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Variability and stability analysis of walking of transfemoral amputees

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ABSTRACT

Variability and stability of walking of eight transfemoral amputees and eight healthy controls was studied under four conditions: walking inside on a smooth terrain, walking while performing a dual-task and walking outside on (ir)regular surfaces. Trunk accelerations were recorded with a tri-axial accelerometer. Walking speed, mean and coefficient of variation of stride times (ST) and the root mean squares (RMS) of trunk accelerations was calculated. Gait variability and stability were quantified using measures derived from the theory of stochastic dynamics. Regularity was indexed using the sample entropy (SEn) and the scaling exponent α derived form Detrended Fluctuations Analysis. Local stability (LSE) quantified gait stability.

Walking speed was lower, but ST variability was not different for amputees than controls. RMS of medio-lateral accelerations was higher for amputees; SEn was higher, implying less predictable accelerations, and LSE higher, indicating decreased stability. The largest condition effect was present for walking outside: trunk RMS increased and LSE decreased.

Differences in walking between amputees and healthy controls and their responses to perturbations revealed themselves in the magnitude, variability and stability measures of trunk accelerations. These results imply that quantifying the dynamical structure of trunk accelerations can differentiate between groups with different walking abilities and between conditions of increasing difficulty and may therefore provide a useful diagnostic tool.

1. Introduction

Learning to walk with a prosthesis is challenging. Not only do people with a lower limb amputation miss part of their motor system but also the sensory system is affected. Due to the amputation information, normally supplied by sensors of the musculoskeletal system and skin of the lower extremity is missing. Because of this lack of information and the changed physical aspects of the leg, kinetics, kinematics and ability of walking are affected.

Walking ability in prosthetic walkers is often quantified by walking speed [1,2], gait symmetry [3] and energy consumption [4,5]. In addition, prosthetic walkers have definite balance deficits [6,7] during standing which may be related to walking ability [8]. Surely, stability or balance control during gait, i.e. ones ability to recover from or adapt to perturbations, appears to be an important factor for determining walking ability. There is, however, no generally accepted way of how to define or quantify stability or dynamic balance control during walking. Moreover, the basic mechanisms by which walking stability is maintained are not completely understood.

Perturbations of stability do not necessarily only come from outside. Even during unimpeded walking, ‘small scale’ perturbations created by neuromuscular noise [9] continuously perturb the locomotor system. Consequently, disturbance to the walking trajectory is an ongoing process requiring continuous attenuation of (kinematic) fluctuations. These perturbations may manifest themselves as the natural variations exhibited during walking, for instance in the stride-to-stride fluctuations or in terms of changes in so-called local stability [10,11]. In the context of variability, weak fluctuations are suggested to indicate more (local) stable states that can be steadily maintained. Measures of local stability quantify the ability of the movement system to respond to or resist ‘natural’ small local perturbations from one cycle to the next (e.g. grow or decay after one subsequent stride) [10,12]. The rate at which small disturbances decay is referred to as local stability. In contrast, global stability refers to resilience of humans to much larger perturbations such as tripping. Theoretically, a system can be locally stable but not global, e.g. small disturbances will decay but large disturbances not [12].

A variety of measures derived from the theory of stochastic dynamics has been used to quantify these time dependent variations in gait patterns, and are suggested to contain information about the control of locomotion and risk of falling, including Detrended Fluctuations Analysis [13–15], Sample Entropy [16],

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Table 1
Participants characteristics.

Subject	Amputees					Controls	
	Age (years)	Gender	Time post-amputation	Cause of amputation	Side of amputation	Age	Gender
1	37	M	4 years	Trauma	Right	37	M
2	44	M	3 months	Trauma	Left	47	M
3	59	M	43 years	Trauma	Left	58	M
4	69	F	1 year	Arteriosclerosis	Left	70	F
5	19	F	7 years	Cancer	Right	24	F
6	30	F	14 years	Cancer	Right	35	F
7	47	M	18 years	Trauma	Right	48	M
8	45	M	39 years	Trauma	Left	41	M
Group	43.8 ± 14.8					45 ± 13.4	

and Lyapunov exponents [17]. Although conceptually different, all these measures assume that walking ability is reflected in dynamic characteristics, in terms of fluctuations, or local stability of gait patterns. The outcome parameters obtained from studies using these methods have proven to be sensitive to differences between various neurological patient populations and control subjects [10,14,15,18] and between conditions [17]. Moreover, some of these outcome parameters have been shown to be more sensitive to these differences then traditional variability parameters [11,19]. Hence, these dynamical parameters may have more power to differentiate between groups and monitor progress during rehabilitation. Furthermore, they can give insight in the neuromuscular organization of walking giving them significant value for both clinical and scientific practice [20,21].

Scarce information, however, is available regarding the value of these parameters for assessing and understanding walking ability of patients with an impairment that does not have a primary neurological origin such as people after lower limb amputation. The aim of the present study was therefore to assess variability and stability of the gait pattern of transfemoral amputees and healthy control subjects. To challenge balance during walking two additional perturbations of different origins were used, a cognitive disturbance and a mechanical perturbation, which have been shown to increase the sensitivity of given measurements to differentiate between groups [22–26]. We hypothesized that individuals walking with a prosthese would exhibit a more variable and less locally stable gait pattern, and be more affected by both cognitive and mechanical disturbances than healthy controls.

2. Materials and methods

2.1. Participants

Eight transfemoral amputees and eight age matched control subjects participated in this study (Table 1). All prosthetic walkers were accustomed to the prostheses and able to walk independently, without walking aid, for at least 20 min. All participants gave written informed consent. This study was approved by the local Ethics Committee.

2.2. Procedure

Amputees walked with their own prosthesis. Two used a microprocessor-controlled knee; all others used mechanical controlled prosthetic knees. All amputees used different kinds of dynamic prosthetic feet. During walking trials, the accelerations of the trunk in three orthogonal directions were measured with a tri-axial ambulant accelerometer (64 mm × 64 mm × 13 mm; DynaPort® MiniMod, McRoberts BV, The Hague, The Netherlands) fixed with an elastic belt near the COM at the level of lumbar segment L3 [27]. Sample frequency was 100 Hz. A radiographic remote control unit was used to start and stop measurements, and to mark curves in the track.

Participants completed at their self selected speed four 6-min walking trials without aid or assistance: (1) indoor walking (IW) around a square trajectory inside a gymnasium (dimensions 17 m × 21 m); (2) As the IW condition but participants had to perform a cognitive dual task (IDT); (3) walking outside on an even terrain (OET) around an equally paved squared circuit (260 m long); (4) walking outside on an uneven terrain (OUT) around a roughly paved squared circuit (250 m long). The order of the four conditions was randomized. After each measurement participants could rest until full recovery.

The dual task was a number-subtracting task [25]. Participants were provided with a start value (e.g. 500) and a subtraction value (e.g. 7) before the experiment started and were asked to make subsequent subtractions aloud while they were walking. The number of subtractions and errors were recorded with a voice recorder.

2.3. Variability and stability analysis

Anterior–posterior (AP) and medio-lateral (ML) acceleration time-series were analyzed. Data were corrected for horizontal tilt [28] and filtered using a low pass 3rd order Butterworth bidirectional filter with a cut-off frequency of 20 Hz.

Moments of foot contact (FC) were determined from AP accelerations and used to calculate stride times (ST). For the prosthetic group strides were defined between subsequent FC's of the prosthetic leg. For all participants and conditions, 250 successive strides were included in all analyses. Means and coefficient of variation of ST (STm; STcv) were calculated for each participant and condition.

For ML and AP trunk accelerations, the magnitudes of the time-series were calculated as the root mean squares (RMS). In addition, we calculated time dependent variations of stride parameters and trunk acceleration patterns. Specifically, the structure of stride variability and trunk accelerations patterns were studied as indicators of dynamic balance ability during walking, using the scaling exponent α [29], the local stability exponent (LSE) [10,30,31] and the sample entropy (SEn) [32] which are described below.

Whereas the standard deviation or coefficient of variation of stride times provides information about the magnitude of stride variability, the extent to which stride interval time-series exhibited long-range correlations (i.e. similar patterns of variation across multiple time scales) can be evaluated using Detrended Fluctuations Analysis (DFA). Before applying DFA outliers in the stride time data, caused by bends in the circuit, were removed from the data using a median filter [18]. The maximum percentage of outliers caused by bends in the circuit that was removed of the data of all subjects was 11.5%, which is acceptable [33]. If the outcome parameter α is between 0.5 and 1, this indicates the presence of long-range power-law correlations in the time-series, i.e. future fluctuations are better predicted by past fluctuation. For uncorrelated time-series (e.g. white noise) α = 0.5. When $0 > \alpha > 0.5$ a different type

Table 2
Effects of group (i.e. amputee vs. control) and condition (walking indoor, walking with dual task; outdoor walking on even and uneven terrain), on stride parameters and acceleration time-series (repeated measures ANOVAs). For the significant effects of group the η^2 is given as a measure of the effect size. A dot indicates no significance.

	Variable	Group			Condition		Group × condition interaction	
		$F_{1,14}$	P	η^2	$F_{3,42}$	P	$F_{1,3}$	P
Speed		5.01	0.04	0.28	14.78	<0.01	–	–
STm		3.79	(0.07)	0.21	7.44	<0.01	–	–
STcv		–	–	–	–	–	–	–
α strides		–	–	–	–	–	–	–
RMS	ML	7.60	0.02	0.35	13.37	<0.01	–	–
	AP	–	–	–	11.54	0.01	–	–
SEn	ML	6.13	0.03	0.31	3.74	0.02	4.08	0.01
	AP	–	–	–	–	–	3.56	0.02
LSE	ML	5.20	0.04	0.27	5.75*	0.03	3.09	0.04
	AP	5.67	0.03	0.29	7.55	<0.01	–	–

* Significant for quadratic relation.

of power-law correlation exists such that large and small values of the time-series are likely to alternate. When α increases above 1–1.5 behavior is no longer determined by power law [34].

The system's resistance to small internal perturbations, such as fluctuations from both external sources, and internal neuromotor "noise" [30] during walking was assessed by means of local stability exponents (LSE). The size of the LSE quantifies the average rate of divergence of initially nearby trajectories in state space over a specified finite time interval. In a stable system, nearby trajectories will converge with time, whereas in an unstable system initially nearby trajectories will diverge with time [10,30]. When a LSE is negative, any perturbation exponentially damp out and initially close trajectories remain close. In contrast, for larger LSE nearby points diverge as time evolves and produces instability. The procedure of computing the LSE involves first the calculation of a phase space reconstruction for each acceleration time-series, by creating time-delayed copies of the time-series $X(t)$, that is $x(t)$, $x(t_i+\tau)$, $x(t_i+2\tau)$,... [35]. The selected τ corresponded to the first minimum of the mutual information function that is, the time at which the original and time-delayed signals are maximally independent [30]. The time-delay estimated was 10% of the gait cycle for all reconstructed state spaces. Following previous studies an embedding dimension of 5 was chosen since this have been proven to be appropriate for kinematic gait data. Thereafter, the nearest neighbours are found by selecting data point closest to *Xi*, from separate cycles with a temporal separation larger than twice the first minimum in the mutual information function. If for instance repeated gait cycles are identical, then a plot of the trajectories will show each cycle on top of each other, and the Euclidean distance between neighbours $d_i(t)$ would be zero for all pairs of nearest neighbours. The $d_i(t)$ between neighbouring trajectories in state space were computed as a function of time, and averaged over many original pairs of initially nearest neighbours. Finally, the rate of change in the distance between nearest neighbours was quantified by the LSE which was estimated by fitting a line of the logarithmic divergence of pairs of neighbouring points over time Δt (strides 0–2). LSE was estimated form the slope of $y(j)=(1/\Delta t)(1/N)\sum_{i=1}^{N}\ln d_j i$. Average stride times were different for participants walking with different speeds, therefore the time axis for the LSE curves of trunk acceleration were rescaled per trial by multiplying by the average stride frequency [10,36].

The degree of predictability or repeatable pattern features in acceleration time-series was indexed by means of the sample entropy (SEn) [32]. A strictly periodic time-series is completely predictable and will have a SEn of zero. SEn is defined as the negative natural logarithm of an estimate of the conditional probability of epochs of length m (in this study $m=5$) that match point-wise within a tolerance r and repeats itself for $m+1$ points. Small SEn values are associated with great regularity while large SEn values represent a small chance of similar data being repeated. The data were first normalized to unit variance, rendering the outcome scale-independent. To optimize the choice of the tolerance parameter r for a given m we applied the approach described by Lake [37]. For the time-series of all subjects and trials a range of values was calculated, and r values were identified with a maximum error of 0.05. Software available at PhysioNet was used to calculate SEn [38].

Performance on the dual task was analyzed by counting the number of subtractions, the absolute amount of subtraction errors and the relative amount of subtraction errors, made by the participants.

2.4. Statistical analysis

For all parameters a repeated measure ANOVA was applied with between factor group (controls vs. amputees) and within effects condition (IW, IDT, OET, OUT). Partial η^2 for main effects of group are provided as an index of the strength of the effect. Significant main condition effects were examined using post hoc t-tests with Bonferroni adjustment for multiple comparisons. Level of significance was set at $P<0.05$.

3. Results

3.1. Stride related parameters

Table 2 provides an overview of all significant main effects of group and condition. Walking speed was significantly lower for the amputee than for the control group. Both the mean stride time (STm) and the coefficient of variation of stride times (STcv) were higher for the amputee than for the control group, however, differences were not significant (Table 3).

Table 3
Mean speed (m/s), stride time STm, coefficient of variation of stride times (STcv) and the α, and standard deviations of the amputee and control group for each condition (IW = walking indoor; IDT = walking indoor while performing a dual task; OET = walking outside on even terrain; OUT = walking outside on uneven terrain).

Condition	Speed (m/s)	STm (s)	STcv (%)	α strides
Amputee group				
IW	1.27 ± 0.22	1.15 ± 0.11	3.3 ± 2.1	0.87 ± 0.22
IDT	1.18 ± 0.18	1.18 ± 0.13	3.3 ± 1.2	0.73 ± 0.21
OET	1.23 ± 0.19	1.16 ± 0.11	3.7 ± 1.9	0.89 ± 0.14
OUT	1.27 ± 0.22	1.14 ± 0.12	4.5 ± 2.2	0.89 ± 0.14
Control group				
IW	1.41 ± 0.15	1.08 ± 0.50	2.2 ± 1.4	0.72 ± 0.13
IDT	1.33 ± 0.19	1.11 ± 0.64	3.0 ± 1.8	0.80 ± 0.20
OET	1.49 ± 0.15	1.06 ± 0.44	2.9 ± 1.9	0.87 ± 0.10
OUT	1.49 ± 0.15	1.07 ± 0.48	3.6 ± 2.6	0.77 ± 0.16

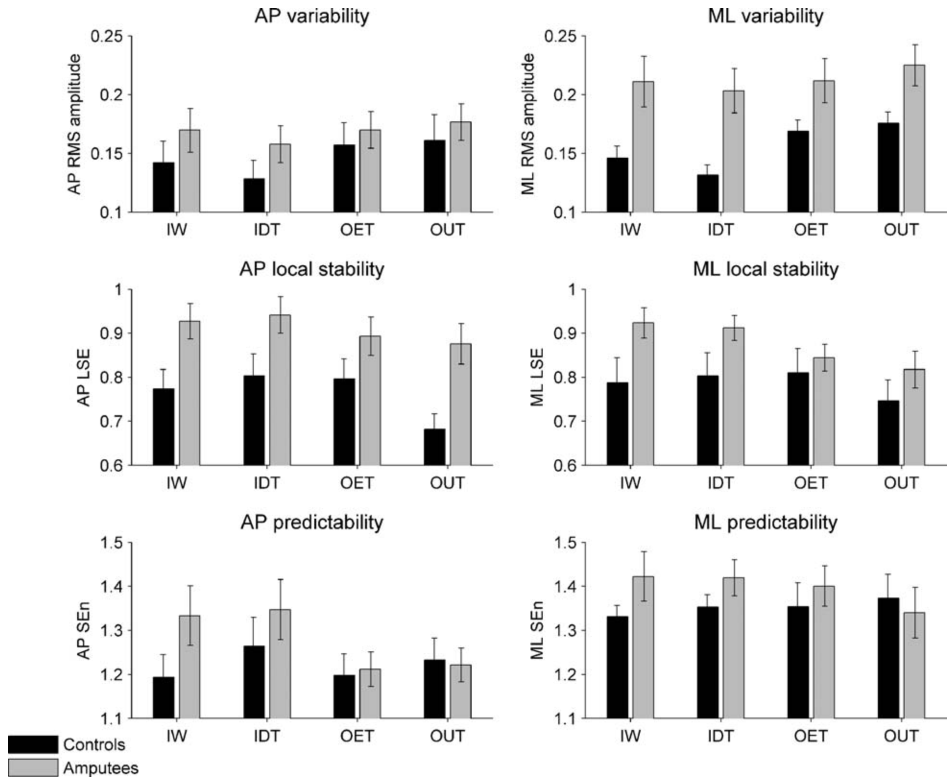

Fig. 1. For the control group (dark bars) and the amputee group (grey bars) the RMS, the local stability exponent (LSE) and the sample entropy (SEn) are presented for anterior–posterior (AP) trunk accelerations (left panels) and medio-lateral (ML) trunk accelerations (right panels). On the *X*-axis the four conditions are presented: walking indoors (IW), walking while performing a dual task (IDT), walking outdoor on even terrain (OET) and walking outdoor on uneven terrain (OUT). Error bars are standard errors.

Main effects for condition were found for speed and (STm). Post hoc comparisons revealed that walking while performing a dual task (IDT) was slower ($P < 0.001$ for all comparisons) and proceeded with longer strides compared to indoor walking without dual task (IW) ($t = 3.63$, $P = 0.002$), walking outdoors on an even terrain (OET) ($t = 4.50$; $P < 0.01$) and walking outdoor on an uneven terrain (OUT) ($t = 3.51$; $P < 0.01$). No interaction effects of group by condition were found. For the stride-to-stride variability or the consistencies of stride times of different time scales as indexed by α, no main effect of group or condition was found.

3.2. Trunk acceleration parameters

Main effects for group were found for the local stability exponent (LSE) of both medio-lateral (ML) and anterior–posterior (AP) time-series (see Table 2) and for the RMS and the sample entropy (SEn) of ML time-series. For amputees, in all conditions local stability was decreased compared to controls, as indicated by a significant ($P < 0.05$) higher LSE in AP and ML directions (Fig. 1). In the amputee group, the RMS of ML time-series was higher compared to controls; however, also the SEn of ML time-series was higher, implying a less predictable and more complex acceleration pattern in the amputee group (see Table 2).

Main condition effects were found for the magnitude of both ML and AP time-series (RMS) and the local stability (LSE), and for the SEn of ML accelerations (Table 2).

Post hoc comparisons showed that, the RMS of AP time-series was larger for walking OET and walking OUT than in the IDT (both $P < 0.001$) condition; and was smaller for IW than walking OET ($P < 0.05$). In addition, the RMS of ML time-series increased with task difficulty (OET and OUT conditions) compared to IW and IDT ($P < 0.01$), while IDT was lower than IW ($P < 0.01$). However, these effects were largest in the control group (Fig. 1), although no significant interaction effect was found. The effect of condition on LSE of AP and ML time-series revealed lower values for walking OUT compared to the other conditions ($P < 0.01$).

A significant group by condition interaction effect was observed for the SEn of ML and AP accelerations and for the LSE of ML time-series (Table 2). LSE interaction of ML time-series was due to a gradual decrease of LSE in the amputee group in all conditions, whereas in the control group the LSE decreased only in the OUT condition. The SEn interaction of ML time-series was due to an increase in regularity in the amputee and a decrease in the control group with task difficulty, compared to IW. For AP time-series, for the amputee group regularity increased in the OUT and OET condition compared to the other conditions, whereas for the control group regularity decreased in the IDT condition and remained similar in the other conditions. (Fig. 1)

The performance on the DT of amputees and control subjects did not differ significantly for the number of subtraction ($F_{1,15} = 0.12$, $P = 0.74$) nor did it for the absolute amount of subtraction errors ($F_{1,15} = 0.002$, $P = 0.96$) and the relative amount of subtraction errors ($F_{2,21} = 0.01$, $P = 0.92$).

4. Discussion

The goal of the present study was to assess the stability and variability of the gait pattern of amputees and compare with that of 'healthy' control participants. Apart from walking inside on a smooth terrain, the effect of a cognitive and two mechanical perturbations (walking outside on (ir)regular surfaces) were studied. Specifically, we expected that group effects and condition differences would reveal themselves in the dynamic structure of variability of the medio-lateral and anterior–posterior accelerations. It was hypothesized that amputees would exhibit more variability, more irregularity, less local stability and be more affected by both cognitive and mechanical disturbances than healthy control subjects.

Walking speed was lower for the prosthetic walkers than for the controls and dual-tasking decreased gait speed in both groups in an equal way as indicated by a non-significant group by condition interaction effect. Between the control and prosthetic group, we found no significant group differences or task effects on stride time variability. Stride-to-stride variability or long-range correlation, have been suggested to be indicative of walking stability, related to risk of fall, and associated with neurological impairments [11,18]. In contrast to the results of these studies assessing various neurological gait disorders, the temporal order in the prosthetic stride time data was similar to that of the controls. Interestingly similar findings were reported for patients with peripheral neuropathy [39]. Given that an amputation is a primarily a peripheral orthopedic and not a neurological higher level (motor) disorder, this finding seems to be in agreement with the hypothesis that the degree of temporal order in a stride time time-series (gait cycle timing) is an expression of processes in the central nervous system, hardly influenced by peripheral processes [11]. However, an alternative explanation that cannot be excluded is that the variability of coarse-grained end point variables like stride time (by definition) collapse the properties of a large number of fine-grained variables of the system that do not unravel the generative, coordinative principles.

Consistent significant group differences were found for trunk acceleration patterns. In the amputee group the variability of the ML trunk accelerations was larger. In addition, accelerations pattern were less regular and locally stable as evidenced by a larger SEn and LSE. All of these responses have been associated with impaired balance control [20,21].

An important question is if the differences in walking speed can explain the obtained results. Walking speed has been show to affect many kinematic variables and amputees had a slower walking speed compared to the healthy individuals. It is often suggested that walking slower may be a pro-active strategy to improve gait stability, just as healthy subjects naturally slow down on an irregular surface or when avoiding obstacles [23,40]. Consequently, speed differences between the groups in our study might have influenced the variability and stability parameters. However, our results showed that both healthy subjects and prosthetic walkers slightly increased local stability when walking on irregular surface without a significantly slower speed. More importantly, even with lower walking speed, local stability was decreased and variability increased in the prosthetic walkers. This would be opposite to the expectation and suggesting changes in neuromuscular control. This finding is in line with studies reporting that even if healthy subject walked at the same preferred speeds as elderly, elderly still exhibited significantly decreased local stability compared to young subject, implying that speed alone cannot explain differences in stability [41].

The increased variability and loss of local stability and predictability in particularly the medio-lateral acceleration patterns of the trunk in the amputee group compared to the control group may be related to an increase in lateral sway. This is in line with the observation that amputees with an inferior balance generally show an increase in lateral sway during quiet standing and walk with greater lateral trunk motion, compared to healthy persons [6]. Alternatively, changes in ML trunk acceleration patterns might be related the clinical observation that during gait amputees tend to hang over toward their prosthetic side [42,43]. This hanging over is suggested to be a strategy to compensate for asymmetrical contact times [43], but may be at the cost of increasing variability and decreasing local stability. Irrespective of the underlying mechanisms, the result of the present study supports the concept that walking ability may reveal itself in local stability and variability of trunk acceleration patterns [44,45].

Condition effects were most profound for walking on an irregular surface. In both groups stride time and trunk variability increased but also local stability was higher, indicating that in this more challenging environment both groups accommodate their gait as much as possible by increasing the local stability even at the cost of an increased variability [36]. However, the amputee subjects were less able to achieve the same effect as the control subjects. The dual-task condition mostly decreased the predictability (increased AP SEn values) of the trunk accelerations. A decrease in predictability is suggested to be related to an increase in cognitive involvement (attention) [20,21] such as during dual-tasking. Interestingly, predictability of the trunk acceleration in the amputee group increased in the outdoor conditions compared to the control group, as evidenced by the interaction effect. This would mean that amputees employ more conscious control when walking on uneven terrains.

A limitation of the present study was the heterogeneous amputee group with respect to age, amputee cause and type of prosthesis. To control for age differences the control group was age matched with the amputee group. The large differences in age could have affected dual-task performance. Overall, no significant group effects on dual-task performance were observed. However, in both groups, two subjects had an age at which age related effects on dual-task performance are expected (amputee group: 59 and 69 year; and control group: 58 and 70 year). Both elderly subjects made slightly more faults (not significantly), but since subjects were age matched this did not affected the overall results. Although type of prosthesis certainly can effect walking, the main objective of the present study was to examine the general effect of walking with a transfemoral amputee using dynamic parameters to quantify walking ability not to study the effect of walking with different types of prosthesis. Future studies can elaborate on the findings of the present study, and for instance apply the used outcome measures to differentiate between amputees with different walking abilities and experiences, and evaluate the effect of walking with different types of prosthesis. Furthermore, the amputee subjects were (with exception of two subjects) experienced prosthetic walker, with one subject participating at a high level in athletic sports. Therefore the result cannot be generalized to subjects with recent lower limb prosthetics and it remains to be established how learning and training influences gait variability and stability.

An important line for further research is to establish if the variability and stability measures adopted here predict a subject's capacity/ability to respond to larger perturbation (global stability) and ability to respond to trips and slips, and avoid obstacles. Gaining detailed insight into stability and variability characteristics of prosthetic walkers is of great clinical interest as in lower leg prosthetic walkers balance confidence and stability are suggested to be correlated strongly with walking performance and social activity [46]. In contrast to more conventional measures, which in the case of walking consider each cycle as being independent, ignoring previous states or steps, the applied methods assess fluctuations throughout the gait cycle, and as such provide insight into how behavior unfolds, taking into account previous states of the system. Consequently, these measures might help to identify those who are able to adapt walking ability (in challenging circumstances) and those who are not. Furthermore the more detailed knowledge acquired from this type of analyses could be used to develop specific interventions aimed at improving gait adaptability. Note that, although the measures used in the present study all quantify the time dependent variations in gait patterns each provide a different kind of information. The local stability exponent relates to the ability of the system to resist small perturbation. The sample entropy provides information about the predictability of the signal, that is the repeatability over time. However, the SEn does not take into account long-term correlations (assess multiple time scales) higher entropy values will be obtained for uncorrelated time-series than for time-series that exhibit long-term correlates, DFA on the other hand can generally be interpreted as a measure of consistency that does quantify correlations over multiple time scales.

In conclusion, we have provide further evidence that, measures derived from the theory of stochastic dynamics may be usefully employed to quantify the time-varying structure of patterns in an orthopedic patient group. Applying these measures to different patient populations may enhance fundamental gait analysis and could provide a useful diagnostic tool to reveal differences in the gait patterns between patients and controls and their responses to gait perturbations.

Authors' contributions

C.J.L. and H.H. were the main investigators of the study and contributed to the conception and design of the study, analyzed the gait data, drafted and wrote the manuscript. E.A. was involved in the design of the study and in the data acquisition. W.P. recruited participants, was involved in the design of the study and revising of the manuscript.

Conflict of interests

The authors, Claudine Lamoth, Erik Ainsworth, Wojtek Polomski and Han Houdijk, declare that they have no proprietary, financial, professional, or other personal competing interests of any nature or kind.

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