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Multiple gait parameters derived from iPod accelerometry predict age-related gait changes

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ABSTRACT

Introduction: Normative data of how natural aging affects gait can serve as a frame of reference for changes in gait dynamics due to pathologies. Therefore, the present study aims (1) to identify gait variables sensitive to age-related changes in gait over the adult life span using the iPod and (2) to assess if these variables accurately distinguish young (aged 18–45) from healthy older (aged 46–75) adults.
Methods: Trunk accelerations were recorded with an iPod Touch in 59 healthy adults during three minutes of overground walking. Gait variables included gait speed and accelerometry-based gait variables (stride, amplitude, frequency, and trajectory-related variables) in the anterior-posterior (AP) and medio-lateral (ML) directions. Multivariate partial least square analysis (PLS) identified variables sensitive to age-related differences in gait. To classify young and old adults, a PLS-discriminant analysis (PLS-DA) was used to test the accuracy of these variables.
Results: The PLS model explained 42% of variation in age. Influential variables were: mean stride time, phase variability index, root mean square, stride variability, AP sample entropy and ML maximal Lyaponov exponent. PLS-DA classified 83% of the participants correctly with a sensitivity of 83% and specificity of 71%.
Discussion: Contrary to the frequently reported high gait variability observed in old adults with frailty and fall history, the present study showed that younger compared with older healthy adults had a more variable, less predictable and more symmetrical gait pattern. A model based on a combination of variables reflecting gait dynamics, could distinguish healthy younger adults from older adults.

1. Introduction

Natural aging and pathological conditions modify gait. Age-related declines in muscle strength, mass, quality, and neural activation produce characteristic modifications in the kinematics, kinetics, and energetics of gait [1–3]. Although age-related changes in neuromuscular function are well documented [4], less is known about how gait changes across the adult lifespan [5,6]. Identifying subtle changes in gait from young adulthood to old age could provide an objective basis for clinicians to prescribe interventions and delay the onset of mobility disability.

Wearable technologies seem to revolutionize gait analysis. Smart devices, like smartphones and iPods, are equipped with built-in accelerometers, which offers new opportunities for clinicians and researchers to easily and relatively inexpensively record and characterize gait in detail [7,8]. Data extracted from accelerometers worn on the trunk allow the identification of foot contacts from anterior-posterior (AP) accelerations; such data can serve as a basis for sophisticated stride analyses [9]. Additional processing of the amplitude and frequency content of trunk acceleration signals can be used to characterize dynamic balance control during gait through metrics such as self-affinity, regularity, and local stability of the trunk [10,11]. There is increasing evidence suggesting that these variability-related and stability-related gait variables can distinguish the difference in gait patterns of healthy young adults and old adults, old adults with and old adults without cognitive disorders and fallers and non-fallers [12–14] and complement information provided by gait speed alone [15].

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Even though accelerometry-based gait analysis generates a wealth of information, most studies focus on one or two characteristics of the acceleration signal (e.g., stride-related parameters: stride time, stride time variability). Such an approach makes it difficult to comprehensively examine the inter-relationship between variables that could reveal additional dimensions of gait. A detailed characterization of the relationship between gait outcomes on the one hand and the association of these variables with age on the other, could provide a better understanding of how natural aging affects gait. To this aim, we pursued two complementary objectives. The first objective determined the relationship between different gait variables and the association of these variables with age. The second objective quantified the discriminative power of the identified gait variables to distinguish younger from older adults. Our strategy was to complement commonly used gait variables (i.e., gait speed, stride time) with gait outcomes that reflect the dynamic characteristics of gait, with respect to variability and local stability. To identify the sensitive gait variables across the lifetime and determine the discriminative power of these variables, we used an unbiased, blind approach with no a-priori assumptions about the gait variables that could be most important with respect to aging. We used a Partial Least Square analysis (PLS) and PLS-discriminant analysis for the analyses.

2. Methods

2.1. Participants

We recruited 59 healthy adults from the community in the age range of 18 to 75 (mean age: 45 (18); 47% male). The participants included in the young group had a mean age of 28 (7) years (age range 19–41; $n = 29$; 59% male) and in the older group the mean age was 62 (8) years (age range 47–74; $n = 30$; 33% male). Participants were included if they were free of orthopaedic and neurological conditions and used no medications that might affect gait. This study was part of a project designed to analyse gait and balance by smart devices (iPod Touch) [7].

The Ethical Committee of the Center of Human Movement Sciences at the University Medical Center Groningen approved the research protocol and all participants signed written informed consent.

2.2. Gait assessment

Each participant walked back and forth along a 10-m long course with a one-meter wide curve at the two turns for three minutes at a self-selected habitual speed, a total of two times. Gait variables obtained in the first trial were included in dataset 1 to build a model. Variables obtained in the second trial were included in dataset 2 for validation of this model. Mean gait speed was computed based on the distance covered during the three-minute test.

Trunk accelerations were measured during walking with an iPod touch G4 (iOS 6, Apple Inc.; sample frequency 88–92 Hz) affixed to the trunk with an elastic belt near the level of lumbar segment L3. A custom-made application ‘iMoveDetection’ was installed on the iPod to collect and store the accelerometer data from the built-in tri-axial accelerometer [7].

Anterior-posterior (AP) and medio-lateral (ML) accelerations were analysed using custom-made software in MATLAB (version 2012b, The MathWorks Inc., Natick, MA, USA). Acceleration data were interpolated to a constant sampling rate of 100 Hz. The data were detrended and filtered (Butterworth filter, 4th order; cut-off frequency 20 Hz). Outliers caused by the turns in the walking track were removed from the data using a median filter [16].

To derive stride-related variables, foot contacts were determined from the AP accelerations. Negative peaks were detected in the smoothed signal (Butterworth filter, 4th order; cut-off frequency 5 Hz) to determine foot contacts, which were used to determine stride time [9]. The mean and the coefficient of variation (CV) of stride times was calculated for each participant. Furthermore, the phase variability index (PVI) representing the relative time between successive contralateral foot contacts was determined as:

$$P_i = \frac{FCR_{t(i)} - FCL_{t(i)}}{FCL_{t(i)} - FCL_{t(i)}} \times 360^\circ$$

FCL and FCR are respectively the left and right foot contact at time t(i). The PVI is calculated from the variability of the relative phases around 180° using circular statistics. Lower values indicate gait symmetry and more consistent timing [17].

The magnitude of ML and AP trunk accelerations was indexed by the root mean squares (RMS) [18]. The variability of the stride acceleration amplitude (VarAccAmp) was determined by normalizing the data (100 point per stride), superimposing all strides and calculating the average of the point-by-point standard deviations [18].

The index of Harmonicity (IH) represents the smoothness of the AP and ML accelerations. By a discrete Fourier transformation the power spectrum of the accelerations was estimated and the peak power of the first subsequent 10 harmonics was determined. The power spectral densities (PSD) were normalized by dividing the power by the sum of the total power spectrum [19]. The IH was defined as:

$$IH = \frac{P_1}{\sum_{i=1}^{10} P_i}$$

P_1 is the cumulative sum of the PSD of the fundamental frequency, divided by the first 10 super-harmonics $\sum P_i$. PSD of each peak was calculated within frequency bands of +0.1 and −0.1. An IH of 1 indicates a harmonic smooth gait pattern.

Detrended Fluctuations Analysis (DFA), Sample Entropy (SEn) and the maximal Lyapunov exponent (λ_{max}) were calculated. The DFA quantified long-range correlations in stride time intervals, revealing the predictability of future fluctuations by past fluctuations. Stride time data were divided into windows of equal length n (n = N/7, N = signal length) ranging from 17–25 for the individual participant. In each window a linear trend line was fitted and the average fluctuation F(n) around the line was calculated. The slope of the fitted line in log F(n) versus log n is the estimated scaling exponent a. The presence of long-term correlations in the signal is indicated by values $0.5 \geq \alpha \geq 1$. A value closer to 1 represents a more correlated pattern. Large and small values of the time-series are likely to alternate when $\alpha < 0.5$ [20].

The SEn AP and ML represent the predictability of the gait pattern. The SEn is the negative natural logarithm of the conditional probability of epochs of length m ($m = 2$ in this study) that match point-wise, repeating itself for $m + 1$ points within a tolerance of r ($r = 0.1$). Smaller SEn values are associated with greater predictability of acceleration patterns [21].

The λ_{max} of ML and AP accelerations, quantifying the ability to resist small perturbations during walking, is a measure of local stability. Gait trajectories, corresponding to the gait cycles, were constructed in a state space. The log of the expansion or contraction of the Euclidean distance between the gait trajectories quantified λ_{max}. The λ_{max} was estimated with the method of Wolf using an embedding of 10 dimensions with 7 samples time delay. A larger λ_{max} represents greater sensitivity to local perturbations [22].