Human Movement Science 29 (2010) 125–136

Contents lists available at ScienceDirect

Human Movement Science

journal homepage: www.elsevier.com/locate/humov

An investigation of stride interval stationarity in a paediatric population

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ARTICLE INFO

Article history:
Available online 8 January 2010

PsycINFO classification:
2240
2330

Keywords:
Statistical tests
Walking
Locomotion

ABSTRACT

Fluctuations in the stride interval of human gait have been found to exhibit statistical persistence over hundreds of strides, the extent of which changes with age, pathology, and speed-constrained walking. Thus, recent investigations have focused on quantifying this scaling behavior in order to gain insight into locomotor control. While the ability of a given analysis technique to provide an accurate scaling estimate depends largely on the stationary properties of the given series, direct investigation of stride interval stationarity has been largely overlooked. In the present study we test the stride interval time series obtained from able-bodied children for weak stationarity. Specifically, we analyze signals obtained during three distinct modes of self-paced locomotion: (i) overground walking, (ii) unsupported (hands-free) treadmill walking, and (iii) handrail-supported treadmill walking. Using the reverse arrangements test, we identify non-stationary signals in all three walking conditions and find the major known cause to be due to time-varying first and second moments. We further discuss our findings in terms of locomotor control and the differences between the locomotor modalities investigated. Overall, our results advocate against scaling analysis techniques that assume stationarity.

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doi:10.1016/j.humov.2009.09.002

1. Introduction

The stride interval, defined as the time between consecutive heel strikes of the same foot, has been increasingly studied in recent years. In particular, much interest has lied in quantifying the statistical persistence of stride interval time series which are known to be correlated up to thousands of strides (Hausdorff et al., 1996). Since the original discovery of these persistent fluctuations (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995), scaling estimates have shown sensitivity to ageing, pathology, and speed-constrained gait, as well as the potential to differentiate between fallers and non-fallers (Chau & Rizvi, 2002; Hausdorff et al., 2000; Hausdorff et al., 1997; Hausdorff, Zemany, Peng, & Goldberger, 1999; Herman, Giladi, Gurevich, & Hausdorff, 2005; Jordan, Challis, & Newell, 2007). Thus, through careful quantification of the underlying scaling behavior, stride interval analysis may provide us with a deeper understanding of the locomotor control system and could eventually become a useful clinical tool.

The ability of a particular analysis technique to provide an accurate scaling estimate depends largely on the nature of the given series. When dealing with fractal processes, typically assumed a priori to describe stride interval time series (Delignières & Torre, 2009), it is first necessary to classify signals as either fractional Gaussian noise (fGn) or fractional Brownian motion (fBm) to ensure that the most relevant analysis technique can be applied (Eke, Herman, Kocsis, & Kozak, 2002). Indeed, the different properties of fGn and fBm processes, where the first is stationary and the second is non-stationary, necessarily require the application of different estimation techniques to ensure meaningful scaling estimates (Delignières et al., 2006). Unfortunately, matters are further complicated when dealing with series at the $1/f$ boundary, where it becomes difficult to distinguish between fGn and fBm processes using current methods (Delignières et al., 2006; Eke et al., 2000).

Until recently, investigators were unaware of this need to classify signals as either fGn or fBm prior to the application of scaling techniques. Thus, the interpretation of previous work must be approached with caution (Delignières et al., 2006). To this end, it would appear that the stationarity of stride interval time series has not been directly and systematically analyzed to date, even though such knowledge would enable a more informed choice of scaling method. Instead, the use of detrended fluctuation analysis (DFA) to quantify the statistical persistence in stride interval time series has seemingly become an automatic and habitual practice, likely due to the earliest reports which made use of this technique (Hausdorff et al., 1995, 1996). Fortunately, DFA does offer the advantage that it is less affected by non-stationarities (Peng et al., 1994) (i.e., time-varying changes in the statistical properties of a process), known to be common in physiological data (Stanley et al., 1999), than alternative methods sometimes adopted such as spectral analysis and rescaled range analysis (Peng, Hausdorff, & Goldberger, 2000). Nonetheless, careful quantification of stride interval stationarity may provide insight to either justify or refute the choice of DFA as the most appropriate analysis technique for estimating stride interval persistence.

Some qualitative observations have been made surrounding the stationarity of gait. Hausdorff et al. (1995) observed that stride intervals recorded over 3500 strides remained quite stationary, falling between 1.0 and 1.2 s for an entire hour-long walking trial. On the other hand, a subsequent investigation by the same group (Hausdorff et al., 1996) revealed the appearance of "variations in the local average with time" for certain individual time series. They further suggested that these apparent non-stationarities may be the result of a loss of focus on the walking task at hand, or due to the absence of external constraints that might otherwise regulate stride interval behavior. In support of this latter idea, a stationarity analysis of human gait kinematics performed by Dingwell and Cusumano (2000) identified mild non-stationarities in the lower extremity joint angles of some individuals during overground walking, but found them to largely disappear during subsequent treadmill walking. The authors attributed suppression of the non-stationarities, identified as very low frequency drifting, to the externally imposed speed constraint that is inherent in treadmill walking.

Analysis of stride interval data from a paediatric population is of particular interest since the statistical persistence present in the stride interval time series of children have been largely unexplored. An initial study by Hausdorff et al. (1999) suggested that quantification of the stride-to-stride fluctuations of children may serve to improve the "early detection and classification of gait disorders in children". In support of this idea, an investigation by Chau and Rizvi (2002) revealed decreased stride interval correlations in children with spastic diplegia when compared to the able-bodied children, of similar age, reported on by Hausdorff et al. (1999). Therefore, in line with the overall effort to establish the quantitative assessment of stride interval persistence for clinical purposes, we investigate the stationarity of paediatric stride interval time series as an important first step.

In particular, we investigate series obtained in two distinctly different gait environments. We analyze stride interval time series emerging from overground walking in a level hallway; a gait environment similar to that of everyday walking where the individual is free to modulate his or her walking pattern at will. For completeness and comparison, we also analyze time series obtained from treadmill walking (both with and without handrail support). This locomotor modality, often implemented in clinical and research settings, imposes external constraints including constant optic flow feedback and speed fixation, the latter of which has been suggested to suppress non-stationarities in gait kinematics (Dingwell & Cusumano, 2000).

2. Methodology

2.1. Data collection

Stride interval time series were obtained from 31 asymptomatic children (20 female, 11 male) with a mean age of 7.0 ± 1.6 years. Each child completed a total of three, 10 min walking trials including: (i) overground walking (OW), (ii) unsupported treadmill walking (UTW) (without handrail support) and (iii) supported treadmill walking (STW) (with side-handrail support). Condition sequences were pseudo-randomized, ensuring that each of the six possible permutations was completed once every six participants. Subjects rested for at least seven minutes before each walking trial. Furthermore, subjects were instructed to walk at their own comfortable walking speed as if "walking to school" or "going for a walk in the park". The preferred UTW and STW speeds were established after the rest period, immediately prior to the start of each respective trial. With the subject walking on the treadmill (GK200T, Mobility Research, USA) at a relatively slow speed, the speed was increased in 0.1 mph increments until the subject reported that his or her preferred speed had been reached. The speed was then increased by at least 0.5 mph and subsequently decreased in 0.1 mph increments until the subject again reported that his or her preferred speed had been reached. This procedure was then repeated and the mean of the four reported speeds was taken as the preferred walking speed for the given treadmill walking condition.

Prior to data collection, subjects were given at least five minutes to become accustomed to treadmill walking and the measurement equipment. This practice period continued until the child reported feeling comfortable with the setup and visually appeared to be walking naturally. Children were recruited through the staff and community programs of Bloorview Kids Rehab (located in Toronto, Ontario, Canada) and the institutional Research Ethics Board approved the study.

During walking trials, heel strike was measured bilaterally via two ultra-thin, force sensitive resistors (Model 406, Interlink Electronics, USA) fastened to the sole of the subject's shoe underneath the heel. Heel contact with the walking surface was reflected by a change in voltage which was sampled at 250 Hz and recorded to the data acquisition card (CF-6004, National Instruments, USA) of a personal digital assistant (Axim x51v, Dell, USA) worn on the subject's abdomen via a waist harness.[1]

For each walking trial, data collection was initiated (pre-walk) and terminated (post-walk) while the subject was standing still. Given that the protocol called for analysis of a 10 min walking period, approximately 10.5 min of data were recorded for each trial. This served to ensure that, after removal of start-up and ending effects, full 10 min gait recordings would be available for analysis.

[1] During treadmill walking trials subjects were attached to an overhead safety support (LGJr200, Mobility Research, USA) but were fully weight bearing. Participants also wore a portable metabolic cart ($K4b^2$, Cosmed, Italy) throughout the duration of the trials as part of a separate investigation. This system includes a face mask, heart rate monitor, data collection unit and battery, the latter two of which were attached to the subject's back via the waist harness. The total weight of the study equipment worn by subjects was 2.5 kg.

2.2. Stationarity

2.2.1. Stationary series

Assume that X_t is a real-valued random variable representing the observation made at stride interval t and that a series $\{X_t\}$ denotes a family of these real-valued random variables. Without loss of generality, we index the observations such that $t \in \mathbb{Z}$, where $\mathbb{Z}$ is the set of integers. A series $\{X_t\}$ is considered to be *strongly* (or *strict-sense*) stationary if its statistical properties are shift-invariant (Papoulis, 1991), i.e.,

$$f_{X_{t_1},X_{t_2},\ldots,X_{t_n}}(x_1,x_2,\ldots,x_n) = f_{X_{t_{1+h}},X_{t_{2+h}},\ldots,X_{t_{n+h}}}(x_1,x_2,\ldots,x_n), \tag{1}$$

where x_i denotes a particular realization of the random variable $X_{t_i}, i = 1,2,\ldots,n$ and $h \in \mathbb{Z}$. More generally, a series is *weakly* (or *wide-sense*) stationary if only its first two moments do not vary with time, such that the mean is constant, i.e.,

$$E(X_{t_1}) = E(_{X_{t_{1+h}}}) \tag{2}$$

and the covariance between two observations made at different times depends only on their time lag and not on their temporal location, i.e.,

$$Cov(X_{t_1},X_{t_2}) = Cov(X_{t_{1+h}},X_{t_{2+h}}). \tag{3}$$

2.2.2. Reverse arrangements test

The reverse arrangements test (RAT) is a non-parametric test used to evaluate the weak stationarity of a time series (Bendat & Piersol, 2000). Specifically, the test searches for monotonic trends in the mean square values that are calculated along non-overlapping intervals of a particular signal of interest. The mean square value, given by,

$$E(X^2) = E(X)^2 + Var(X) \tag{4}$$

captures the first two moments of the time series for assessment of weak stationarity. The RAT is often used to evaluate the weak stationarity of physiological and biomedical signals (Alves & Chau, 2008; Bilodeau, Cincera, Arsenault, & Gravel, 1997; Chau, Chau, Casas, Berall, & Kenny, 2005; Hampson, Munro, Paterson, & Dainty, 2005; Harris, Riedel, Matesi, & Smith, 1993; Nhan & Chau, 2009; Novak, Honos, & Schondorf, 1996).

Considering a sample realization of the previously defined time series, $\{x_1,x_2,\ldots,x_N\}$, the reverse arrangements test is implemented as follows:

(1) The sample is divided into M equal and non-overlapping intervals, I_i, where $i = 1,2,\ldots,M$.
(2) For each interval, the mean square value y_i is calculated, i.e., $y_i = (1/n)\sum_{k\epsilon I_i} x_k^2$, where n is the number of points within each interval and $k = 1,2,\ldots n$.
(3) The total number of reverse arrangements, A, present within the sequence of mean square values $y_1,y_2,\ldots,y_M$, are counted. A reverse arrangement occurs when one mean square value is greater than a subsequent mean square value, i.e., when $y_i > y_j$ for $i < j$.
(4) The resulting value, A, is compared to the value that would be expected from a realization of a weakly stationary random process. In the case that the sample time series under consideration is weakly stationary, the expected value of A has a normal distribution with mean $\mu_A = N(N-1)/4$ and variance $\sigma_A^2 = N(N-1)(2N+5)/72$ (Bendat & Piersol, 2000). The null hypothesis that $\{y_i\}$ is weakly stationary is rejected if A falls outside the critical values defined by a significance level of α.

The critical values can be determined from calculation of the stationarity test statistic, z_A, where,

$$z_A = \frac{A - \mu_A}{\sigma_A} \tag{5}$$

and $z_A \sim N(0,1)$. At a significance level α, the critical values are given by $z_{\alpha/2}$ and $z_{1-\alpha/2}$ such that, for a standard normal deviate at a 5% level of significance, we have $z_{\alpha/2} = -1.96$ and $z_{1-\alpha/2} = 1.96$.

Comparison of the stationarity test statistic with the critical values at the significance level of interest should be interpreted as follows:

- $|z_A| < z_{1-\alpha/2}$. The null hypothesis that the time series is weakly stationary is accepted.
- $z_A \leqslant z_{\alpha/2}$. The number of reverse arrangements is less than the number expected of a stationary signal, implying that an upward trend in mean square sequence is present.
- $z_A \geqslant z_{1-\alpha/2}$. The number of reverse arrangements is greater than the number expected of a stationary signal, implying that a downward trend in the mean square sequence is present.

2.3. Data analysis

2.3.1. Stride interval analysis

To extract stride intervals from the heel strike recordings, the initiation and completion of each walking trial was manually selected to remove the extraneous static portion of the recordings (i.e., when the subject was standing stationary). The first 10 s of each trial was then eliminated to ensure that the subject had finished accelerating from rest to his or her preferred walking speed and the subsequent 10 min of data were used for analysis.

A step function of zeroes and ones, denoting heel contact and heel off respectively, was then generated from each of the voltage signals. Stride intervals were isolated based on an automatic stride interval extraction algorithm adapted from Chau and Rizvi (2002). Briefly, this involved identifying candidate stride times (i.e., all changes in the step function from 1 to 0) and then selecting the most probable event times based on a mean stride estimate. The mean stride estimate is taken as the mean stride interval from a subset of stride intervals, after having eliminated the outliers that may otherwise skew the mean calculation.

From the set of probabilistic stride intervals extracted, we subsequently eliminated the strides that fell outside 0.01% and 99.99% of a gamma distribution fit, considering these strides as unphysiologically long or short. Ultimately, the number of stride intervals comprising each time series ranged between 446 and 706, depending on the cadence of the participant.

2.3.2. Stationarity testing

Given that results of the reverse arrangements test are sensitive to window size, M, we tested the stationarity at window sizes ranging from 10 to 45 strides, in five stride increments. The minimum window size was constrained to include at least 10 stride intervals and the maximum window size was constrained to include at least 10 windows (for all series but one). In this way, we maintained an adequate number of data points as required to estimate a single statistical parameter (Chau et al., 2005) when calculating both the mean squared value within each interval and the total number of reverse arrangements.

In general, time series lengths were not exact multiples of the chosen window sizes. Therefore, strides that were not included within the intervals for analysis were equally omitted from both ends of the signal. After selecting an appropriate window size for further analysis, we subsequently examined the effect of our choice of trimming location by comparing results when trimming the outstanding stride intervals from the beginning, the end and equally from both ends, of the signals.

To determine which, if either, of the first two moments could be identified as possible contributors to the identified non-stationary signal, we divided the signal into non-overlapping intervals of the chosen length, and computed the mean and variance of the time series within each of these windows. The null hypothesis of time invariance was then tested with regression analysis. Finally, time series for which time-varying means and/or variances were identified were further classified as either having an increasing or decreasing trend. In this case, rejection of the null hypothesis due to a significantly non-zero positive or negative slope indicated the presence of an increasing or decreasing trend, respectively.

Unless indicated, all tests were performed at a 5% level of significance and left and right foot data were considered separately.

3. Results

3.1. Effect of window size

A total of 186 stride interval time series (31 from each condition for both the right and left feet) were acquired for analysis of stationarity using the reverse arrangements test. Results showing the percentage of non-stationary time series identified at each window size, during the three walking con-

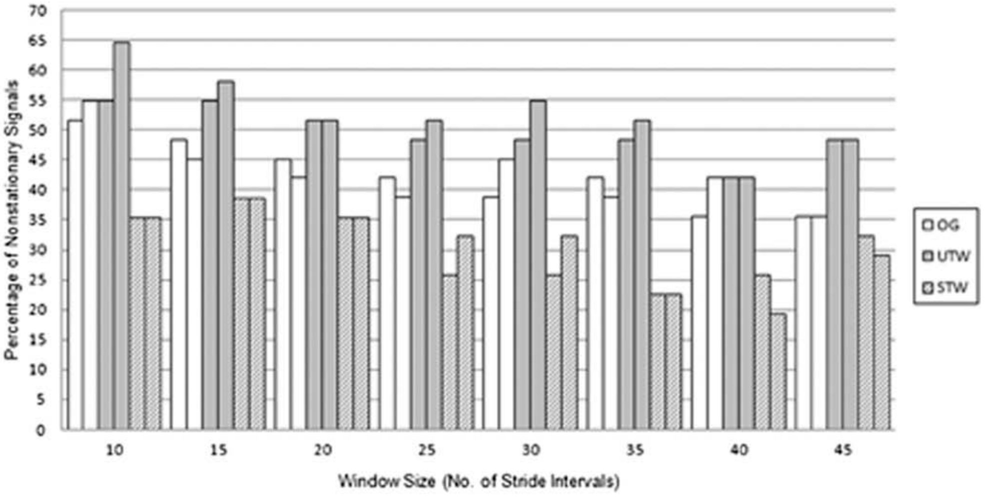

Fig. 1. The effect of window size on the percentage of non-stationary time series identified for each walking condition. The first and second bars of each pair depict results of the right and left foot, respectively. OW = overground walking; UTW = unsupported treadmill walking; STW = supported treadmill walking.

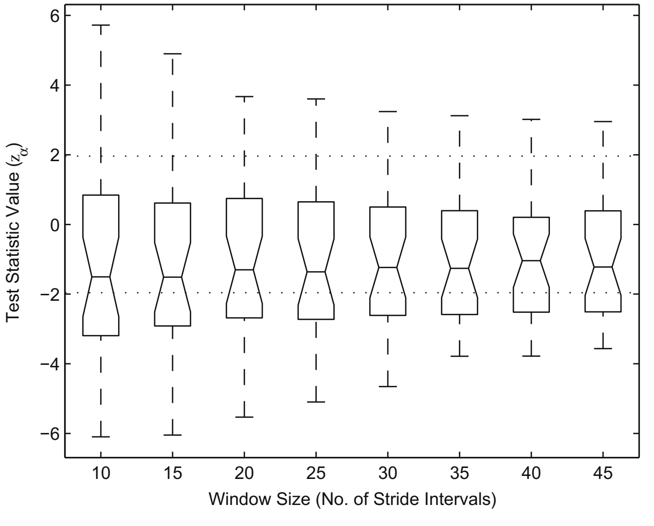

Fig. 2. The effect of window size on the stationarity test statistic, z_α, for right foot data generated during unsupported treadmill walking. Horizontal dashed lines define the boundary between stationarity and non-stationarity, i.e., $|z_\alpha| < 1.96$.

ditions under study, are presented in Fig. 1. In general, the least number of non-stationary signals were identified during STW while the most non-stationary signals were identified during UTW.

A representative boxplot showing the distribution of test statistic values for all right foot time series emerging from UTW trials is presented in Fig. 2. The median of the test statistic values clearly fell within the stationary range (i.e., $|z_\alpha| < 1.96$) and were essentially the same for the given window sizes. The same result held for time series emerging from treadmill walking conditions and for left foot data. A Kruskal–Wallis test found that the mean ranks of stationary test statistics were not significantly different among window sizes ($p > .96$) in all cases (i.e., for left and right foot data and all walking conditions). Thus, the test statistic alone does not suggest a window size preference for further analysis.

As evident in Fig. 1, the percentage of non-stationary time series identified in each walking condition tends to decrease with increasing window size. Since at larger window sizes a given time series is divided into fewer segments, a shorter mean square sequence is generated. With a shorter sequence, fewer comparisons between subsequent mean square values can be made, reducing the number of opportunities for detection of a reverse arrangement. This constraint also reduces the variation in the number of reverse arrangements likely to be identified between signals, as is apparent from the progressive shortening of the boxplot whiskers seen in Fig. 2. The reduction in the number of non-stationary signals detected at larger window sizes also agrees with intuition, since even a slow varying trend would begin to appear stationary when observed at sufficiently large window sizes. Thus, the reverse arrangements test is least reliable at the largest window sizes, where non-stationarities due to fast varying trends may be masked. Considering the tradeoff between maintaining an adequate number of stride intervals within each window for calculation of each mean square value and generating a sufficiently long mean square sequence for identification of non-stationarities, we chose a mid-range window size of 25 stride intervals for all subsequent analysis. At this window size, a total of 74 signals (36 – right foot, 38 – left foot) were identified as non-stationary.

3.2. Effect of trimming location

A Kruskal–Wallis test found that stationarity test statistics were not significantly influenced by the choice of trimming location for either foot and all walking conditions ($p > .74$). Therefore, our arbitrary choice to trim from both ends of the time series is of no consequence.

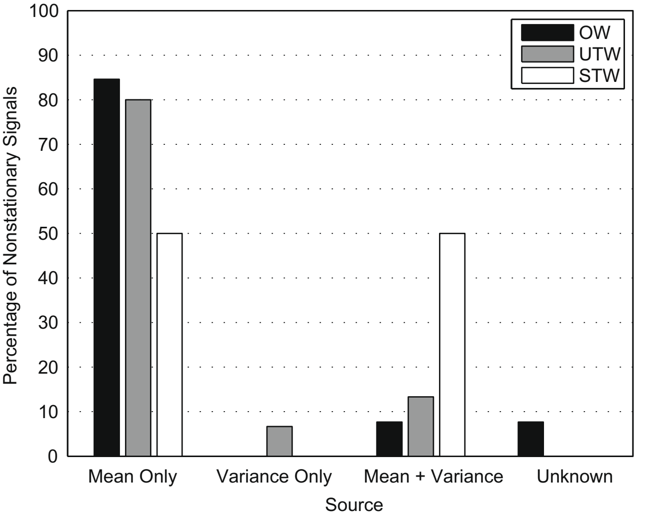

Fig. 3. Sources contributing to non-stationarity of the time series, as a percentage of the non-stationary signals identified within each particular walking condition. Data presented is for the right foot. OW = overground walking; UTW = unsupported treadmill walking; STW = supported treadmill walking.

3.3. Sources of non-stationarity

As summarized in Fig. 3, the majority of identified non-stationarities could be attributed to a change in the mean stride interval over time. To this end, very few signals demonstrated time-dependant variance alone, though some had both non-stationary means and variances. In particular, it was found that for both treadmill walking modalities, 75% of unstable means were due to an increasing mean trend, indicating that stride intervals increased over time. On the other hand, during overground walking just over half (55%) of the unstable means tested positive for an increasing mean trend.

4. Discussion

4.1. A locomotor control perspective

The identification of non-stationary signals within each walking condition is somewhat indicative of the complexities underlying locomotor control. Even during self-paced overground gait, time-varying changes in the stride interval time series occur within a 10 min period and are largely due to a time-dependent mean. It is possible that these changes in time occurred due to fatigue, boredom, loss of concentration, conscious modulation of gait to regain interest in the task (i.e., to entertain oneself), or in anticipation of task completion (e.g., Hausdorff et al., 1999; Wall & Charteris, 1980). On the other hand, a certain amount of non-stationarity may be inherent to the locomotor control system; a reflection of its effort to integrate complex information coming from proprioceptive, vestibular and visual sensors (Dietz, 2002). Some support to this second possibility is provided through the identification of non-stationary signals during treadmill walking. This locomotor modality is characterized by a constant-speed constraint and static visual feedback, two external cues that are known to influence human locomotor control (Hirasaki, Moore, Raphan, & Cohen, 1999; Jordan et al., 2007; Orendurff et al., 2004; Prokop, Schubert, & Berger, 1997; Warren, Kay, Zosh, Duchon, & Sahuc, 2001). Intuitively, one might expect the constant-speed constraint of treadmill walking to induce a more stable stride interval time series as compared to unconstrained overground ambulation. On the contrary, our results suggest that treadmill walking without handrail support induces at least as many, if not more, non-stationarities. However, during the more constrained treadmill walking task in which side-handrail support was implemented, far fewer non-stationary time series were identified.

A number of changes to the afferent systems involved in treadmill walking may have contributed to the increased number of non-stationary signals identified during UTW. From a behavioral perspective, subjects were largely naive to treadmill walking, conceivably resulting in an initially cautious gait. Although given the opportunity to become accustomed to this locomotor modality at the outset of the study, we expect that some unobvious and unreported anxiety may have remained. This would likely have diminished over the 10 min trial, contributing to a time-dependent change in a subject's stride interval as he or she became more familiar and confident with treadmill walking. A number of studies comparing overground and treadmill walking have also identified biomechanical differences in gait (Alton, Baldey, Caplan, & Morrissey, 1998; Dingwell, Cusumano, Cavanagh, & Sternad, 2001; Matsas, Taylor, & McBurney, 2000; Murray, Spurr, Sepic, Gardner, & Mollinger, 1985; Nigg, De Boer, & Fisher, 1995; Riley, Paolini, Croce, Paylo, & Kerrigan, 2007; Savelberg, Vorstenbosch, Kamman, van de Weijer, & Schambardt, 1998; Stolze et al., 1997; van Ingen Schenau, 1980). These are largely explained in terms of mechanical differences in the walking surface, the loss of optic flow feedback, the constant-speed constraint, and behavioral adjustments to a less familiar task. It has been found that as the locomotor system adapts to these differences, an initial period of treadmill familiarization is required before repeated measurements of certain gait parameters cease to change significantly within a walking session (Lavcanska, Taylor, & Schache, 2005; Matsas et al., 2000; van de Putte, 2006; Wall & Charteris, 1980; White, Gilchrist, & Christina, 2002). Of particular relevance to our results, both Wall and Charteris (1980) and Matsas et al. (2000) found that stride time increases with treadmill habituation. In line with this, of the 12 non-stationary signals identified as having a time-dependent mean during UTW (Fig. 3), 75% could be attributed to an increasing trend in the mean, suggesting that these children were still habituating to this locomotor modality.

The reduction in the number of non-stationary signals identified during STW likely occurred due to the additional proprioceptive information available for regulation of locomotor control. In line with this result, Dickstein and Laufer (2004) found that additional somatosensory input provided by light fingertip touch during treadmill walking facilitates spatial orientation and reduces body sway. From a purely anthropometric perspective, by grasping the handrails, the reasonable range for each child's foot placement (and hence stride length) is effectively reduced, restricted by the extent of his or her arm reach. This limitation on stride length imposes an additional constraint on the user's stride interval on top of the constant-speed constraint of the treadmill. Seemingly, the handrails act to somewhat anchor somatosensory feedback, perhaps contributing to fewer non-stationary signals during supported treadmill walking.

We also consider the influence of gait maturity on our results. Since the various afferent systems contributing to regulation of locomotor control may not have reached full maturity in children, the capacity of these systems to efficiently generate stable movement patterns may be reduced (Stolze et al., 1997). This idea may also have contributed to the identification of more non-stationary signals during UTW than during OW in our paediatric study. Conversely, during STW, the additional locomotor constraints discussed above may have sufficiently augmented locomotor regulation so as to overcome the suggested age-sensitivity to treadmill walking. To this end, it would be interesting to assess whether or not the same trend, suggesting an increased number of non-stationary signals during UTW, would also appear in an investigation of stride interval stationarity in an adult population.

4.2. Relevance to analysis of stride interval dynamics

This investigation reveals that the stride interval time series emerging from paediatric gait under varying degrees of locomotor constraint is often, though not always, non-stationary. While the stride interval time series of 11 children (age range 5–9 years old; 5 males) were found to be weakly stationary for all walking trials, other children produced non-stationary signals under at least one walking condition and two children (ages 5 and 8 years; both male) produced non-stationary series for all three walks. Finally, considering the possibility of maturation effects within our sample population, we also note that non-stationary signals were identified in at least one walking condition across the entire age spectrum under analysis. Thus, we have confirmed, at least for a paediatric population, the often assumed notion that stride interval time series exhibit non-stationary behavior in many cases. Given this finding, when estimating the fractal behavior of gait, we emphasize the importance of implementing scaling analysis techniques that are robust to non-stationarities.

DFA is one method that was developed to account for the non-stationary behavior of series generated from certain DNA sequences (Peng et al., 1994). This method, often applied to stride interval time series and other physiological processes, has since been tested with simulated fGn and fBm data, alongside numerous alternative techniques, with findings depending largely on the nature and length of the series under analysis (Delignières et al., 2006; Eke et al., 2000). While other methods seem to produce more accurate estimates when dealing strictly with fGn or fBm processes, DFA or a modified power spectral density approach typically provide more robust estimates for series near the $1/f$ boundary (Delignières et al., 2006). Considering that the scaling behavior of human stride interval time series is generally considered to fall within this range (Hausdorff et al., 1995), and given the identification of both stationary and non-stationary signals in this investigation, DFA and modified power spectral density would seem to hold the most promise for estimation of statistical persistence within stride interval data.

Nonetheless, both methods still present considerable challenges to gait researchers. While Delignières et al. (2006) fittingly suggest that the low variability associated with the modified power spectral density method render it most appropriate for comparisons between mean scaling exponents, this variability is significantly increased for series containing less than 512 data points. Within the scientific and rehabilitation communities where stride interval quantification is of interest, it is not uncommon for the population under study to have gait difficulty, rendering acquisition of a sufficiently long time series frequently impossible. When considering DFA analysis, seemingly most appropriate when the goal is not to compare but rather to quantify the persistence of a series sample (due to its low bias), there are other issues to consider. For example, depending on the signal's underlying correlation properties, certain non-stationarities are still known to influence the scaling estimate (Chen, Ivanov, Hu, & Stanley, 2002; Hu, Ivanov, Chen, Carpena, & Stanley, 2001). In addition, use of DFA requires that the investigator choose a box size fitting range to be used in the analysis; a choice that can have a significant influence on the scaling estimate. These issues are often handled differently by researchers, complicating the interpretation of results and the ability to draw comparative conclusions across studies (Hausdorff, 2007) and highlighting the need for a widely-acceptable and standardized approach for use in the gait literature.

It has been suggested that an integrated approach be adopted for scaling analysis, in which multiple methods be consistently implemented (Rangarajan & Ding, 2000). This approach would not only facilitate comparison between studies, but may also improve within study estimates. Where the results of one method may otherwise lead to false conclusions, inconsistencies revealed by another technique would enable one to more accurately determine the true scaling behavior of a given time series (Rangarajan & Ding, 2000). Of course, such an approach is only of use if the scaling methods are appropriately chosen based on the underlying signal properties, and only then if the associated user-selected parameters are consistently implemented. For example, when evaluating the statistical persistence of stride interval fluctuations, the pair of estimators most commonly compared are those derived from DFA and spectral analysis (Hausdorff et al., 1995; Hausdorff et al., 1996). Given that spectral analysis is sensitive to non-stationarities, we question the utility of making such a comparison and suggest instead the use of alternative techniques that, like DFA, are less affected by non-stationary behavior.

5. Conclusion

In order to better understand the human locomotor control system, it is important to carefully characterize gait dynamics. In particular, to determine the appropriateness of various scaling analysis techniques for quantification of the correlation properties of stride interval time series, it is important to know the extent to which the signal of interest is stationary. This study assesses for the first time the extent to which stride interval time series, obtained from a paediatric population, are weakly stationary. We reveal non-stationary signals in all walking conditions, including the most constrained locomotor modality in which children walked on a treadmill with handrail support. We have thus confirmed that, as is true for many physiological signals, paediatric stride interval time series are often non-stationary. Therefore, when seeking to quantify the statistical persistence of stride interval fluctuations, scaling analysis techniques that are less affected by non-stationarities should be implemented. To this end, much has been done as of late to facilitate the selection and implementation of these techniques when dealing with physiological data. However, this body of work has largely focused on simulated data and other physiological processes, with little empirical investigation of stride interval time series specifically. Evidently, if scaling analysis of stride interval time series is to gain true clinical value, a methodological effort to standardize approaches is needed.

Acknowledgements

The authors would like to acknowledge the support provided by the Natural Sciences and Engineering Research Council of Canada, the Hilda and William Courtney Clayton Paediatric Research Fund, the Bloorview Children's Hospital Foundation and the Canada Research Chairs Program.

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