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Speeding up or slowing down?: Gait adaptations to preserve gait stability in response to balance perturbations

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ABSTRACT

It has frequently been proposed that lowering walking speed is a strategy to enhance gait stability and to decrease the probability of falling. However, previous studies have not been able to establish a clear relation between walking speed and gait stability. We investigated whether people do indeed lower walking speed when gait stability is challenged, and whether this reduces the probability of falling.

Nine healthy subjects walked on the Computer Assisted Rehabilitation ENvironment (CAREN) system, while quasi-random medio-lateral translations of the walking surface were imposed at four different intensities. A self-paced treadmill setting allowed subjects to regulate their walking speed throughout the trials. Walking speed, step length, step frequency, step width, local dynamic stability (LDS), and margins of stability (MoS) were measured.

Subjects did not change walking speed in response to the balance perturbations ($p = 0.118$), but made shorter, faster, and wider steps ($p < 0.01$) with increasing perturbation intensity. Subjects became locally less stable in response to the perturbations ($p < 0.01$), but increased their MoS in medio-lateral ($p < 0.01$) and backward ($p < 0.01$) direction.

In conclusion, not a lower walking speed, but a combination of decreased step length and increased step frequency and step width seems to be the strategy of choice to cope with medio-lateral balance perturbations, which increases MoS and thus decreases the risk of falling.

1. Introduction

It is generally assumed that walking speed is reduced to cope with an increased probability of falling, due to environmental or internal disturbances of stability [1–3]. In line with this assumption, several recent studies have examined the effects of walking speed on local dynamic stability (LDS) [1–4]. LDS, as captured by the short-term Lyapunov exponent (λ_s) reflects the response of people to small perturbations, and is therefore seen as an index of the stability of human walking [1]. Besides LDS has been shown to be correlated to balance impairments and fall risk [5–9]. However, studies on the relation between walking speed and LDS have provided contradictory and inconclusive results [1–4]. It therefore remains unclear whether slow walking is more stable than fast walking.

Besides using LDS-measures, the probability of falling has been analyzed in terms of margins of stability (MoS) [10–13]. This measure has a more logical relationship with the probability of falling than LDS-measures. The MoS is quantified as the distance between the centre of mass (CoM) motion state (i.e. its position and velocity) relative to the base of support. Mathematical modelling of human walking as an inverted pendulum allows for theoretical hypotheses on the effect of walking speed on MoS and therefore on the probability of falling [13]. Following this model, the probability of making a backward fall can be reduced by decreasing step length or increasing CoM velocity, the latter being directly related to an increased walking speed [10,13]. Hof et al. [11,14] provided an analytical expression for this model and extended it towards the probability of falling in medio-lateral (ML) direction [12]. This model does not predict a direct influence of walking speed on the size of the MoS in ML-direction, but it does predict that the ML-MoS will increase by increasing step width and step frequency [12], the latter could coincide with an increase in walking speed.

Hence, despite the common belief that reducing walking speed might reduce the probability of falling; there is little empirical

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evidence to support this. Moreover, although several studies have attempted to assess the effect of walking speed on gait stability, it has never been assessed whether people really select a slower walking speed in challenging conditions and how possible changes in walking speed affect LDS and MoS.

The main purpose of this study was to investigate if subjects adapt walking speed when gait stability is challenged. For this purpose we used a self-paced treadmill, which made it possible for subjects to continuously adapt their walking speed to imposed ML balance perturbations. Simultaneously, we observed the effect of the balance perturbations on step length, step frequency, and step width. Subsequently, we assessed the effect of potential adaptations in walking speed on LDS and the MoS in anterio-posterior (AP) and ML-direction, by making a comparison between trials at self-paced speed and trials at a fixed speed, in which subjects could not adapt walking speed to the perturbations.

2. Methods

2.1. Subjects

Nine healthy adult subjects (4 men and 5 women, age: 32.2 ± 7.5 years, height: 1.77 ± 0.12 m, weight 72.2 ± 14.0 kg) were included. The study was approved by the local ethical committee and subjects gave written informed consent prior to their participation.

2.2. Equipment

All subjects walked on the Computer Assisted Rehabilitation ENvironment (CAREN) system (Motek Medical b.v., Amsterdam, The Netherlands). The CAREN system consists of an instrumented treadmill mounted onto a 6-degree-of-freedom motion platform in combination with a Virtual Environment (VE) projected on a 180° semi-cylindrical screen (Fig. 1, upper left panel). During the experiment, the motion platform was used to induce perturbations in ML-direction during walking. The VE used in this experiment was a virtual road, surrounded by trees to create an optical flow while walking on the treadmill (Fig. 1, upper right panel). Motek Medicals D-flow software was used to control the system and to synchronize the instantaneous treadmill speed and scene progression. Twelve high resolution infra-red cameras (Vicon, Oxford, UK) and the Vicon Lower Body Plug-in-Gait marker set were used to capture kinematic data. For a part of the experimental trials the treadmill was used in the self-paced mode. This allow subjects to modify walking speed at will, by servo-controlling the motor with a real time algorithm that took into account the pelvis position in the AP-direction, as measured by the markers attached to the pelvis, and a reference position corresponding to the AP-midline of the treadmill. A safety harness system suspended overhead prevented the subjects from falling but did not provide any weight support.

2.3. Protocol

2.3.1. Warming up

Subjects completed two warming-up trials of 3 min, to become familiar with walking on the (self-paced) treadmill and the VE, before the protocol started. During the first warming-up trial subjects walked at a fixed walking speed, around their comfortable walking speed. During the second warming-up trial, subjects had the opportunity to practice with the self paced mode of the treadmill, but were asked to walk at comfortable walking speed during the final minute.

2.4. Experimental trials

The protocol consisted of 10 trials of 4 min walking. Besides an unperturbed condition, balance perturbations were applied, at four different intensities, by translating the walking surface in ML direction, following a multi-sine function, which made the perturbation unpredictable for the subjects. This perturbation was already used before by McAndrew et al. [15,16]:

$$D(t) = A[1.0\sin(0.16 \times 2\pi t) + 0.8\sin(0.21 \times 2\pi t) + 1.4\sin(0.24 \times 2\pi t) + 0.5\sin(0.49 \times 2\pi t)] \quad (1)$$

where $D(t)$ is the translation distance (m), t is time (s), and A is the scaling factor which was used to vary the intensity of the perturbation. Scaling factors of 0.05, 0.10, 0.15 and 0.20 were used. To illustrate the character of the perturbation the pattern of

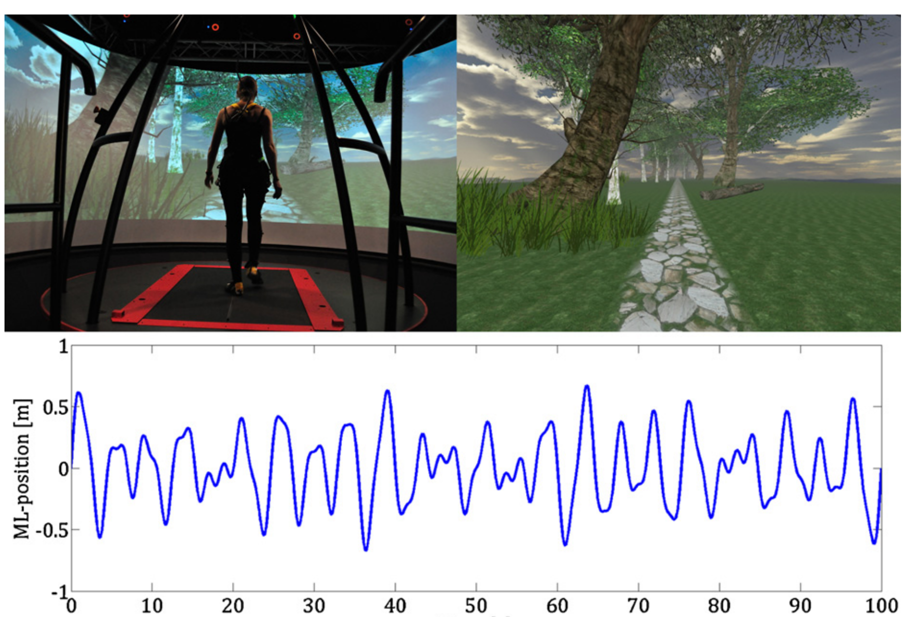

Fig. 1. *Upper left panel:* Experimental setup: CAREN. *Upper right panel:* Virtual environment used in the experiment. *Lower panel:* Time-series for one period of the perturbation with a scaling factor (A) of 0.2. Frequency of this perturbation varied from 0.16 to 0.49 Hz, maximum excursion of the platform during this perturbation was 0.67 m.

the perturbation with a scaling factor of 0.2 is shown in Fig. 1, lower panel. The four perturbation conditions and the unperturbed trial were all repeated twice, once at self-paced walking speed, where subjects continuously had the opportunity to adapt their walking speed to the balance perturbations, and once at a fixed walking speed, where subjects did not have the opportunity to adapt their walking speed to the balance perturbations. Fixed walking speed was set to the comfortable walking speed that was measured during warming up in the self-paced mode, and was therefore comparable with a comfortable walking speed during unperturbed walking. During the self-paced conditions subjects started at a fixed speed of 1 m/s. After 30 s, the self-paced mode was switched on. Before every trial instructions about the upcoming trial were given. All trials were imposed at random.

2.5. Data collection

During the trials in which the subjects walked at a self-paced walking speed, the speed of the treadmill was recorded. Kinematic data of markers attached at the lateral malleoli of the ankles and the pelvis (left and right anterior superior iliac spines (LASI & RASI), and left and right posterior superior iliac spines (LPSI & RPSI)) were collected with the Vicon system at a sampling rate of 120 Hz. The last 3 min of each trial were used for data analysis. Before data analysis, both speed data and kinematic data, except for the calculation of LDS, were low-pass filtered with a bi-directional Butterworth filter with a cut-off frequency of 2 Hz.

2.6. Data analysis

2.6.1. Walking speed

Walking speed was calculated as the average treadmill speed over the last 3 min for every trial executed at self-paced walking speed.

2.6.2. Step parameters

Step frequency was determined as the inverse of the average duration between two subsequent heel-strikes, where heel-strikes were detected as the local maxima of the position of the ankle markers in the AP-direction. Step width was calculated as ML-distance between both ankle markers at the moment of heel-contact and step length was defined as the AP-distance between these markers at the moment of heel-contact.

2.6.3. Local dynamic stability

To calculate LDS, position data of the markers placed on LASI, RASI, LPSI, and RPSI were used. Given the difficulties associated with filtering nonlinear signals, data were analysed without filtering [17]. Local pelvis reference frames were defined following the 'Conventional Gait Model' [18,19]. Linear accelerations of the ML, AP, and vertical (VT) direction were calculated as the second derivative of the position of the origin. Rotational velocities in three directions were calculated following the method defined by Zatsiorsky [20]. The first 150 consecutive strides of each time-series were analysed, because estimates of LDS may be biased by time-series length and number of strides [21,22]. Time-series were time-normalized, using a shape-preserving spline interpolation, such that each time-series of 150 strides had a total length of 15,000 samples [2,4]. Subsequently, 12D state spaces were reconstructed from the time-normalized 3D linear acceleration and 3D rotational velocities time series, each with their 25 samples delayed copies [3,22,23].

From the constructed state spaces, Euclidean distances between neighbouring trajectories in state space were calculated as a function of time and averaged over all original nearest neighbour pairs to obtain the average logarithmic rate of divergence. The slope of the resulting divergence curves for the interval between 0 and 50 samples provides an estimate of LDS in terms of the short-term Lyapunov exponent for the period of approximately 0–1 step ($\lambda_{\text{S-step}}$) [4,24].

2.6.4. Margins of stability

To calculate the margins of stability (MoS), a method derived from the procedure used by Hof was used [11,12]. In this study the extrapolated centre of mass (XCoM), was defined as the origin of the local pelvis reference frame [18,19], representing the CoM, plus its velocity times a factor $\sqrt{l/g}$, with l being the maximal height of the origin of the pelvis and g the acceleration of gravity. The MoS were calculated for both the AP- and ML-direction as the position of the lateral malleolus of the ankle of the leading foot (representing the border of the base of support) minus the position of the XCoM for the moment at which the MoS reached its minimum value within the period of one step [11,12]. Although basically similar our method differs from Hof [11,12] who used force plate data for calculating XCoM and MoS. MoS was averaged for the first 150 steps of the last 3 min of each trial.

2.7. Statistical design

2×5 within factorial ANOVAs were performed, with perturbation intensity and speed condition (self-paced or fixed speed) as within variables, to search for significant differences in walking speed, step length, step frequency, step width, $\lambda_{\text{S-step}}$, and the MoS in AP- and ML-direction. When a significant effect of perturbation intensity was found, simple contrasts were used to investigate for which particular perturbation intensities the concerning variable differed from unperturbed walking. Significant interaction effects were further investigated by executing paired-samples *t*-tests with a Bonferroni correction for each perturbation condition. Statistical analyses were performed using SPSS 17.0 (SPSS Inc., Chicago, IL).

3. Results

All subjects completed the experiment and no one fell during the perturbation trials.

During the self-paced trials, subjects did not significantly lower their walking speed in response to the balance perturbations ($F = 2.00$; $p = 0.118$; df = 4; Fig. 2). During the fixed speed trials, walking speed was lower compared to the self-paced trials ($F = 11.034$; $p = 0.011$; df = 1); however, no interaction with perturbation intensity was found ($F = 2.00$; $p = 0.118$; df = 4).

Despite the absence of adaptations in gait speed to the different perturbation intensities, the underlying step parameters, step length and step frequency, were significantly affected by the perturbations. Step length decreased with perturbation intensity

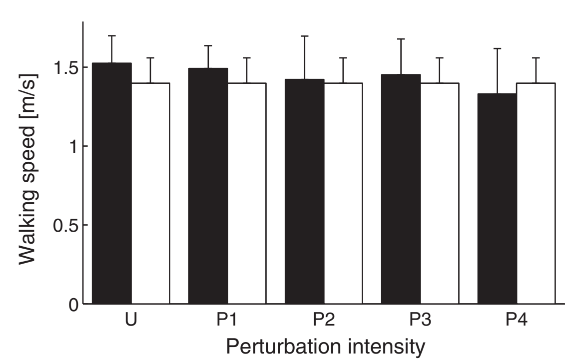

Fig. 2. Average and standard deviation of walking speed ($n = 9$) for all experimental conditions. Black bars represent self-paced walking and white bars represent fixed speed walking (U = unperturbed walking; P1–P4 = perturbation intensity 1–4).

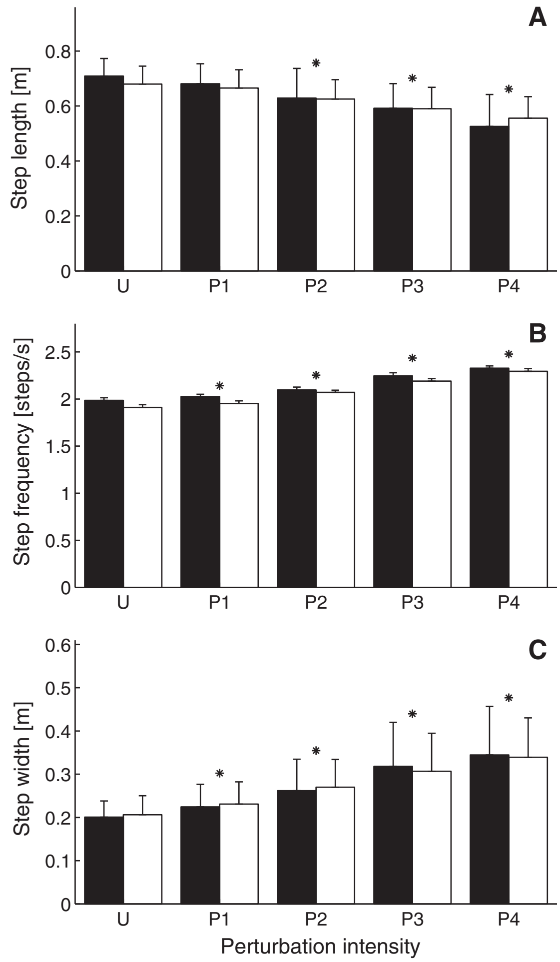

Fig. 3. Averages and standard deviations of step length (A), step frequency (B), step width (C), ($n = 9$) for all experimental conditions. Black bars represent self-paced walking and white bars represent fixed speed walking (U = unperturbed walking; P1–P4 = perturbation intensity 1–4). *The perturbation intensities, for which the concerning step parameter differed from unperturbed walking.

($F = 23.118$; $p < 0.01$; df = 4), and differed from unperturbed walking for the second to fourth perturbation intensity (Fig. 3a). Step frequency increased with an increase in perturbation intensity ($F = 35.713$; $p < 0.01$; df = 4), and differed from unperturbed walking for all perturbation intensities (Fig. 3b). Step width was significantly larger at all the perturbation intensities, compared to unperturbed walking ($F = 26.805$; $p < 0.01$; df = 1.457 after a Greenhouse–Geisser correction for non-sphericity) (Fig. 3c). Step length and step width did not differ between the two speed conditions. Step frequency was higher for the self-paced condition, compared to the fixed speed condition ($F = 16.983$; $p < 0.01$; df = 1). No interactions were found for these step parameters.

A significant increase in $\lambda_{S\text{-step}}$ with perturbation intensity ($F = 28.090$; $p < 0.01$; df = 4) was observed and $\lambda_{S\text{-step}}$ differed from unperturbed walking from the second perturbation intensity (Fig. 4a). No main effect of speed condition was found on $\lambda_{S\text{-step}}$ ($F = 2.460$; $p = 0.155$; df = 1), but there was a significant interaction of perturbation intensity and speed condition ($F = 3.670$; $p = 0.014$; df = 4). However, a post hoc test with Bonferroni correction showed a significant difference in $\lambda_{S\text{-step}}$ between self-paced and fixed-speed walking only for the unperturbed condition ($p = 0.015$).

MoS were all positive in ML-direction and negative in AP-direction at initial contact which means that the XCoM was located

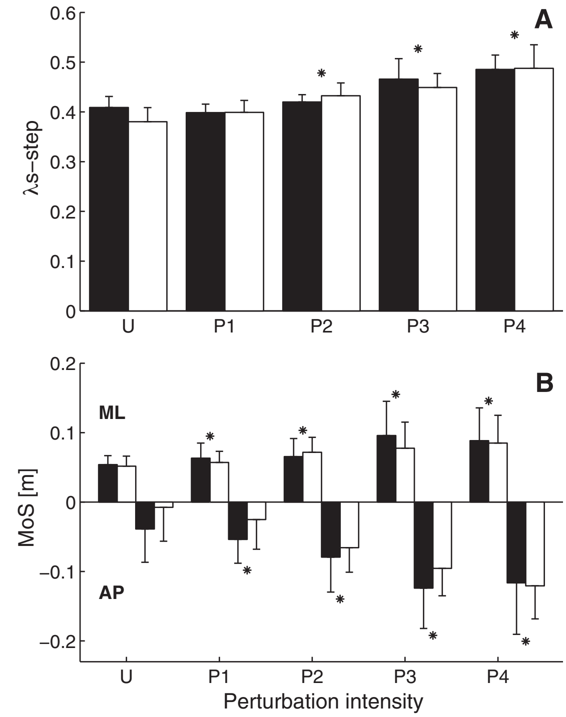

Fig. 4. Average and standard deviation of $\lambda_{S\text{-step}}$ (A) and MoS in ML-(upper panel) and AP-direction (lower panel) ($n = 9$) for all experimental conditions. Black bars represent self-paced walking and white bars represent fixed speed walking (U = unperturbed walking; P1–P4 = perturbation intensity 1–4). *The perturbation intensities, for which $\lambda_{S\text{-step}}$ and the MoS differed from unperturbed walking.

medial and anterior with regards to the marker attached to the lateral malleolus of the leading foot (Fig. 4b). ML MoS increased ($F = 8.041$; $p = 0.016$; df = 1.275 after a Greenhouse–Geisser correction for non-sphericity) and AP MoS decreased, i.e. became more negative ($F = 24.001$; $p < 0.01$; df = 4) in response to the perturbations, and differed from unperturbed walking for all perturbation intensities. For the AP MoS a main effect of speed-condition was found ($F = 7.392$; $p = 0.03$; df = 1).

4. Discussion

In this study, we investigated whether and how healthy people adapt walking speed when stability is challenged, and how these speed changes affect local dynamic stability, as captured by λ_s, and margins of stability (MoS) in boh AP- and ML-direction. Notably, subjects did not lower their walking speed in response to the balance perturbations, which is in contrast to the assumption that lowering walking speed is a strategy to decrease the probability of falling [1–3]. However, subjects did change the underlying step parameters, step frequency and step length. Decreases in step length and increases in step frequency were found with increasing perturbation intensity. In addition, subjects increased their step width in response to the perturbations. These changes were also found when walking speed was kept constant across all perturbation conditions, in accordance with previous findings of McAndrew et al. [15].

Although walking speed did not change with perturbation intensity a systematic speed difference between the self-paced and fixed speed condition was found. Probably the fixed speed determined during the practice trial was an underestimation of prefered walking speed. Because the MoS in AP direction is directly dependent on walking speed this systematic speed difference explained the difference in AP MoS between self-paced walking and walking at fixed speed [13,14].

The adaptations in step length, frequency and width in response to the perturbations suggest that these adaptations are part of a strategy to decrease the probability of falling. Nevertheless, these adaptations did not prevent $\lambda_{S\text{-step}}$ to increase, with increasing perturbation intensity. This result implies that the perturbations caused an increased risk of falling, which is in line with the results found by McAndrew et al. [16]. At the same time we found that subjects increased their backward and sideward MoS, which implies a decrease in risk of falling for these directions. This seems to be contradictory, but subjects probably created a sufficiently wide margin within which a decrease in local dynamic stability can be allowed, without increasing the risk of falling. This is in agreement with the results of the study of Hof et al. [12], who found larger ML MoS for above-knee amputees during walking compared to healthy controls, although amputees are locally less stable during walking than able-bodied people [5].

The increases in backward and sideward MoS in response to the perturbations are a direct consequence of the adaptations in step length, step frequency and step width. A basic requirement of walking is that the COM passes the stance foot during each single support phase. Otherwise a backward fall will occur. Consequently, the XCoM should always be in front of the dorsal border of the BoS [10,13]. Pai and Patton [13] demonstrated that decreasing step length, in combination with an unchanged walking speed, causes an increase of the MoS in backward direction. In ML-direction subjects should prevent that the XCoM exceeds the lateral border of the BoS. Hof et al. [12] demonstrated that increasing step width and step frequency contribute to an increase in ML MoS. Therefore step parameters like step frequency, step length and step width, instead of walking speed, seem to be important moderators of the probability of falling.

Although the adaptations in walking pattern in response to the perturbations that were found in this study seem to evoke a clear benefit in terms of increased MoS and therefore can reduce fall risk, it should be noted that they might be specific for the continuous perturbation in ML direction used in this study. The generalization of this response to perturbations in other directions or in situations with discrete perturbations should be further explored.

In conclusion, the results of the present study indicate that the strategy of choice to cope with ML continuous balance perturbations is not a reduction of walking speed, but rather a combination of decreased step length and increased step frequency and step width. As a consequence of the simultaneous decrease in step length and increase in step frequency the unchanged walking speed in response to the perturbations can be regarded as a coincidental result of these adaptations. Although the effect on LDS cannot be inferred from our data, the observed changes in step parameters increase MoS, and therefore seem to decrease the probability of falling.

Conflict of interest

Authors state that no conflicts of interest are present in the research.

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