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EFFECTS OF AGE AND WALKING SPEED ON LONG-RANGE AUTOCORRELATIONS AND FLUCTUATION MAGNITUDE OF STRIDE DURATION

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Abstract—Stride duration variability is considered a marker of gait balance and can be investigated in at least two different ways. Fluctuation magnitude can be addressed by classical mathematical methods, whereas fluctuation dynamics between strides can be characterized using the autocorrelation function. Although each approach has revealed changes of these parameters in different age-groups, most studies have focused on spontaneous walking speeds, which vary across groups and is described as a possible confounder in the assessment of stride duration variability. In the present study, the influence of speed on stride duration fluctuations was first analyzed in six young adults walking at six different speeds on a treadmill. Second, the results of 18 subjects from three different age-groups (≈5, 25, and 75 years old) were compared to assess the effect of age on the same variables at three different speeds. Fluctuation dynamics was evaluated, thanks to combined mathematical methods recently validated in the context of physiological time series, to increase the level of confidence in the results. Fluctuation magnitude was assessed by coefficients of variation (*CV*) on the same and large number of 512 gait strides, to enhance the validity of comparisons between both parameters. Long-range autocorrelations were highlighted in all time series, and characteristics were not influenced by gait speed and age of the participants. This suggests that the dynamics of variability is efficient for comparing subjects presenting with different spontaneous speed, and supports the hypothesis that long-range variability of human gait reflects a centrally controlled behavior. In contrast, *CV* was inversely related to walking speed and the age of the subjects. Slower speeds increased *CV* values, and fluctuation magnitude was also significantly larger for children compared with young and old adults. This confirms that fluctuation magnitude and dynamics could be complementary tools for more complete gait characterization. **© 2012 IBRO. Published by Elsevier Ltd. All rights reserved.**

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Abbreviations: CV, coefficient of variation; DFA, detrended fluctuation analysis; RRA, rescaled range analysis; SD, standard deviation; 10 MWT, 10-meter walk test.

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Walking is an essential motor skill that is widely used by humans during the activities of daily life. However, mechanisms of gait control can be disrupted by certain neurological diseases or aging, resulting in an increased gait unsteadiness and a risk of falling. This remains a major health care and rehabilitation problem, leading to injuries, fear of falling, decreased autonomy, nursing home admission, or even death. Detection of markers of gait imbalance is important for preventing falls and for assessing the efficacy of rehabilitative tools for gait balance. In the literature, gait variability is frequently mentioned as a good marker of gait balance (Hausdorff et al., 2001, 2007). In particular, the variability of stride duration, which is defined as the time between two consecutive heel strikes of the same foot, is of particular interest because it reflects the walking rhythm of an individual and can be considered one of the final outputs of the locomotor system (Bollens et al., 2010; Hausdorff et al., 2001). Stride duration variability can be assessed by two different ways—classical versus complex mathematical methods—that may be complementary in evaluating gait balance.

Classical mathematical methods allow for the determination of the fluctuation magnitude. The standard deviation (*SD*) and the coefficient of variation (*CV*) regard any given variable in the time series as independent of all previous values and following the same distribution. High *SD* and *CV* values of stride duration have been largely associated with gait instability and risk of falling in older adults (Beauchet et al., 2009a; Hausdorff et al., 1997a,b; Maki, 1997; Verghese et al., 2009). However, a current limitation in assessment of stride duration variability is that most studies use the spontaneous speed, which is often different between groups of subjects. Gait speed is described as a possible confounder in the assessment of fluctuation magnitude, although its precise influence remains controversial. On one hand, Jordan et al. reported a linear decrease in stride duration *CV* values with increase in velocity, in 15 young healthy adults walking from 80 to 120% of spontaneous speed on a treadmill (Jordan et al., 2007). With an equivalent protocol, other authors showed similar results in patients with Parkinson's disease (Frenkel-Toledo et al., 2005) and in older adults (Kang and Dingwell, 2008). On the other hand, Beauchet et al. found a quadratic and statistically significant relationship between gait speed and stride duration *CV* values in 29 young healthy

adults (Beauchet et al., 2009a), but their speeds ranged from 10 to 100% of preferred walking velocity and were not strictly constant during trials because subjects walked on level ground. Anyway, as a result of this possible linear or quadratic relationship with walking velocity, increased *SD* and *CV* values detected in unsteady patients could simply be explained by their reduced gait speed rather than a true risk of falling.

Complex mathematical methods are necessary to assess the long-term dynamics of fluctuations in stride duration. Indeed, it is known that consecutive strides are not independent from each other. They fluctuate in a very complex fashion and exhibit long-range autocorrelations that can span over hundreds of consecutive strides (Bollens et al., 2010; Hausdorff et al., 1995, 1996). Significant questions remain about the correct interpretation of such properties that are not unequivocally considered as a characteristic of healthy organisms (Gates and Dingwell, 2007; Dingwell and Cusumano, 2010). However, long-range autocorrelations have been proposed as a discriminating marker between fallers and non-fallers in the elderly subjects (Herman et al., 2005) and were significantly related to other indexes of stability as Lyapunov exponent and standard deviation of relative phase (Jordan et al., 2009). Long-range autocorrelations are also disrupted in unsteady patients presenting with central nervous diseases, including Huntington's, Parkinson's, and amyotrophic lateral sclerosis (Hausdorff et al., 1997a, 2000; Hausdorff, 2009). As for the magnitude of fluctuations, it has been suggested that the "strength" of long-range autocorrelations present in a stride duration time series could be dependent on gait speed. It would follow a quasi U-shaped function, with the minimum values at the preferred walking speed (Hausdorff et al., 1996; Jordan et al., 2007; Jordan and Newell, 2008).

A large number of mathematical methods have been described to assess the presence of long-range autocorrelations in time series. A non-exhaustive list includes random walk methods, power spectral density analysis, surrogate data tests, rate of moment convergence analysis, and multiscale entropy. Hence, it is difficult to draw uniform conclusions from studies assessing stride duration fluctuation dynamics. Moreover, mathematical properties of processes generating long-range autocorrelations are asymptotic, whereas physiological time series are inescapably finite. They always include a small sample of data, making, for example, the analysis of gait time series quite challenging. Recently, Crevecoeur et al. validated an integrated approach combining different mathematical methods to assess the fluctuation dynamics in physiological time series (Crevecoeur et al., 2010). The influence of gait speed on the presence of long-range autocorrelations has never been addressed with those reference methods, which would considerably increase the level of confidence in the results.

Walking depends moreover on very complex mechanisms of control. Information from the central and peripheral nervous systems is integrated to produce a relatively stable gait pattern (Hausdorff et al., 1995). The presence of long-range autocorrelations in walking variability seems also more and more obvious, but neurophysiological mechanisms generating such correlations remain a matter of debate. Breakdown of long-range autocorrelations in patients with central nervous diseases (Huntington's, Parkinson's, amyotrophic lateral sclerosis) suggested that supraspinal centers were involved in the regulation of long-term variability observed in gait (Hausdorff et al., 1997a, 2000). Fluctuation dynamics seemed also unaltered by severe peripheral neuropathy (Gates and Dingwell, 2007), whereas uncorrelated white noise was highlighted during metronomically paced walking (Hausdorff et al., 1996). This confirmed the potential role played by the central nervous system. However, in a reassessment of the original data, Delignières and Torre recently showed that both free and metronomic walking exhibited long-range autocorrelations that differed depending on the testing conditions (Delignières and Torre, 2009). They introduced a model of coupling Central Pattern Generators (CPG) that successfully accounted for the long-range autocorrelations evidenced in all conditions (West and Scafetta, 2003), which had also been evoked previously (Hausdorff et al., 1995). Finally, Gates et al. suggested that long-range autocorrelations observed in gait could simply result from uncorrelated white noise produced at the neural level and somehow filtered by the musculo-skeletal system (Gates et al., 2007).

As a result of the multiple levels of control, development of gait in children is a gradual process that occurs with time and experience. Gait is considered as mature between 3 years (Sutherland et al., 1980) and 12 years of age (Peterson et al., 2006), depending on the variables explored. Similarly, walking performance progressively dysfunctions from the seventh decade of life, owing to successive neuromuscular adaptations (Prince et al., 1997). The age of the subjects has already been supposed to modify stride duration variability during life. However, the existing literature suggests that age does not have the same influence on both the magnitude and dynamics of the fluctuations, (Hausdorff, 2007; Herman et al., 2005). *SD* and *CV* values of stride duration would follow a U-shape trend during life. Reported values are very low for young, healthy adults and are significantly higher for children (Diop et al., 2004; Hausdorff et al., 1999) and the elderly subjects (Callisaya et al., 2010; Kang and Dingwell, 2008; Malatesta et al., 2003). Conversely, using detrended fluctuation analysis (DFA), Hausdorff et al. suggested that the "strength" of long-range autocorrelations during level-ground walking progressively and linearly decreases over age, from childhood (Hausdorff et al., 1999) to old age (Hausdorff et al., 1997a). The validity of such observations should however be confirmed through studies assessing simultaneously different groups of age (children—young adults—older adults), and using the same validated mathematical methods.

The first objective of this study was to assess the effect of gait speed on the magnitude and dynamics of fluctuations in stride duration. The second objective was to investigate the influence of age on the same parameters. Pri-

Table 1. Anthropometric characteristics of subjects for each age-group

Characteristics	Children	Young adults	Older adults
Age (years)	5.3±0.2	21.2±1.9	72.5±4.7
Height (m)	1.14±0.06	1.77±0.09	1.66±0.11
Body mass (kg)	21.1±4.5	78.6±12.6	66.6±10.8
Spontaneous walking speed (m s^{-1})	1.16±0.16	1.16±0.14	0.97±0.22

mary outcome was to determine the presence of long-range autocorrelations using an integrated approach that was previously validated in the context of physiological time series, to obtain a high level of confidence (Crevecoeur et al., 2010). Secondary outcome was to evaluate fluctuation magnitude through *CV* on the same and large number of 512 gait strides.

EXPERIMENTAL PROCEDURES

Subjects

Eighteen healthy subjects with no history of neuromuscular or orthopedic disorders participated in this study: six children (from 4.8 to 5.5 years old), six young adults (from 19.7 to 24.2 years old), and six older adults (from 67.4 to 79.2 years old). All were able to walk at least 512 consecutive strides at different gait speeds on a treadmill. Anthropometric characteristics of the subjects are provided in Table 1. The study was approved by the local ethics committee. Each adult participant provided informed written consent, and parents were asked to sign the consent on behalf of their children.

Apparatus

The different walking tests were performed on a treadmill that was 1.5 m in length and 0.5-m wide, with a motor power of 2.2 kW (Mercury LTmed, HPCosmos, Germany). A foot switch was placed under the right heel of each subject to precisely detect the moment of heel strike (sampling rate: 500 Hz). After a few minutes warm-up, the time between successive heel contacts was automatically computed to determine stride durations during each complete trial (Bollens et al., 2010).

Tasks and procedures

To assess the effects of gait speed on stride duration variability, the six young adults were asked to walk successively at 20, 40, 70, 100, 130, and 160% of their spontaneous speed, which was determined by the 10-m walk test (10 MWT) (Wade, 1992). Time of acquisition was variable, ranging from 15 (160% of spontaneous speed) to 30 min (20% of spontaneous speed) to obtain at least 512 gait cycles during each walking test.

To evaluate the influence of age on stride duration variability, children and older adults walked consecutively at the following three different walking speeds: slow (0.28 m s^{-1} for 40 min), medium (0.83 m s^{-1} for 15 min), and fast (1.39 m s^{-1} for 12 min). Three temporal series, obtained at gait speeds close to 0.28 m s^{-1} (1 km h^{-1}), 0.83 m s^{-1} (3 km h^{-1}), and 1.39 m s^{-1} (5 km h^{-1}) in the first part of the study, were also selected from each young adult (speeds close to 0.28 m s^{-1} ranged from 0.19 to 0.25 m s^{-1}; speeds close to 0.83 m s^{-1} ranged from 0.69 to 0.92 m s^{-1}; and speeds close to 1.39 m s^{-1} ranged from 1.28 to 1.53 m s^{-1}). Data obtained from the three groups of subjects were then compared separately at the different walking speeds to assess the effects of age on stride duration fluctuations.

The sequence of acquisition was randomized for each subject, and walking trials were separated by periods of rest to avoid fatigue.

Data analysis

Fluctuation dynamics. The presence of long-range autocorrelations was determined using an integrated approach previously validated in the context of physiological time series, and described with more details in other articles (Crevecoeur et al., 2010; Rangarajan and Ding, 2000).

- Rescaled Range Analysis (RRA) was used to estimate the Hurst exponent (*H*) (Hurst et al., 1965). Briefly, the original time series of total length N was integrated and divided into subsets of size τ. After removing the linear trend, the maximum range of each subset (R) was normalized to the standard deviation of the original time series (S). R/S was computed for subsets of distinct lengths (from τ=10 to τ=N/2). The slope of the relationship between log (R/S) and log (τ) determined *H*.
- Power spectral density of the time series was calculated with Fourier transform analysis, and exponent α was estimated from the slope of a linear regression on a log (power) versus log (frequency) plot.
- Values of *H* and α, evaluated separately for series of 512 consecutive strides, were verified to be consistent with each other through the asymptotic relation $d=H-[(1+\alpha)/2]$.

The presence of long-range autocorrelations can be determined with a high level of confidence when the following three criteria are met:

- $H>0.5$
- α is significantly different from 0 and lower than 1
- $d\leq 0.10$

Inconsistencies between *H* and α strongly encourage further investigation of the data, which was done through two additional methods: the randomly shuffled surrogate data test (Theiler et al., 1992) and the rate of moment convergence analysis (Bhattacharya et al., 2005; Crevecoeur et al., 2010). Although these techniques do not permit to conclude for the presence of long-range dependency, they test the null hypothesis that the series is an uncorrelated random process.

The randomly shuffled surrogate data test is largely used in the literature (Bollens et al., 2010; Hausdorff et al., 1995, 1996). For each time series, 100 surrogate data sets are obtained by randomly modifying the sequential ordering of the data. *H* and α are calculated for each new series, and the mean and *SD* of the 100 new scaling exponents are compared with the exponent of the original time series. The deviation (σ) of the original exponent relative to the normalized distribution of exponents obtained from randomly shuffled surrogates indicates whether the original series is similar to a white noise process. If $\sigma\geq 2$, white noise can be rejected at the $P<0.05$ level (Bollens et al., 2010).

The rate of moment convergence analysis was demonstrated to directly support the presence of a significant trend in the power spectral density, which highlights the interest in this method when the values of *H* and α are inconsistent with each other (Crevecoeur et al., 2010). The mean of the original series truncated at different points was compared with the same estimate obtained from randomly shuffled surrogates. A difference between original and surrogate series provides evidence that sequential ordering of the data differs from a white noise process.

Fluctuation magnitude. Stride duration coefficient of variation ($CV=[SD/\text{Mean}]\times 100$), expressed in percentage, was calculated for the 512 consecutive strides that were previously selected for each time series, to assess the magnitude of fluctuations.

Statistics

Sigmastat (Systat, Richmond, CA, USA) 3.5 software was used for all statistical analyses. The effects of gait speed on *H*, α, *d,* and *CV* were examined in young adults using a one-way repeated-measures (RM) analysis of variance (ANOVA). To evaluate the influence of age on the same parameters, a one-way analysis of variance (ANOVA) was used separately at the three different walking speeds (slow, medium, and fast). A post hoc test with Bonferroni correction completed the analysis to determine which groups were significantly different. Results were reported significant if $P<0.05$.

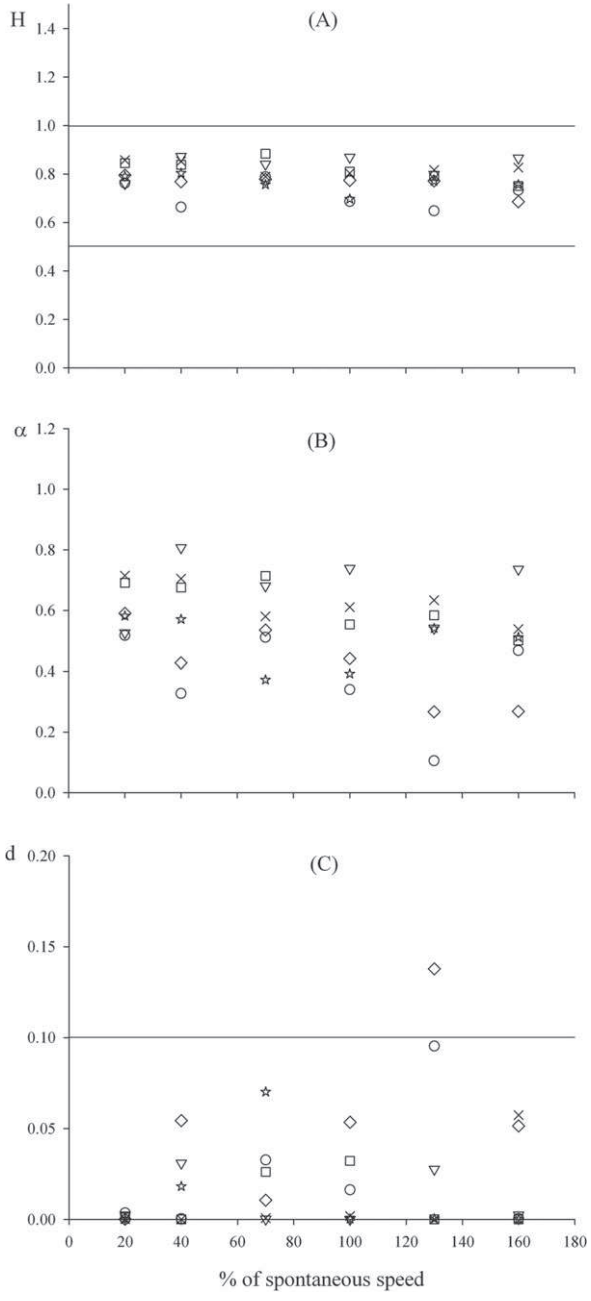


Fig. 1. Values of Hurst exponent (A), α exponent (B), and relation *d* (C) for the six young adults walking at different percentages of their spontaneous speed. A different symbol is representative of each participant (○=Subject 1; ☆=Subject 2; ▽=Subject 3; ×=Subject 4; ☆=Subject 5; ◇=Subject 6). For Hurst exponent (A) and relation *d* (C), horizontal lines correspond to the limits of expected long-range autocorrelations.

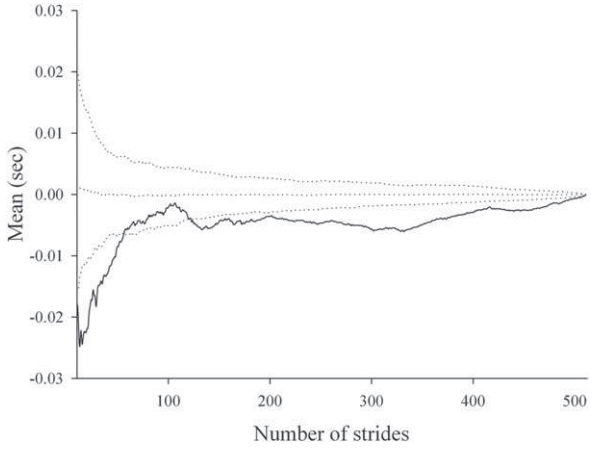


Fig. 2. Results of the rate of moment convergence analysis for Subject # 6 walking at 130% of spontaneous speed. Solid line represents the mean of the original time series. Mean±1.96 *SD* obtained from the 100 surrogate data sets is represented by dotted lines.

RESULTS

Influence of speed

The integrated approach showed the presence of long-range autocorrelations at different walking speeds in young adults with a high level of confidence (Fig. 1). All *H* values were superior to 0.5, and the α exponent was significantly different from 0 for all participants at the different imposed speeds. The value of relation *d* was also largely lower than the pre-specified limit of 0.10 (mean value of *d*: 0.02±0.03) for all but one of the walking tests. Randomly shuffled surrogate data tests showed that this particular time series (Subject #6 at 130% of spontaneous speed) could be statistically distinguished from white noise with $\sigma=5.1$ for *H* and $\sigma=3.8$ for α. The results of the moment convergence rate analysis calculated for that time series confirmed this result, as shown in Fig. 2. The sample average remained significantly lower than the randomly shuffled averages until 512 gait cycles. Results of statistical analysis also revealed that the values of Hurst exponent ($P=0.379$), α exponent ($P=0.124$), and relation *d* ($P=0.300$) were independent of walking speed in young

Table 2. Mean values of *H*, α, *d,* and *CV* for young adults walking at different % of spontaneous speed

Gait speed	*H*	α	*d*	*CV*
20%	0.8	0.6	0	0.1
40%	0.8	0.59	0.02	0.05
70%	0.81	0.57	0.02	0.03
100%	0.77	0.51	0.02	0.02
130%	0.77	0.45	0.04	0.02
160%	0.77	0.5	0.02	0.02
P-value	0.379	0.124	0.3	<0.001*

* Statistically significant.

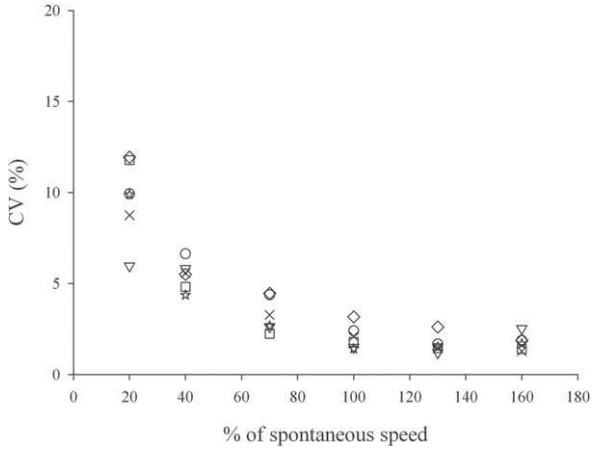


Fig. 3. *CV* of stride durations for the six young adults, in function of the different walking speeds. Each symbol represents a different subject (○=Subject 1; ☆=Subject 2; ▽=Subject 3; ×=Subject 4; □=Subject 5; ◇=Subject 6).

healthy subjects walking on a treadmill (see also mean values in Table 2).

In contrast, *CV* values were inversely related to gait speed. As presented in Fig. 3, all values were between 6 and 12% at 20% of spontaneous speed and lower than 5% for all participants greater than 70% of spontaneous speed. Results of one-way RM ANOVA and post hoc tests confirmed that the results obtained at the two slowest speeds (20 and 40% of spontaneous speed) were statistically greater than the results at other speeds ($P<0.001$).

Effect of age

Of the 54 time series (18 subjects at three different walking speeds) used in this part of the study, all *H* values were superior to 0.5, and α was always significantly different from 0. Relation *d* exceeded the limit of 0.10 in only four cases (see Fig. 4), including one series of a young adult discussed previously (Subject #6 at 130% of spontaneous speed). Randomly shuffled surrogate data tests revealed values of σ superior to 2 for the three other series, concerning Hurst exponent as well as α exponent. Rate of moment convergence analysis results was very similar to those presented in Fig. 2. Thus, presence of long-range autocorrelations was demonstrated in 92.5% of the cases, and the existence of white noise could be excluded for the other time series after further investigation of the data. Mean values of *H*, α, and *d* were very similar between age-groups, and statistical analyses confirmed that age of the subjects did not influence the characteristics of long-range autocorrelations, whatever the walking speed (Table 3).

In contrast, the magnitude of stride duration fluctuations was influenced by the age of participants. Results presented in Fig. 5 show that *CV* values were much larger for children than for both groups of adults, whereas values were very similar between young and older adults. This difference is statistically significant at the three walking speeds, as presented in Table 3.

DISCUSSION

This article suggests that the properties of the autocorrelation function associated with gait time series are not influenced by speed and age. Conversely, this study shows that magnitude of fluctuations is inversely related to the walking speed and age of the subjects. *CV* values were significantly larger for children compared with young and

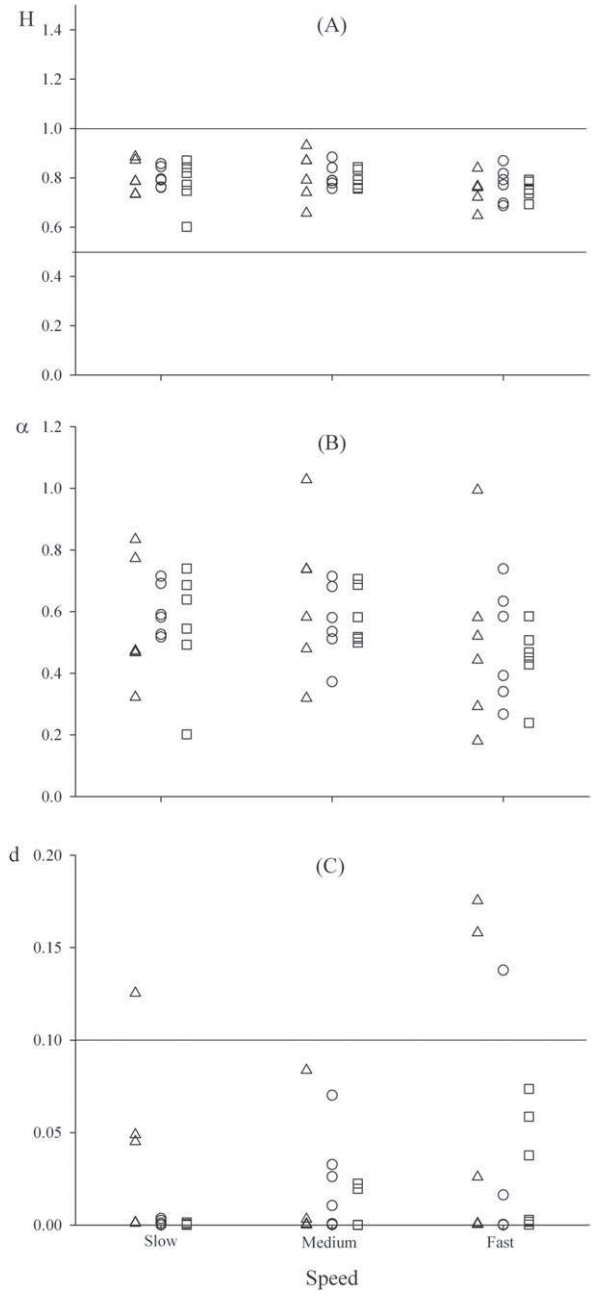


Fig. 4. Values of Hurst exponent (A), α exponent (B), and relation *d* (C) for the 18 participants walking at three different speeds (slow≈0.28 m s^{-1}; medium≈0.83 m s^{-1}; fast≈1.39 m s^{-1}). Distinct symbols were used for the three groups of subjects: children (△), young adults (○), and older adults (□). For Hurst exponent (A) and relation *d* (C), horizontal lines correspond to the limits of expected long-range autocorrelations.

Table 3. Effects of age on mean values of long-range autocorrelations and fluctuation magnitude of stride duration

Groups	Slow speed (≈0.28 m s^{-1})				Medium speed (≈0.83 m s^{-1})				Fast speed (≈1.39 m s^{-1})			
	H	α	*d*	*CV* (%)	*H*	α	*d*	*CV* (%)	*H*	α	*d*	*CV* (%)
Children	0.80	0.56	0.04	14.0	0.81	0.65	0.01	6.8	0.75	0.50	0.06	4.4
Young adults	0.80	0.60	0.00	9.7	0.81	0.57	0.02	3.3	0.77	0.49	0.03	1.8
Older adults	0.77	0.55	0.00	8.4	0.79	0.58	0.01	3.4	0.75	0.45	0.03	1.6
P-value	0.783	0.836	0.063	0.011*	0.901	0.683	0.554	0.002*	0.764	0.884	0.568	<0.001*

* Statistically significant.

older adults, and for slower speeds compared with fast speeds. The small number of subjects included in each group could be considered as a limit of the present study. However, differences highlighted in *CV* exhibited a high level of statistical significance, whereas most of the statistical results remained far from significance regarding the assessment of long-range autocorrelations.

These conclusions contrast somewhat with previous studies that assessed the presence of long-range autocorrelations while walking. Values of Hurst exponent have previously been suggested to be influenced by subject's walking speed, following a quadratic relationship (Hausdorff et al., 1996; Jordan et al., 2007). The comparison of results obtained from different studies has also suggested that *H* values decrease progressively from childhood to old age (Hausdorff et al., 1997a, 1999). However, the results of the present study are supported by key methodological characteristics that differentiate it from the existing literature.

This study was the first to simultaneously assess the presence of long-range autocorrelations in three different age-groups (children, young adults, and older adults), using the same methods of evaluation (constant number of gait strides, combined mathematical methods). This was necessary to increase the validity of comparisons. Participants were also compared at three different walking speeds (≈0.28, 0.83, and 1.39 m s^{-1}), which had never been done previously. Regarding the effects of walking

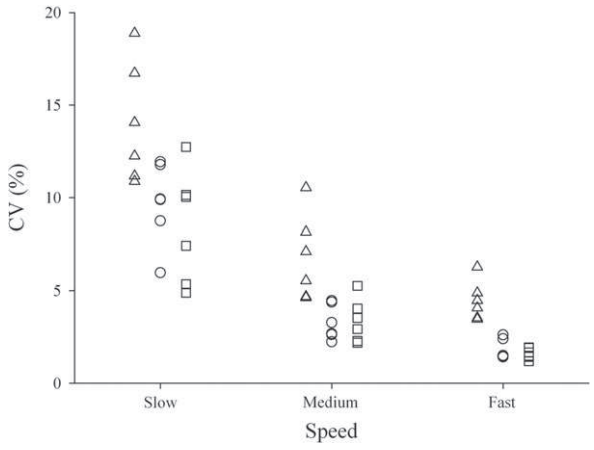


Fig. 5. *CV* of stride durations for the 18 subjects walking at three different speeds (slow≈0.28 m s^{-1}; medium≈0.83 m s^{-1}; fast≈1.39 m s^{-1}). Different symbols were used for each group of subjects: children (△), young adults (○), and older adults (□).

velocity, this study was the first to investigate the presence of long-range autocorrelations among a large range of speeds (from 20 to 160% of spontaneous speed). Moreover, treadmill walking was used to impose different precise gait speeds on the subjects, which had not always been done in the past (Hausdorff et al., 1996). Stride duration variability was recently demonstrated to exhibit comparable and reproducible long-range autocorrelations in young healthy subjects walking at spontaneous speed on level ground and on treadmill (Bollens et al., 2010; Chang et al., 2009). This further validated the treadmill as a useful tool for assessing stride duration fluctuation dynamics, particularly interesting to impose a precise speed to the subject, and to avoid any local changes in average stride duration owing to the fact that no external constraints were imposed to maintain a constant speed during the entire trial.

Methods previously validated in the context of physiological time series were moreover systematically used on large temporal series of 512 gait strides (Crevecoeur et al., 2010). Individual values of each participant were detailed in the present article, and global results (mean±*SD*) for the group of subjects are always presented in the literature. We show that the properties of interdependence between consecutive gait cycles, as much as we could characterize them on series of 512 data points, remained invariant across the groups of different ages and walking speeds. The combined mathematical methods used in this study do not give an ultimate proof of the presence of long-range autocorrelations. In particular, the possibility of a double false-positive result, simultaneously evidenced by RRA and PSD, cannot be ruled out by the cross-validation *d*. However, this approach increases the level of confidence in comparison with studies using either method alone.

The integrated approach proposed by Rangarajan and Ding (Rangarajan and Ding, 2000) had previously been tested and validated on artificial and physiological series (Crevecoeur et al., 2010). However, power spectral density and RRA are not the only candidates to combine to assess the presence of long-range autocorrelations in physiological time series. They constitute a particular case of a more general approach (Eke et al., 2000; Delignières et al., 2006). A different version of power spectral density has, for example, been developed in the frequency domain (Eke et al., 2000, 2002), whereas DFA is also largely used in the temporal domain. Those methods are critical to identify the process under investigation. They allow distinguishing stationary from diffusion processes, which was beyond the

scope of the present study. In this article, we assumed that the initial process generating the gait time series was stationary. Given that participants walked on a treadmill, variance of stride duration fluctuations could not increase with time like the variance of a diffusion process. This assumption justified the choice of RRA and classical power spectral density analysis.

Similarly, randomly shuffled surrogate data test and moment convergence analysis were used to further investigate the data when H, α, and d did not simultaneously reach expected values. Such methods had been rightly criticized in the past (Wagenmakers et al., 2004), but they are commonly used in the literature concerning gait. The null hypothesis tested in those methods is the absence of correlation in the series, but they cannot certify that the correlations in the series are long-range in nature. Fortunately, such tests were necessary for only 4 of the 72 time series acquired in the present study. Advanced techniques based on fitting the parameters of auto-regressive fractionally integrated moving average models (ARFIMA) should be considered to specifically address whether these series contain short- or long-range correlations (Wagenmakers et al., 2004; Torre et al., 2007). However, the rate of moment convergence shown in Fig. 2 also suggests that the sequential ordering of the samples influences the estimates of the partial mean for more than 300 consecutive strides, and use of more sophisticated methods was beyond the scope of the present study for only 5% of the time series.

The persistence of similar long-range autocorrelations for a wide variety of walking speeds is an important observation of the present study. Because many gait disorders are associated with a decrease in gait speed, it is important to highlight markers of gait stability that are independent of speed. Stride duration variability was previously described as a good marker of gait imbalance (Beauchet et al., 2009a; Hausdorff et al., 1996, 1997a; Herman et al., 2005; Jordan et al., 2009; Maki, 1997), but a decrease in walking speed was also considered a potential confounder when evaluating stride duration variability (Beauchet et al., 2009a; Hausdorff et al., 1996; Jordan et al., 2007). This study showed that the characteristics of long-range autocorrelations are intrinsic to the locomotor system and independent on gait speed. Consequently, the dynamics of variability seems to be efficient for comparing populations of subjects presenting with different spontaneous speed.

However, future studies are expected to more clearly define the clinical implications of stride duration variability assessments. Optimal amount of fluctuation magnitude remains unknown. Lower *CV* values were reported in many studies to reflect a healthier state, and increased variability was linked to a greater risk of falling (Hausdorff et al., 1997a,b; Maki, 1997; Verghese et al., 2009). However, a certain degree of variability has also been reported to be necessary to maintain stability, and too large or too little fluctuations were equivalently mentioned as potential predictors of falls, especially regarding step width (Brach et al., 2005; Beauchet et al., 2009b). Similarly, conflicting hypotheses have been proposed, but not proven, regarding the interpretation of the long-range autocorrelations (Hausdorff et al., 1997a,b; Hausdorff, 2009; Jordan et al., 2007). The potential relationship between assessment of stride duration variability and gait balance cannot be inferred from the present study. It must be further investigated and established. Prospective studies evaluating the occurrence of falls in patients presenting with differences in amount of stride duration variability should be conducted using reference mathematical methods.

The aim of the present article was not to evidence the precise mechanisms controlling dynamics of stride duration fluctuations. However, future studies should be conducted to identify the underlying mechanisms that give rise to these observed and quantified behaviors. Their real physiological insights currently remain a matter of debate. In that context, persistence of similar long-range autocorrelations from 5 to 75 years of age constitutes a second important result of the present study and allows making some neurophysiological assumptions. On the one hand, the rapid emergence of mature long-range autocorrelations in children does not parallel the slow development of anthropometric parameters. This observation supports the hypothesis that long-range variability of human gait reflects a centrally controlled behavior (Cheron et al., 2001). On the other hand, peripheral modifications are known to largely predict the primary changes in gait pattern occurring with old age. Increased stiffness of periarticular soft tissues and modifications in gastrocnemius muscles properties (decline in isometric force, reduction in type II fiber areas, decrease in mitochondrial enzyme activity) irremediably develop in healthy older adults from 60 to 70 years of age. Those changes largely contribute to loss in ankle power generation and consecutively to reduced gait speed and step length evidenced in healthy older adults (Prince et al., 1997; DeVita and Hortobagyi, 2000; Menz et al., 2003). Persistence of long-range autocorrelations at more than 70 years of age further suggests that biomechanical modifications do not influence the stride duration long term variability, whose control would be centrally mediated.

To obtain similar biomechanical constraints on the locomotor system, it had probably been more appropriate to impose fractions of spontaneous speed, rather than similar absolute speeds, to compare the three groups of subjects. However, it had been demonstrated in the first part of the study that gait speed had no influence on the values of H, α, and d. Walking at the same absolute speed was thus not a confounder in the assessment of age effects on the presence of long-range autocorrelations. It must also be noticed that time series of young adults were not strictly obtained at the same slow, medium, and fast speeds as children and older adults. However, those walking speeds remained very similar between age-groups, which should not have influenced the results of the present study.

Unlike fluctuation dynamics, the magnitude of stride duration variability demonstrated to be dependent on gait speed and age of the participants. Slower speeds increased *CV* values, which had already been suggested (Frenkel-Toledo et al., 2005; Jordan et al., 2007; Kang and Dingwell, 2008). *CV* values were also inversely related to age of subjects. They were not different between young

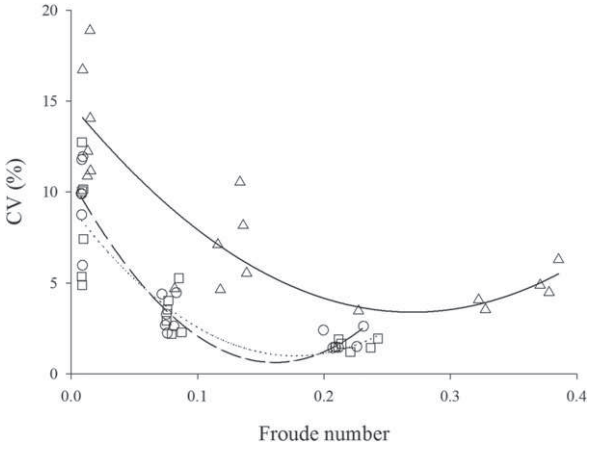


Fig. 6. Representation of the *CV* values of the 18 subjects at three different gait speeds, as a function of the Froude number. Distinct symbols were used for the three groups of subjects: children (△), young adults (○), and older adults (□). Three lines were respectively drawn across the results of the three groups of subjects, using quadratic function: children (—), young adults (– – –), and older adults (. . .).

and older adults, which is in contrast with existing literature (Callisaya et al., 2010; Kang and Dingwell, 2008; Malatesta et al., 2003). However, the older participants in the present study were particularly fit and were all able to walk for several minutes at three different walking speeds on a treadmill. This could explain the differences highlighted in this study compared with previous studies that only assessed short-term variability over a few strides (Callisaya et al., 2010). Conversely, *CV* values were significantly larger for children compared with young and older adults. Moreover, this observation persisted at the three different speeds that were similar between groups.

Some authors have suggested that increased variability could be related to the difficulty children might have in adapting to walking on a treadmill (Fairley et al., 2010). However, higher *CV* values had been similarly observed in children during level ground walking, contradicting this hypothesis (Hausdorff et al., 1999). The variation could simply be related to biomechanical constraints, imposed by similar absolute speeds between the three groups of subjects and caused by the reduced height of children compared with adults. Therefore, we normalized walking speed by the leg length of participants using the Froude number:

$$FR = \frac{V^2}{gL}$$

where *V* is the walking speed, *g* is gravity, and *L* is the leg length of the subject (Alexander, 1989; Dierick et al., 2004). The results presented in Fig. 6 show that *CV* values remained larger for children than for both groups of adult subjects, suggesting that the increased variability in children cannot be explained by height.

The effects of speed and age were thus completely different in influencing the magnitude and dynamics of stride duration fluctuations. This observation was not surprising, given that the two measures have previously been described as completely independent of one another (Hausdorff, 2007; Herman et al., 2005). However, accuracy of both estimates is proportional to the number of steps that is collected. *CV* values and characteristics of long-range autocorrelations were calculated on the same and large number of 512 gait cycles throughout the present study, which increased the validity of comparison between both markers of variability and constituted a third important issue of this article. In an attempt to design a more complete characterization of gait, we suggest like previous authors that the dynamics and magnitude of fluctuations should be considered complementary tools to generate a body of parameters that reflect different aspects of gait variability (Hausdorff, 2007; Herman et al., 2005).

In conclusion, this study demonstrated that characteristics of long-range autocorrelations highlighted in stride duration variability are constant over a large range of gait speeds and invariant in populations of different ages. On the other hand, *CV* values are inversely related to gait speed and the age of the participants. This confirms that they could be complementary tools in the gait characterization. The absence of speed effect on the dynamics of stride duration fluctuations indicates that it could be an efficient measurement to compare groups of subjects presenting with differences in spontaneous speed. Persistence of similar long-range autocorrelations from 5 to 75 years of age suggests that biomechanical modifications do not influence the stride duration long-term variability, and reflects a centrally controlled behavior. Future studies are expected to give a clear interpretation of stride duration variability and to understand its potential clinical implications.

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