Raffalt, P. C., Stergiou, N., Sommerfeld, J. H., Likens, A. D. (2021). The temporal pattern and the probability distribution of visual cueing can alter the structure of stride-to-stride variability. *Neuroscience Letters, 763*, Artikkel 136193. http://dx.doi.org/10.1016/j.neulet.2021.136193

ORIGINAL RESEARCH ARTICLE

Title:

The temporal pattern and the probability distribution of visual cueing can alter the structure of stride-to-stride variability

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Abstract

The structure of the stride-to-stride time intervals during paced walking can be altered by the temporal pattern of the pacing cues, however, it is unknown if an altered probability distribution of these cues could also affect stride-to-stride time intervals. We investigated the effect of the temporal pattern and probability distribution of visual pacing cues on the temporal structure of the variability of the stride-to-stride time intervals during walking. Participants completed self-paced walking (SPW) and walking paced by visual cueing that had a temporal pattern of either pink noise presented with a normal distribution (PNND), shuffled pink noise presented with a normal distribution (SPNND), white noise presented with a normal distribution (WNND), and white noise presented with a uniform distribution (WNUD). The temporal structure of the stride-to-stride time intervals was quantified using the scaling exponent calculated from Detrended Fluctuation Analysis. The scaling exponent was higher during the SPW and PNND trials than during the SPNND, WNND and WNUD trials and it was lower during the WNUD trial compared to the SPNND trial. The results revealed that both the temporal pattern and the probability distribution of the visual pacing cues can affect the scaling exponent of the variability of the stride-to-stride time intervals. This information is fundamental in understanding how visual input is involved in the control of gait.

Keywords: paced walking, visual cues, variable metronomes, gait, fractal structure, color noise

Introduction

Sensorimotor synchronization during human locomotion is responsible for the entrainment of footsteps to the external cues from auditory and visual signals [5, 23]. Using this coupling between the sensory and motor neural system, externally paced walking is considered a valuable tool for gait rehabilitation in a variety of gait related disorders [2, 3, 11, 20]. In addition to the footstep synchronization, exposure to either auditory or visual pacing cueing has been reported to alter the temporal structure of the natural variability observed in the stride-to-stride time intervals [12, 13, 19, 25, 26].

Hunt et al. (2014) [12] used Detrended Fluctuation Analysis (DFA) to quantify these alterations in the stride-to-stride time intervals of young adults during paced overground walking with auditory cues and un-paced walking. DFA returns a scaling exponent which, if above 0.5, indicates statistical persistence meaning that a deviation in stride time in one direction is statistically likely to be followed by a deviation in the same direction. A scaling exponent below 0.5 indicates statistical anti-persistence meaning that a deviation in stride time in one direction is statistically likely to be followed by a deviation in the opposite direction. Lastly, a scaling exponent close to 0.5 indicates an uncorrelated structure, such that the fluctuations in the stride-to-stride time intervals have no temporal correlation. In Hunt et al. (2014) [12], the authors presented conditions where the subjects walked listening to cues possessing a temporal pattern that was either white noise (i.e. a random signal with a flat power spectrum) or a pink noise (i.e. a signal with a power spectral density inversely proportional to the frequency). In both cases, the temporal structure of the variability observed in the stride-to-stride time intervals possessed statistical persistence (i.e. scaling exponent above 0.5). However, when walking with the pink noise pacing cues, the scaling exponent of the stride-to-stride time interval variability was

significantly higher compared to walking with the white noise pacing cues. Furthermore, the observed temporal structure of the stride-to-stride time interval variability during walking with pink noise cues was similar to un-paced walking in the young adults [12]. This result also demonstrated a superiority of the pink noise pacing cues over the classic isochronous pacing cues, because the pink noise pacing cues resulted in walking that exhibit the temporal structure of the natural variability of the stride-to-stride time intervals as observed in healthy young adults. As Hunt et al. (2014) [12] identified, the isochronous pacing cues resulted in an uncorrelated temporal structure of the stride-to-stride time intervals. These observations have been further supported by other studies using both auditory [16, 28] and visual cues [19, 27, 28]. In sum, the existing literature has determined that external pacing cues affects the temporal structure of the natural variability observed in the stride-to-stride time intervals during walking. As noted, the temporal structure of this natural variability is similar to the variability observed when individuals are asked to walk with pink noise pacing cues [12, 13, 16, 19, 25-28].

During paced walking, the temporal pattern of the pacing signal dictates the order in which different cues are presented. This means that, during walking with pink noise pacing cues, the inter-cue time intervals possess statistical persistence with a scaling exponent of 1.0 and during walking with white noise pacing cues, the inter-cue time intervals possess an uncorrelated pattern with a scaling exponent of 0.5. Furthermore, the probability distribution of the pacing signals determines the probability of receiving a specific cue. In other words, if the provided cues have a normal probability distribution (i.e. the distribution of inter-cue time intervals follows a normal distribution curve), then there is a greater probability that inter-cue time intervals which are closer to the mean inter-cues time interval will be presented than the inter-cue time intervals which are further away from the mean. Alternatively, if the provided cues

have a uniform probability distribution (i.e. the distribution of inter-cue time intervals follows a uniform distribution), then there is an equal probability for all inter-cue time intervals to be presented, regardless of their value relative to the mean inter-cue time interval. Therefore, using different combinations (pink or white noise with normal or uniform probability distribution) in the provided cues could present distinct differences in sensory input. Importantly, based on the existing literature, it cannot be determined whether the observed differences in the temporal structure of the stride-to-stride time interval variability when walking with pink or white noise pacing cues originate from the difference in the temporal pattern of the two pacing signals or from potential differences in the underlying probability distributions.

The aim of the present study was to decipher the role of the temporal pattern (i.e. pink and white noise) and the probability distribution (i.e. normal and uniform) of the visual pacing cues on the temporal structure of the natural variability of the stride-to-stride time intervals during walking. To accomplish this aim, we tested the following temporal patterns of the pacing signals: a) pink noise with a normal distribution (PNND), b) randomly shuffled pink noise with a normal distribution (SPNND), c) white noise with a normal distribution (WNND) and d) white noise with a uniform distribution (WNUD) (Figure 1). We quantified the temporal structure of the stride-to-stride time interval variability using the scaling exponent calculated from the DFA. We hypothesized the following: 1) the scaling exponent of the stride-to-stride time interval variability during un-paced walking would not be different from that observed during walking with the PNND visual pacing signal, 2) the scaling exponent of the stride-to-stride time interval variability would be higher when exposed to the PNND pacing signal compared to the SPNND pacing signal, and 3) the scaling exponent of the stride-to-stride time interval variability during

walking with either SPNND or WNND visual pacing signals would be higher compared to walking with WNUD pacing signal. ø

INSERT FIGURE 1 HERE

Method

Participants

Thirteen healthy young participants (males/females: 10/3, mean ± SD age: 25 ± 3.8 years, body height: 177.2 ± 12.3 cm and body mass: 80.2 ± 16.1 kg) with no neurological or musculoskeletal disorders were recruited. The participants provided informed written consent prior to participation. The study was approved by the Institutional Review Board of the University of Nebraska Medical Center, and the study was carried out in accordance with the approved guidelines. Participants were excluded if they had to be reminded more than once per trial to match their right heel strike to the moving bar reaching the bottom stationary bar, they were excluded as being unable to follow instructions. Following this criteria, three of 13 participants were excluded from the analysis. This resulted in the data from a total of 10 participants to be included in the analysis. Prior to the data collection, a sample size calculation was performed following the recommendation of Kuznetsov and Rhea (2017) [15] which revealed that the inclusion of a least 10 participants would provide an adequate statistical power.

Experimental setup

Upon arrival to the laboratory, the participants were fitted with footswitch sensors (Noraxon, Scottsdale, USA) placed under both heels for identification of heel strike events with a sampling frequency of 1500 Hz. This sampling frequency was chosen in order to detect the heel strikes events with more than 1 millisecond precision. The participants completed 5 overground walking trials including a minimum of 700 strides (approximately 13-minute duration) with 5 minutes rest in-between. The walking trials were performed on an indoor 1/8th mile long track. During the first trial, participants completed self-paced walking (SPW). The subsequent four trials were completed in randomized order and consisted of paced walking with the following

pacing signals PNND, SPNND, WNND and WNUD. Previous studies from our laboratory have emphasized the importance of visual input for the control of treadmill walking [6, 7]. Additionally, Vaz et al. (2020) [28] reported a superiority of visual compared to auditory cues during paced treadmill walking when evaluating the temporal structure of the natural variability observed in the stride-to-stride time intervals. Therefore, the present study used visual pacing cues. The individual mean stride time and corresponding standard deviation from each participant during the first walking trial were used to scale the stride-to-stride time intervals of the four pacing signals. Time series with the different pacing signals were generated using custom made scripts in MATLAB (MathWorks Inc. Natick, MA).

The participants wore non-prescription glasses in which the visual pacing cues was displayed on a mini HDMI screen (Vufine, Sunnyvale, CA, USA; Figure 2). The visual cues consisted of a horizontal bar moving vertically between two stationary bars (Figure 2). The participants were instructed to match their right heel strikes to the moving bar reaching the top stationary bar and match their left heel strikes to the moving bar reaching the bottom stationary bar.

INSERT FIGURE 2 HERE

Data analysis

Stride times were calculated as the time between two consecutive right heel strikes. The first 50 and last 50 strides were excluded and time series with a total of 600 strides were used for further analysis [8]. The temporal structure of the stride-to-stride time interval variability was quantified using DFA [10]. According to this technique, the time series in question x(i) is first integrated by calculating the cumulative sum of the deviations around the mean (Equation 1).

Equation 1: $y(k) = \sum_{i}^{k}[x(i) - x_{ave}]$

The time series is then divided into windows of equal length, *n* and a least square line is fitted to each window. The *y* coordinate of the straight-line segments is designated by $y_n(k)$ and used to detrend the time series y(k) before calculating the root mean square fluctuation (equation 2).

Equation 2: $$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N_n}[y(k) - y_n(k)]^2}$$

This procedure is repeated across the entire time series in order to establish a relationship between the average fluctuation, $F(n)$, as a function of window size *n.* The fluctuations can be characterized by the scaling exponent determined by the slope of the linear relationship between $\log F(n)$ to $\log n$ [18]. As recommended by Almurad and Delignières (2016) [1], an average evenly-spaced DFA algorithm was used in the present study. In the current study, a box size range of [16, N/9] and a scaling region of 10 – 30 were used for the DFA.

Statistics

A one-sample Kolmogorov-Smirnov test was applied to investigate if stride-to-stride time intervals deviated from a normal distribution. A two-sample Kolmogorov-Smirnov test was applied to investigate if the stride-to-stride time intervals and the corresponding visual cues during each trial had similar probability distributions. This test returns a D-value which quantifies the difference in probability distribution between the two signals in question. If the D-value was below the critical D-limit (with level of significance set at 0.05), the two signals were considered to have similar probability distribution. Furthermore, the D-value was used as a proxy measure of the cue-matching performance, i.e. the difference in timing of the visual cues and the footsteps. The lower the D-value, the greater cue-matching performance.

The use of frequentist p-values in making binary statistical inference (i.e., significant, non-significant) has been widely criticized [17, 21, 22, 29]. We have adopted a Bayesian analytical approach that focuses on strength of evidence in making statistical inference in non-

absolute terms (see above references) – details on this approach are provided below. A one-way Bayesian repeated measure ANOVA was performed to investigate the effect of the different pacing signals on the scaling exponent, the D-value from the one-sample and two-sample Kolmogorov-Smirnov tests. The present study used an objective Bayesian ANOVA with default Cauchy priors. This approach includes computing and interpreting the Bayes Factor (BF_{10}) as an alternative to the traditional p-value in frequentist statistics, which has been the subject of a number of critiques. BF_{10} is a ratio representing the information in favor of the alternative hypothesis relative to the null hypothesis (e.g., $BF_{10} = 3$ means that the alternative hypothesis is three time more likely than the null hypothesis). For interpretation of the BF_{10}, the following intervals related to the strength of the evidence in support of the alternative hypothesis are used: $BF_{10} = 1 – 3$ represents anecdotal evidence (i.e. weak or limited evidence), $BF_{10} = 3 – 10$ represents substantial evidence, $BF_{10} = 10 – 30$ represents strong evidence, $BF_{10} = 30 – 100$ represents very strong evidence and $BF_{10} > 100$ represents decisive evidence. The following intervals of the BF_{10} related to the strength of the evidence in support of the null hypothesis are used: $BF_{10} = 1/3 – 1$ represents anecdotal evidence (i.e. weak or limited evidence), $BF_{10} = 1/10 – 1/3$ represents substantial evidence, $BF_{10} = 1/30 – 1/10$ represents strong evidence, $BF_{10} = 1/100 – 1/30$ represents very strong evidence and $BF_{10} < 1/100$ represents decisive evidence [31]. $BF_{10} = 1$ provides no evidence in favor of either the null or alternative hypothesis. Note that these interpretive ranges are meant to be rules of thumb, not absolute rules. Post hoc tests were performed to investigate between-trials differences in the D-value and scaling exponent. Posterior odds were corrected for multiple comparisons [30]. All statistical analyses were performed in JASP (JASP Team, 2019).

Results

Scaling exponent of the visual cues

As a manipulation check, scaling exponents were calculated for each visual cue signal (Table 1). As expected, for the trial with the PNND pacing signal, the average scaling exponent was 1.00 and for the three other signals it was approximately 0.5.

INSERT TABLE 1 HERE

Scaling exponent of stride-to-stride time intervals

There was decisive evidence ($BF_{10} = 1.65 \times 10^{10}$) to indicate that the type of pacing signal had an effect on the scaling exponent (Figure 3).

INSERT FIGURE 3 HERE

After correcting for multiple comparisons, the post hoc tests (Table 2, Posterior Odds) revealed anecdotal evidence of no difference in the scaling exponent between the SPW trial and the trial with the PNND pacing signal, anecdotal evidence of a difference in the scaling exponent between the SPW trial and the trial with the SPNND pacing signal and substantial and strong evidence of a difference in scaling exponent between the SPW trial and the trial with the WNND pacing signal and between the SPW trial and the trial with the WNUD pacing signal, respectively. When comparing the scaling exponent of the trial with the PNND pacing signal with the scaling exponents from the trials with SPNND, WNND and WNUD pacing signal, there was decisive evidence of a difference in all cases. There was substantial evidence of no difference between the scaling exponents of the trial with the SPNND pacing signal and the trial with the WNND pacing signal and substantial evidence of a difference between the scaling exponents of the trials with the SPNND pacing signal and WNUD pacing signal. Finally,

evidence of a difference in scaling exponents was too weak to discern between the trials with the WNND and WNUD pacing signal.

INSERT TABLE 2 HERE

Normality distribution and cue-matching performance

There was decisive evidence ($BF_{10} = 2.12 \times 10^5$) to indicate that the type of pacing signal had an effect on the normality of the stride-to-stride time interval distribution (Figure 4).

INSERT FIGURE 4 HERE

After correcting for multiple comparisons, the post hoc test (Table 3, Posterior Odds) revealed very strong evidence that the normality of stride-to-stride time interval distributions differed between the trial with the PNND pacing signal and the trial with the WNUD pacing signal. There was strong evidence that the normality of stride-to-stride time interval distributions during the trial with the WNUD pacing signal was different from the trials with the SPNND pacing signal and with the WNND pacing signal. There was anecdotal evidence of differences in the normality of stride-to-stride time interval distributions between trial with the PNND pacing signal and trials with the SPNND pacing signal. Lastly, there was anecdotal evidence that normality of stride-to-stride time interval distributions did not differ between the trial with the PNND pacing signal and the trial with the WNND pacing signal and substantial evidence that normality of stride-to-stride time interval distributions did not differ between the trial with the trial with the SPNND pacing signal and the trial with the WNND pacing signal.

INSERT TABLE 3 HERE

There was decisive evidence ($BF_{10} = 2.11 \times 10^6$) to indicate that the type of pacing signal had an effect on the cue-matching performance (Figure 5).

INSERT FIGURE 5 HERE

After correcting for multiple comparisons, the post hoc test (Table 4, Posterior Odds) revealed very strong evidence of a difference in the cue-matching performance between the trial with the PNND pacing signal and the three other pacing trials. There was substantial evidence that cue-matching performance was equivalent among the trials with the SPNND, WNND and WNUD pacing signals.

INSERT TABLE 4 HERE

Discussion

The aim of the present study was to decipher the role of the temporal pattern (i.e. pink and white noise) and the probability distribution (i.e. normal and uniform) of the visual pacing cues on the temporal structure of natural variability of the stride-to-stride time intervals during walking. This was achieved by using four different temporal patterns of the pacing signals; pink noise with a normal distribution, randomly shuffled pink noise with a normal distribution, white noise with a normal distribution and white noise with a uniform distribution (Figure 1), and quantifying the temporal structure of the stride-to-stride time interval variability by the scaling exponent calculated from the DFA.

While previous studies have compared the effect of pacing cues with white and pink noise patterns during walking [12, 13], the present study used a shuffled pink noise pattern in addition to the white noise pattern. This approach ensures that the spatial information in the PNND and SPNND pacing signals is the same and only the temporal information is altered. We hypothesized that 1) the scaling exponent of the stride-to-stride time interval variability during un-paced walking would not be different from that observed during walking with the PNND visual pacing signal, 2) the scaling exponent of the stride-to-stride time interval variability would be higher when exposed to the PNND pacing signal compared to the SPNND pacing signal and 3) the scaling exponent of the stride-to-stride time interval variability during walking with either SPNND or WNND visual pacing signals would be higher compared to walking with WNUD pacing signal.

Self-paced walking vs. pink noise pacing

The first hypothesis was supported as the results showed that the scaling exponent of the stride-to-stride time interval variability during the SPW trial did not differ from the trial

involving the PNND pacing. This observation is in agreement with previous studies using auditory [12, 13, 28] and visual cueing [27, 28] who also observed that the scaling exponent of the stride-to-stride time interval variability during walking with pink noise pacing did not seem to differ from that of un-paced natural walking in young adults. The scaling exponents during the SPW trial and the trial with the PNND pacing were on average 0.85 and 0.96, respectively, which also corresponds well to previous observations [12, 28]. Thus, the results of the present study confirms that the natural variability observed in the stride-to-stride time intervals during walking is similar to the one observed when individuals are asked to walk with pink noise pacing [12, 13, 16, 19, 25-28].

The importance of pink noise pacing

The second hypothesis was also supported as the results showed a higher scaling exponent of the stride-to-stride time interval variability during the trial with the PNND pacing compared to the trial with the SPNND pacing. This suggests that the temporal information embedded in the pink noise is responsible for the structure in the stride-to-stride time intervals during the trial with the PNND pacing and that this structure can be altered by removing the temporal correlations in the pacing signal alone. Using a passive walker model, it has previously been shown that the temporal structure of natural variability of stride-to-stride time intervals during SPW does not require the presence of higher order neural control structures but can emerge from the dynamical interactions of passive structures alone [9, 14]. These studies were performed with a passive walker and thus it is possible that the passive dynamics of such models could be sufficient to generate chaos during walking. Here we do not counter the importance of the passive dynamics in generating a fractal structure in gait variability but we also suggest that sensory information could eventually play an important role in controlling this pattern.

The affinity to normal distribution

The third hypothesis had limited support as the results showed a higher scaling exponent of the stride-to-stride time interval variability during the trial with the SPNND pacing compared to the trial with the WNUD pacing, but there was insufficient evidence to determine whether the trial with the WNND pacing produced larger scaling exponents than the WNUD trial. A more compelling case would have been made were both comparisons to have produced at least substantial evidence. Of note, however, is that strongest evidence we observed of a difference between trials was between the PNND and WNUD trials, suggesting that the WNUD trial is especially degrading to natural structures of variability. Pending replication, these results favor the interpretation that the probability distribution of the visual cues does influence the temporal structure in the stride-to-stride time intervals. Furthermore, the results indicate that a specific likelihood of obtaining visual input is crucial for the motor control of gait. In other words, it seems critical for the control of walking that specific visual information is more likely to be obtained than other information; suggesting a clear priority of the available visual input. This supports previous observations of the stride-to-stride time intervals being normally distributed in healthy individuals during SPW, which also indicates an affinity to normal distributions in motor control of un-paced walking [32, 33].

Combined with the cue-matching performance data, the above results suggest an affinity in the sensorimotor system towards a normal probability distribution of both the sensory input and executed movement pattern. Unconstrained by task, the sensorimotor system produces stride-to-stride time intervals with a pink noise structure that conforms to a normal distribution. Moreover, cue-matching performance was best when visual cues exhibited both a pink noise structure and a normal distribution. A notable limitation of that interpretation is that our study

did not include a trial with a pacing signal that had a pink noise pattern and uniform distribution. However, another study conducted in our laboratory addresses this issue and suggests that both the noise type patterns and the probability distributions, present in visual cues, exert seemingly independent effects on stride-to-stride time interval variability. Thus, when changing from a pink to a white noise pattern in the pacing signals, the scaling exponent of the on stride-to-stride time interval variability decreased, regardless of the probability distribution (i.e. normal or uniform). Also when changing from normal to uniform distribution in the pacing signals, the scaling exponent decreased, regardless of the noise type pattern (i.e. pink or with) [4].

The present study included young healthy adults with no neuromuscular impairments. It is to the best of our knowledge, unknown if altering the probability distribution of the paced signals would affect the complexity of stride-to-stride time intervals in older adults or patients with neurological disorders differently than the young healthy adults in the present study. Thus, future studies should determine the importance of adjusting the probability distribution of the pacing signals when used for gait training or rehabilitation purposes. Experimenters should be sure that the desired dynamics of the stride-to-stride time intervals are reflected in the temporal pattern and probability distribution of the pacing signals. Insights into distributional changes with age or neurological disorders may allow for the development of pacing signals specifically designed for improved rehabilitation strategies.

Temporal pattern and distribution of pacing cues in the context of Optimal Movement Variability

The Optimal Movement Hypothesis (OMVH) suggests that variability is an essential feature of human movement and that healthy variability takes optimal forms [24]. Elaborated, this hypothesis suggests that human movements strike a balance between predictability and

complexity. Movement patterns that are completely unpredictable lack structure necessary to produce coherent movements; movement patterns that are completely predictable lack the flexibility needed to adapt movement to an ever-changing environment. Complexity refers to the behavioral richness in a sequence of movements. Sensorimotor systems only capable of producing one or a few states have too small a repertoire to meet changing environmental constraints. High complexity, however, combined with a moderate level of predictability allows the sensorimotor system a large, coherent repertoire from which to select behavioral solutions to internal (i.e., intended actions) and external constraints (i.e., environmental fluctuations). This is often captured as an inverted "U" shaped function (see figure 2 in Stergiou, Harbourne, & Cavanaugh (2006) [24]).

The current results support the essential elements of the OMVH because stride intervals observed during SPW trials strike the specific balance implied by that hypothesis. Idealized pink noise, being statistically similar to natural healthy stride-to-stride variability, entails a large range of possible values while maintaining a high degree of local predictability. However, our inclusion of uniform white noise raises questions about whether too much complexity is detrimental in sensorimotor systems. Indeed, our results showed that WNUD trials produced the lowest scaling exponents and the greatest deviations from normality. From a probability standpoint, the complexity of a signal may be characterized by its distributional entropy. Entropy is at a maximum in a uniform distribution as all values are equally likely to occur. The entropy of a normal distribution is, by definition, less than uniform noise, reflecting a lower but non-zero complexity. One potential interpretation of our results, then, is that the uniformly distributed white noise is too distributionally complex which creates an extra challenge for sensorimotor synchronization, perhaps creating a mismatch between the tendencies of the

sensorimotor system and the to-be-coordinated stimulus. In any case, differential movement patterns corresponding to different visual cue patterns underscore the need to form a rigorous definition of complexity in the context of human movements. That is, we contend that we have reached a critical point in the trajectory of the OMVH where it is time to formulate the following question: What are the appropriate measures, continuums, or qualities that we, as human movement scientists, should use to distinguish complex from non-complex movements? This is a deceptively difficult question. We are currently engaged in both theoretical and empirical work to address this question, and we hope this brief treatment will stimulate others consider this issue as well.

Declarations

Funding

This study was supported by National Institutes of Health (NIGMS/P20GM109090). NS is also supported by the Center for Research in Human Movement Variability, NIA/R15AG063106 and NINDS/R01NS114282.

Conflict of interest/Competing interests

The authors declare that they have no conflict of interest.

Availability of data and material

Data will be made available on reasonable request.

Code availability

Code will be made available on reasonable request.

Ethics approval

The study was approved by the Institutional Review Board of the University of Nebraska Medical Center, and the study was carried out in accordance with the approved guidelines.

Consent to participate

The participants provided informed written consent prior to participation.

Consent to publication

The participants provided informed written consent prior to participation for the publication of the results.

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Legends

Table 1 Scaling exponent for the visual cues for each subject for each trial

Table 2 Post hoc comparisons of scaling exponent from different pacing signals

Table 3 Post hoc comparisons of the normality distribution of footsteps

Table 4 Post hoc comparisons of asynchrony between footsteps and visual cues

Fig. 1 Examples of the four different pacing stimulus signals (left graphs) and their distribution (right graphs). Top graphs: pink noise signal with a normal distribution (PNND). Second from the top graphs: shuffled pink noise signal with a normal distribution (SPNND). Second from the bottom graphs: white noise signal with normal distribution (WNND). Bottom graphs: white noise with uniform distribution (WNUD)

Fig. 2 Pacing signal viewed by participants through the glasses. The grey bar moves up and down between the two white bars. Right heel strike should occur when the moving bar reaches the top stationary bar and left heel strike should occur when it reaches the bottom stationary bar

Fig. 3 Scaling exponent for the stride-to-stride time intervals during the five trials. SPW: self-paced walking trial, PNND: trial with pink noise signal with a normal distribution, SPNND: trial with shuffled pink noise signal with a normal distribution, WNND: trial with white noise signal with a normal distribution, WNUD: trial with white noise signal with a uniform distribution. The dotted horizontal lines indicate 0.5 and 1.0. Mean and median values are indicated by the dashed and solid lines within the box, respectively

Fig. 4 Normality distribution of footstep during four stimulation trials. PNND: trial with pink noise signal with a normal distribution, SPNND: trial with shuffled pink noise signal with a normal distribution, WNND: trial with white noise signal with a normal distribution, WNUD:

trial with white noise signal with a uniform distribution. Mean and median values are indicated by the dashed and solid lines within the box, respectively

Fig. 5 Cue-matching of the footstep and the visual cues for the four stimulation trials. PNND: trial with pink noise signal with a normal distribution, SPNND: trial with shuffled pink noise signal with a normal distribution, WNND: trial with white noise signal with a normal distribution, WNUD: trial with white noise signal with a uniform distribution. The lower the D-value, the greater the cue-matching performance. Mean and median values are indicated by the dashed and solid lines within the box, respectively

Table 1: Scaling exponent for the visual cues for each subject during each trial.

Subject	PNND	SPNND	WNND	WNUD
1	1.00	0.61	0.49	0.51
2	1.01	0.47	0.51	0.45
3	1.03	0.5	0.51	0.51
4	0.98	0.52	0.47	0.52
5	0.97	0.52	0.51	0.49
6	1.02	0.52	0.52	0.5
7	0.97	0.51	0.5	0.51
8	0.99	0.53	0.57	0.51
9	0.97	0.54	0.53	0.5
10	1.02	0.59	0.53	0.51
Group mean ± SD	1.00 ± 0.02	0.53 ± 0.04	0.51 ± 0.03	0.50 ± 0.02

Table 2: Post hoc comparisons of scaling exponent from different pacing signals.

		Prior Odds	Posterior Odds	$BF_{10,U}$	Error %
SPW	PNND	0.3	0.7	2.1	4.34e -4
	SPNND	0.3	2.8	8.8	8.98e -5
	WNND	0.3	5.0	15.7	5.65e -7
	WNUD	0.3	24.5	76.8	1.56e -4
PNND	SPNND	0.3	177.4	555.1	1.03e -5
	WNND	0.3	310.1	970.6	6.08e -7
	WNUD	0.3	9513.6	29775.7	4.42e -8
SPNND	WNND	0.3	0.3	0.9	0.01
	WNUD	0.3	3.1	9.8	7.53e -5
WNND	WNUD	0.3	0.9	2.8	1.72e -4

Note. The posterior odds have been corrected for multiple testing by fixing to 0.5 the prior probability that the null hypothesis holds across all comparisons (Westfall, Johnson, & Utts, 1997). Individual comparisons are based on the default t-test with a Cauchy (0, r =1/sqrt(2)) prior. The "U" in the Bayes factor denotes that it is uncorrected.

Table 3: Post hoc comparisons of the normality distribution of footsteps.

		Prior Odds	Posterior Odds	$BF_{10,U}$	Error %
PNND	SPNND	0.414	1.359	3.280	3.788e -4
	WNND	0.414	0.909	2.195	3.388e -4
	WNUD	0.414	30.327	73.216	1.520e -4
SPNND	WNND	0.414	0.272	0.656	0.002
	WNUD	0.414	17.742	42.833	3.112e -5
WNND	WNUD	0.414	12.778	30.848	1.595e -4

Note. The posterior odds have been corrected for multiple testing by fixing to 0.5 the prior probability that the null hypothesis holds across all comparisons [30]. Individual comparisons are based on the default t-test with a Cauchy (0, r =1/sqrt(2)) prior. The "U" in the Bayes factor denotes that it is uncorrected.

Table 4: Post hoc comparisons of asynchrony between footsteps and visual cues.

		Prior Odds	Posterior Odds	$BF_{10,U}$	Error %
PNND	SPNND	0.414	170.7	412.1	6.867e -6
	WNND	0.414	1153.1	2783.8	1.027e -6
	WNUD	0.414	2355.6	5687.0	6.334e -8
SPNND	WNND	0.414	0.16	0.40	0.005
	WNUD	0.414	0.15	0.36	0.005
WNND	WNUD	0.414	0.13	0.31	0.007

Note. The posterior odds have been corrected for multiple testing by fixing to 0.5 the prior probability that the null hypothesis holds across all comparisons (Westfall, Johnson, & Utts, 1997). Individual comparisons are based on the default t-test with a Cauchy (0, r =1/sqrt(2)) prior. The "U" in the Bayes factor denotes that it is uncorrected.

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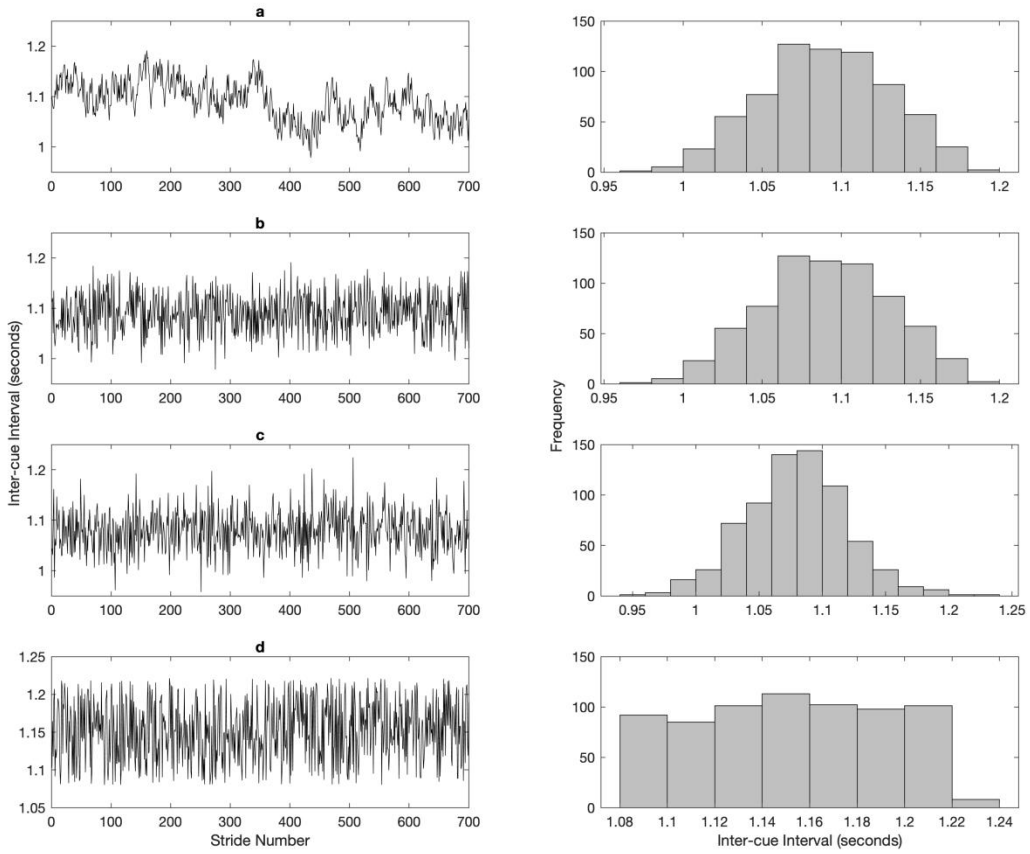

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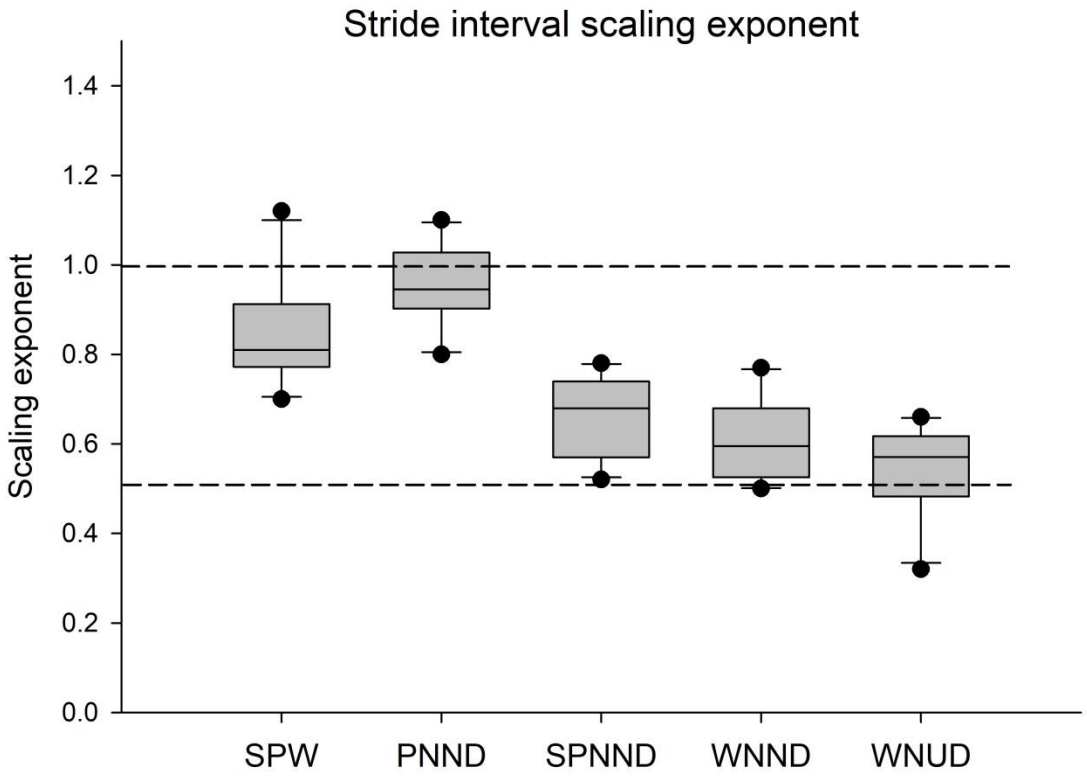

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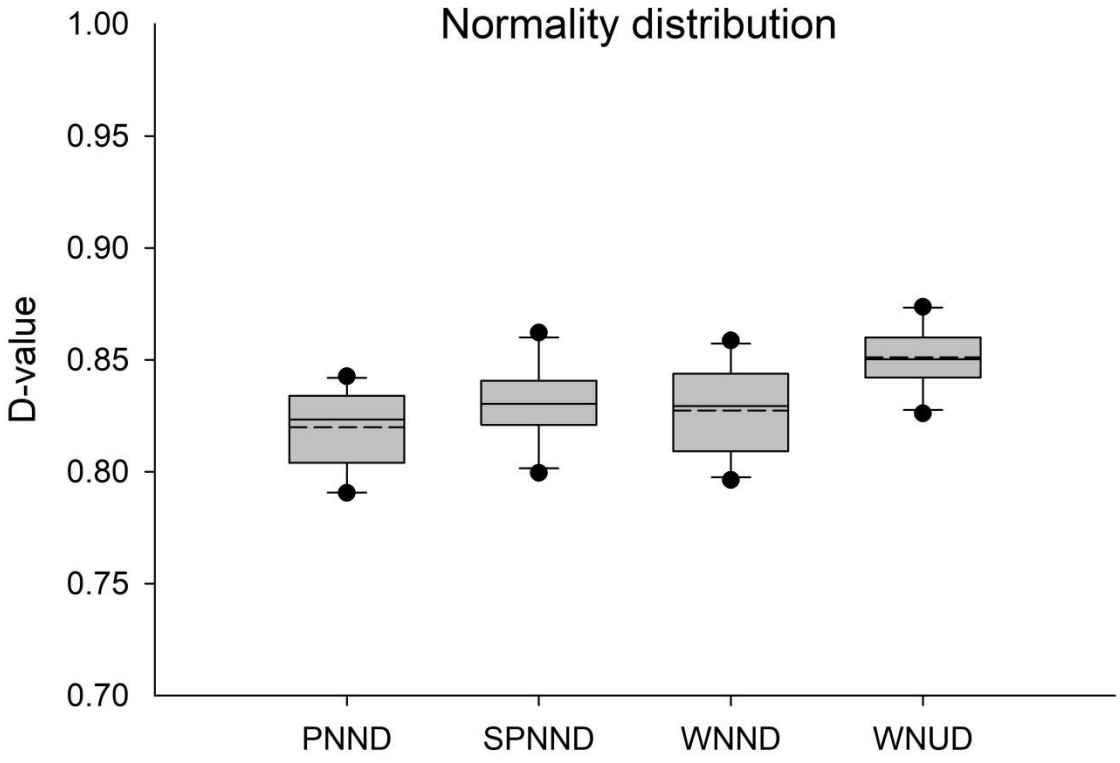

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