bias when calculating gait stability measures. Other temporal parameter detection systems, such as foot switches or pressure sensors attached to the sole, involve several problems [14] (e.g. difficulties in sensor attachment when assessing subjects with abnormal gait). To overcome this possible source of error, nonlinear analysis techniques may offer a powerful tool. In particular, some of these stability related measures do not depend on step detection. In this study the Harmonic ratio (HR) [17,18], the Index of harmonicity (IH) [19], Multiscale entropy (MSE) [20], and Recurrence quantification analysis (RQA) [21] of trunk accelerations during gait were analysed [17–22]. The relationship between these measures and fall risk has not been analysed and reported before.

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HR, derived from trunk acceleration signals and based on amplitudes in frequency spectra, provides information on how smoothly subjects control their trunk during walking, giving an indication of whole body balance and coordination [17,18].

Similarly to HR, IH assesses the contribution of the oscillating components to the observed coordination patterns by means of spectral analysis [19], quantifying the contribution of the stride frequency to the signal power relative to higher harmonics.

MSE quantifies the complexity of a time series at multiple spatio-temporal scales [20], since biological systems are likely to present structures at different scales.

RQA is a nonlinear technique that has been applied recently to biological time series, including gait data [22]. Based on local recurrence of data points in the reconstructed phase space, it provides a characterization of a variety of features of the time series, such as the quantification of deterministic structure and non-stationariness [21].

The aim of the present study was to investigate the association between fall history and the aforementioned measures (HR, IH, MSE and RQA) during treadmill walking in a large sample of older subjects.

2. Materials and methods

2.1. Participants

A total of 131 subjects (62.4 $\pm$ 6.1 years; 171 $\pm$ 8 cm; 74 $\pm$ 10 kg) participated in the study, after giving informed written consent. The data have been described earlier by Toebes et al. [23] in a paper on local dynamic stability and stride variability of gait. Three subjects from the original data set were excluded from the analysis due to technical problems during data acquisition.

2.2. Protocol

Participants walked on a treadmill at 4 km/h for 12–17 min, wearing an inertial sensor (Dynaport Hybrid, McRoberts B.V., The Hague, The Netherlands) located on the trunk, below the shoulder blades. Sensing range was $\pm 2g$ (g = 9.81 m/s^2) and sample frequency was 100 Hz. Signals were not filtered. Data of 3 min of walking (after 5–10 min of acclimatization) were acquired. Fall history was obtained by self-report; a subject was classified as a faller if at least one fall had occurred in the 12 months prior to the measurements. 42 subjects (32.1%) experienced at least one fall in the year previous to the experiment. To estimate the habitual physical activity in daily life, the Longitudinal Aging Study Amsterdam Physical Activity Questionnaire (LAPAQ) was used. LAPAQ data were used to calculate the total physical activity score [24]. Subjects were classified as experienced treadmill walkers if they had walked on a treadmill at least twice previously.

2.3. Data analysis

Trunk accelerations in the anterior–posterior (AP) and medio-lateral (ML) directions were analysed. Vertical acceleration signals showed clipping artifacts (on average 0.34% of the signal) in 52% of the subjects, and were therefore not considered in the analysis.

The HR was calculated by decomposing the AP and ML acceleration signals into harmonics using a discrete Fourier transform [18]; the summed amplitudes of the first 10 even harmonics were divided by the summed amplitudes of the first 10 odd harmonics for the AP accelerations, and vice versa for the ML accelerations. This difference is due to the fact that whereas the AP accelerations have two periods every stride, showing a dominance of the second harmonic, representing step frequency and subsequent even harmonics, ML accelerations have only one period per stride, reflecting a dominance of the first (and subsequent odd) harmonics [18]. In order to avoid errors that might be introduced by step detection, HR was not calculated stride by stride, but decomposing the whole signal into its harmonics. A higher HR is an indication of increased smoothness of gait, which can be interpreted as increased stability.

IH was calculated according to Lamoth et al. [19]. The power spectra of the AP and ML acceleration signals were estimated by means of discrete Fourier transform. The peak power at the first six harmonics was estimated and IH was defined as:

$$\mathrm{IH} = \frac{P_0}{\sum_{i=0}^{5} P_i} \tag{1}$$

where P_0 is the power spectral density of the first harmonic and P_i the cumulative sum of power spectral density of the fundamental frequency and the first five super-harmonics. Values close to 1 indicate high harmonicity. Power spectral density of each peak was averaged over a range of $-0.1/+0.1$ Hz around the peak frequency value.

MSE was implemented constructing consecutively more coarse-grained time series; this procedure implies averaging increasing numbers of data points in non-overlapping windows of length τ. Sample entropy (SE) [25] was then calculated for each coarse-grained time series, in order to obtain entropy measures at different scales. SE at each time scale τ is expressed as the negative of the natural logarithm of the conditional probability $C(r)$ that two sequences that are close within a tolerance $r\delta$ for m consecutive points remain close when one more consecutive point is included [26]:

$$\mathrm{SE} = -\ln \frac{C^{m+1}(r)}{C^{m}(r)} \tag{2}$$

r is a fixed radius, m is the number of consecutive data points and δ is the standard deviation of the original series. MSE was calculated for values of τ ranging from 1 to 6, m = 2 and r = 0.2, as suggested by Pincus [27] and later applied by Richman and Moorman to biological time series [25].

The first implementation step of RQA is the reconstruction of the phase space by means of delay embedding [28]. In this study, an embedding dimension of 5 and a delay of 10 samples were used, based on previous studies [29–31]. A distance matrix based on Euclidean distances between normalized embedded vectors was then constructed; the recurrence plot was obtained by selecting a radius of 40% of the max distance, and all cells with values below this threshold were identified as recurrent points. A radius of 40% was chosen to make sure that recurrence rate (RR) responded smoothly and was not too high, and that determinism (DET) did not saturate at the floor of 0 or the ceiling of 100, as approaching these limits would tend to suppress variance in the measure [21].

A number of measures can be obtained by RQA; in this study, RR, DET, averaged diagonal line length (avg_length) and maximum diagonal line length (max_length) were calculated (Eqs. (3)–(6)), reflecting different properties of the system.

$$\mathrm{RR} = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j} \tag{3}$$

where N is the number of points on the phase space trajectory;

$$\mathrm{DET} = \frac{\sum_{l=4}^{N} l P_l}{\mathrm{RR}} \tag{4}$$

where l is the length of diagonal lines, represented through a histogram (P_l);

$$\text{avg\_length} = \frac{\sum_{l=4}^{N} lP(l)}{\sum_{l=4}^{N} P(l)} \quad (5)$$

$$\text{max\_length} = (\{l_i; i = 1, \ldots, N_l\}) \quad (6)$$

where N_l is the number of diagonal lines in the recurrence plot.

SE was calculated using MATLAB (Mathworks, Natick, MA) software available on Physionet [32]. All other estimates were calculated through custom self-made MATLAB (Mathworks, Natick, MA) scripts.

2.4. Statistical analysis

To assess differences in demographics, treadmill experience and physical activity between fallers and non-fallers, Mann–Whitney *U*-test, independent samples *t*-test and chi-square test were used. SPSS Statistics 20.0 (IBM, Armonk, NY, USA) was used for all statistical tests. Statistical significance for all statistical tests was declared if $p < 0.05$.

A factor analysis was performed to assess to what extent the resulting 24 different measures (HR, IH, MSE and RQA, both in AP and ML directions) reflect different properties of the dynamics. To correct for non-normality, all measures were log transformed and then used as input for factor analysis. The scree plot was used to determine the number of extracted factors, and VariMax rotation was used to optimize the loading of variables onto factors.

Log transformed measures were then used as inputs for univariate logistic regression models, to test if measures were able to classify subjects as fallers or non-fallers, considering self-report as the gold standard. The resulting regression models were then checked for confounders (demographic variables, treadmill experience and physical activity score). In addition, a multivariate, forward step-wise logistic regression model was constructed using the most representative variables of each factor as predictors, i.e. the variable with the highest factor loading for each factor. Potential confounders were added to the models one by one and retained when they changed the coefficients by more than 10%.

3. Results

Factor analysis on the 24 log transformed measures led to 7 factors (Table 1), accounting for 89% of the variance (all eigenvalues > 0.8). Absolute factor loading values were >0.5, with the exception of HR in AP direction, which had cross loading on 3 factors and was considered non-specific to a factor. RQA parameters in AP direction showed quite high (absolute value > 0.4) loading on two factors. Parameters of MSE, IH, RQA in the ML direction and HR in the ML direction showed loadings on different factors, reflecting the description of different system dynamics. Parameters for the trunk kinematics in the ML and AP were largely independent as reflected in the factor loadings. In summary, Factor 1 mainly reflected AP entropy and recurrence characteristics, Factor 2 reflected ML entropy, Factor 3 reflected ML recurrence characteristics, Factor 4 reflected ML harmonicity, Factor 5 reflected AP HR, Factor 6 reflected AP harmonicity, and Factor 7 reflected ML HR.

Univariate associations with fall history were found for MSE and RQA measures in the AP direction. The best classification results were obtained for MSE with scale factor $\tau = 2$ ($p < 0.001$) and for maximum length of diagonals in RQA ($p = 0.002$), which correctly classified 72.5% (sensitivity 21.4%, specificity 96.6%) and 71% (sensitivity 16.7%, specificity 96.6%) of cases, respectively. All MSE measures in AP direction showed correlations $> 70\%$. Other measures showed no significant association with fall history (Table 2). The multivariate model retained only AP direction MSE with $\tau = 3$, and this model yielded slightly worse classification than the model using MSE with $\tau = 2$. All models were checked for possible confounders (demographics, physical activity score, treadmill experience); none of the variables changed the coefficients by more than 10%.

No significant differences were found between fallers and non-fallers regarding demographic variables, physical activity score and treadmill experience.

4. Discussion

Currently, fall risk is mainly inferred from fall incidence, but this method obviously provides information only after the event and has proven to be unreliable, especially when dealing with subjects

Table 1
Loading of log transformed variables after factor analysis. Absolute loadings > 0.4 are shown.

Stability measure	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
HR ML							0.951
HR AP	−0.498				0.790		
MSE ML ($\tau = 1$)		0.938					
MSE ML ($\tau = 2$)		0.946					
MSE ML ($\tau = 3$)		0.970					
MSE ML ($\tau = 4$)		0.961					
MSE ML ($\tau = 5$)		0.899					
MSE ML ($\tau = 6$)		0.823					
MSE AP ($\tau = 1$)	0.913						
MSE AP ($\tau = 2$)	0.960						
MSE AP ($\tau = 3$)	0.968						
MSE AP ($\tau = 4$)	0.960						
MSE AP ($\tau = 5$)	0.947						
MSE AP ($\tau = 6$)	0.919						
IH ML				0.860			
IH AP						0.901	
RQA ML RR				0.884			
RQA ML DET			0.716				
RQA ML avg_length			0.848				
RQA ML max_length			0.764				
RQA AP RR	−0.837						
RQA AP DET	−0.721						
RQA AP avg_length	−0.725		0.448				
RQA AP max_length	−0.701		0.437				

Table 2
Result of the univariate logistic regression models. Regression coefficient (β), p-value (p) and 95% confidence interval of β (95% CI_{β}) are shown.

Stability measure	β	p	95% CI_{β}
HR ML	3.135	0.113	−0.74 to 7.01
HR AP	−2.016	0.183	−4.98 to 0.95
MSE ML (τ = 1)	1.579	0.689	−6.15 to 9.31
MSE ML (τ = 2)	0.208	0.951	−6.44 to 6.86
MSE ML (τ = 3)	1.119	0.75	−5.78 to 8.02
MSE ML (τ = 4)	1.915	0.63	−5.87 to 9.70
MSE ML (τ = 5)	3.861	0.376	−4.68 to 12.41
MSE ML (τ = 6)	4.525	0.312	−4.25 to 13.30
MSE AP (τ = 1)	8.994	0.002	3.34 to 14.65
MSE AP (τ = 2)	9.138	0.001	3.68 to 14.60
MSE AP (τ = 3)	9.191	0.001	3.82 to 14.56
MSE AP (τ = 4)	8.594	0.001	3.39 to 13.80
MSE AP (τ = 5)	7.750	0.002	2.80 to 12.70
MSE AP (τ = 6)	7.010	0.004	2.26 to 11.76
IH ML	−3.102	0.105	−6.85 to 0.65
IH AP	−4.072	0.128	−9.32 to 1.17
RQA ML RR	−2.688	0.14	−6.26 to 0.89
RQA ML DET	−0.470	0.843	−5.11 to 4.17
RQA ML avg_length	0.106	0.959	−3.94 to 4.16
RQA ML max_length	−0.001	0.999	−0.94 to 0.94
RQA AP RR	−8.510	0.999	−13.12 to −3.61
RQA AP DET	−4.197	0.001	−7.34 to −1.05
RQA AP avg_length	−6.485	0.009	−11.04 to −1.94
RQA AP max_length	−2.410	0.005	−3.90 to −0.92

with memory impairments [33]. Alternative fall risk measures are therefore required. Quantitative nonlinear dynamic measures applied to acceleration signals can represent a viable alternative. Accelerometry systems are useful for clinical purposes, as they are small, light and portable. Some of these measures (such as HR, IH, MSE and RQA) do not require step detection, excluding a possible source of error. This study aimed to explore the relationship of these measures with fall risk.

One previous study [23] assessed the association between linear and nonlinear measures (namely gait variability and Lyapunov exponents), concluding that these parameters were, individually and combined, positively associated with fall history. Another study [29] investigated the association between Lyapunov exponents and tendency to fall in older adults, but on a significantly smaller sample. The nonlinear measures implemented in this study have already been applied to gait parameters [18–20,22], but their relationship with fall history has, to the authors' knowledge, not been previously investigated.

The factor analysis highlighted quite a sharp separation, supporting the hypothesis that the techniques describe different aspects of the system dynamics; each one of these aspects can reflect different aspects of locomotion features, and could contribute information related to fall risk.

Age effects have previously been shown for HR in AP direction [34]. In our study, however HR and IH did not show any correlation with fall history. Harmonicity of oscillations and rhythmicity of the accelerations of the trunk seem not to provide useful information for fall risk assessment.

Costa et al. found that the spontaneous output of the human locomotor system during usual walking is more complex than walking under slow, fast or metronome paced protocols [20]. The association between MSE and fall history found in the present study seems to suggest that complexity can also be related to fall risk. Modifications in complexity could reflect alterations in locomotor strategy that affect stability. In particular, MSE with a scale factor $\tau = 2$ led to the best classification results, suggesting that frequencies in the band of 17–25 Hz contribute the most; in fact, operating two coarse graining procedures on gait acceleration signal would filter frequencies higher than 25 Hz, while operating three would filter frequencies higher than 17 Hz.

The present findings seem to suggest higher complexity of gait kinematics in subjects with a fall history, while previous studies have associated higher entropy with better health [5,35]. This is perhaps not surprising, since nonlinear time series analysis often showed contradictory results even when applied in the same context, as it has been demonstrated for Floquet multipliers [36]. In addition, non-monotonic relationships could exist. Moreover, results of nonlinear time series analysis of gait accelerations strongly depend on sensor placement [18].

A previous study [22] used RQA to differentiate healthy and hypovestibular subjects; our findings extend this result, showing that RQA can discriminate between healthy and fall-prone subjects. In the present study, RQA measures, and in particular the maximum length of diagonal structures in recurrence plots, were found to correlate with fall history. Max_length is strictly related to the mechanical concept of stability in terms of Lyapunov exponents; in fact, its inverse (called divergence) can roughly reflect the largest Lyapunov exponent [21,37,38]. These results are in line with the existing literature showing an association between short term Lyapunov exponents and fall history [23]. Whereas these two measures express theoretically similar concepts, the calculation process is different; in particular, the RQA algorithm does not depend on step detection.

For all gait variables, specificity of the associations with fall history was low (maximally 21.4%). This may imply that the present methods are not yet suitable to identify individuals at risk of falling and thus the target group for interventions. Combinations with other variables in a multivariate prediction model, e.g. variables that reflect physical capacity, may be necessary. On the other hand, fall history may comprise a substantial number of incidental falls in subjects, exposed to high-risk events, who may not necessarily have an increased risk due to intrinsic factors.

A possible limitation of the present study is the use of a treadmill; conclusions cannot be directly transferred to overground walking, due to the differences between the two motor tasks [39,40]. No procedure was applied to precisely standardize the acceleration signals direction, in terms of sensor placement; however, due to the intrinsic nature of the task and the instrumentation, straight walking was assured. Another limitation is the use of self-report as a gold standard for the classification; despite the disadvantages, this method represents the most established technique for fall risk assessment [3], and hence this choice is unavoidable.

Due to the lack of a standard implementation for the measures used in this work, there is no consensus on how to deal with methodological aspects such as sample frequency of the signal, instrumentation noise and trial length. For this reason, comparison of results from different implementations of the same measures is not straightforward. With respect to the length of the trials, these measures, particularly RQA, have often been applied to short trials (a few steps). In the opinion of the authors, the analysis of longer trials is preferable for several reasons: effects of long range dynamics, acclimatization time and the probability that occasional gait deviations show up during the acquisition. This need however leads to a necessary trade-off between trial length and computational time, which can increase to several hours, especially for RQA.

Transfer from our results to less controlled acceleration data obtained during daily activities, in which step detection is a major problem, requires further exploration.

Further research should address the physiological correlates of these measures; whereas the analysis of acceleration time series provides useful information on gait dynamics and fall risk, the physiological conditions leading to differences in complexity or recurrence of locomotion acceleration signals are yet unknown. The identification of the physiological correlates could lead to the development of appropriately targeted therapies or rehabilitation programmes aiming at fall prevention.

Conflict of interest statement

None

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