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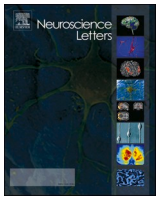

Stride-to-stride time intervals are independently affected by the temporal pattern and probability distribution of visual cues

Peter C. Raffalt [a,b], Joel H. Sommerfeld [b], Nick Stergiou [b,c], Aaron D. Likens [b,*]

[a] Department of Biology, University of Southern Denmark, Campusvej 55, 5230 Odense, Denmark
[b] Department of Biomechanics and Center for Research in Human Movement Variability, Division of Biomechanics and Research Development, University of Nebraska at Omaha, 6160 University Drive South, Omaha, NE 68182, USA
[c] Department of Environmental, Agricultural, and Occupational Health, University of Nebraska Medical Center, 984388 Nebraska Medical Center, Omaha, NE 68198, USA

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ABSTRACT

The temporal structure of the variability of the stride-to-stride time intervals during paced walking is affected by the underlying autocorrelation function (ACF) of the pacing signal. This effect could be accounted for by differences in the underlying probability distribution function (PDF) of the pacing signal. We investigated the isolated and combined effect of the ACF and PDF of the pacing signals on the temporal structure of the stride-to-stride time intervals during visually guided paced overground walking. Ten young, healthy participants completed four walking trials while synchronizing their footstep to a visual pacing signal with a temporal pattern of either pink or white noise (different ACF) and either a Gaussian or normal probability distribution (different PDF). The scaling exponent from the Detrended Fluctuation Analysis was used to quantify the temporal structure of the stride-to-stride time intervals. The ACF and PDF of the pacing signals had independent effects on the scaling exponent of the stride-to-stride time intervals. The scaling exponent was higher during the pink noise pacing trials compared to the white noise pacing trials and higher during the trials with the Gaussian probability distribution compared to the uniform distribution. The results suggest that the sensorimotor system in healthy young individuals has an affinity towards external cues with a pink noise pattern and a Gaussian probability distribution during paced walking.

1. Introduction

Human movements are inherently variable. This can be easily observed in the motor performance of multiple repetitions of a task such as the variations identified in the stride-to-stride time intervals during locomotion [17,29–31]. Interestingly, when exposed to external visual or auditory cues, humans can entrain their footsteps to the pacing signal through the process of sensorimotor synchronization [12,24,28]. This emphasizes the importance of sensory input integration in the motor control of walking and has been utilized as a rehabilitation tool to restore impaired gait function in patients and older adults [2,3,10,25]. Specifically, Hove and colleagues observed that Parkinson's patients restored their impaired gait during walking with an interactive auditory pacing signal which incorporated the dynamics of the patients' gait to generate a cue-step entrainment [10]. The gait restoration effect during the interactive pacing trial was carried over to non-paced walking immediately after the intervention [10]. Additionally, three-weeks training of arm-in-arm walking between a younger and older individual has been observed to improve the gait of the older individual for up to two weeks post the intervention [2]. Furthermore, it is well established that paced walking can alter the temporal structure of the variability in the stride-to-stride time intervals when exposed to different types of pacing signals [2,3,10–12,15,25,32,34,37,39].

To assess the effect of different pacing signals on the variability in stride-to-stride time intervals (their temporal structure), the method of Detrended Fluctuation Analysis (DFA) has been widely used [7–9]. DFA returns a scaling exponent. When the value of the exponent is above 0.5, this indicates statistical persistence in the variability of the stride-to-stride time intervals. This means that a deviation from the mean of the stride-to-stride time in one direction is likely to be followed by a deviation in the same direction. A scaling exponent that has a value below 0.5 indicates a statistical anti-persistence in the variability which means

* Corresponding author.
E-mail address: alikens@unomaha.edu (A.D. Likens).

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that a deviation from the mean of the stride-to-stride time intervals in one direction is likely to be followed by a deviation in the opposite direction. If the scaling exponent is close to 0.5, it indicates that the variability of the stride-to-stride time intervals have an uncorrelated structure with no temporal correlation. In healthy individuals, the scaling exponent of the variability in stride-to-stride time intervals during un-paced walking has been observed to be close to 1.0, indicating that a healthy gait pattern demonstrates variability in the stride-to-stride time intervals with the presence of statistical persistence [8,9,12,33].

Studies from our research team have also used different signal types as pacing signals to alter the temporal structure of the variability of the stride-to-stride time intervals during paced walking and thereby altering the scaling exponent [11,12,20,37,39]. These types of signals include different colors of noise with different underlying autocorrelation functions (ACF) and power spectrum density e.g. white noise which has a flat power spectrum density and pink noise which has decreasing power spectrum density (−3.01 dB/octave). The quantification of the temporal pattern of these pacing signals using DFA reveals that white noise signal has a scaling exponent of 0.5 and pink noise signal has a scaling exponent of 1 [11,13]. Our studies have shown that the temporal structure of the variability of the stride-to-stride time intervals in young healthy individuals during paced walking follows the temporal pattern of the pacing signals. Thus, when walking with a pink noise pacing signal, the scaling exponent of the variability of the stride-to-stride time intervals is close to 1 which indicates the presence of a strong statistical persistence in the variability of the stride-to-stride time intervals. When walking with a white noise pacing signal, the scaling exponent is above but close to 0.5 which indicates that the variability of the stride-to-stride time intervals possess a weak statistical persistence tending towards an uncorrelated structure. Furthermore, if an invariant pacing signal (e.g. an isochronous metronome) is used, the scaling exponent of the variability of the stride-to-stride time intervals is below 0.5 indicating that the variability of the stride-to-stride time intervals possess statistical anti-persistence [11–13,20,37,39]. This indicates that paced walking with a specific temporal pattern embedded in the pacing signal offers a potent manipulator of the temporal structure of stride-to-stride time intervals. In addition, the use of pink noise as the pacing signals induce the same statistical persistence in the stride-to-stride time intervals as during un-paced walking in healthy young individuals.

Recently, we have also observed that paced walking with pink noise pacing signals can restore the temporal structure of the stride-to-stride time intervals of older adults towards that of younger adults as the scaling exponent changed from 0.71 during self-paced walking (SPW) to 0.85 during pink noise paced walking. These restored healthy values were retained after the paced signal was removed (scaling exponent of 0.86) [38]. Furthermore, we also recently observed that paced walking with a pink noise pacing signal elicited greater resilience to external perturbations compared to paced walking with a periodic pacing signal [13,21]. Thus, paced walking with a pink noise pacing signal seems to be a promising tool for gait rehabilitation and fall prevention for fall prone populations [13]. Together, these results also support the Optimal Movement Variability Hypothesis (OMVH) where healthy human movements are believed to be characterized by an optimal combination of moderate predictability and high complexity at which the sensorimotor system possesses the necessary structure to produce coherent movements and sufficient flexibility to adapt to an ever-changing environment [31]. SPW for healthy individuals or paced walking with pink noise pacing signals reflect this optimal state. On the other hand, paced walking with white noise or invariant pacing signals or SPW of older adults and patients, reflect conditions outside this state. It should be stated that in the framework of OMVH, predictability refers to the level of repeatable patterns in the behavior of the system in question. Thus, the investigated behavior can be characterized on the continuum between a highly repetitive or completely random and various entropy measures can be used for the quantification of predictability. In contrast, complexity refers to behavioral characteristic which spans multiple spatial and temporal scales which captures the infinitely entangled components of the system in question. For the quantification of this entity, single or multiscale fractal measures are often used.

During paced walking with different noise types as pacing signal, the temporal order in which the cues are provided is determined by the ACF. However, it could also be influenced by the underlying probability distribution function (PDF) which determines the likelihood of a given cue being provided at a given time point. Two distinctly different probability distributions are Gaussian and uniform. In a pacing signal with a Gaussian probability distribution, there is a greater likelihood of obtaining cues with a value close to the mean value of the signal and less likelihood of receiving cues with a value far from the mean of the signal. In contrast, in a pacing signal with a uniform probability distribution, there is an equal likelihood of receiving any of the cues within the signal. As two frequently used signals for paced walking, white noise and pink noise represent signals with different ACFs [11,12,21,37,39]. However, they can also be generated with different PDFs e.g., either a Gaussian or uniform distribution (Fig. 1).

While the aforementioned differences in the temporal structure of the stride-to-stride time intervals during paced walking have been attributed the differences in the autocorrelation of the pacing signals, we recently observed that the probability distribution of the pacing signals may also influence the temporal structure [20]. During visually paced walking with a Gaussian distributed white noise pacing signal, the DFA scaling exponent of the stride-to-stride time intervals were close to 0.5. However, when using white noise with a uniform distribution as the pacing signal, the scaling exponent decreased further towards 0.5 [20]. This suggests that change in the probability distribution by itself can affect the scaling exponent of the stride-to-stride time intervals. From an OMVH perspective, one possible interpretation of this result is that the inclusion of a uniform distribution increases the distributional complexity of the pacing signals which challenge the sensorimotor synchronization process [20]. The inclusion of a uniform distribution instead of a Gaussian distribution in the white noise pacing signal creates a mismatch between the distributional preference of the sensorimotor system and the externally provided to-be-coordinated stimulus. This mismatch results in the greatest deviation in the scaling exponent of the stride-to-stride time intervals during the uniform white noise condition compared to the un-paced condition. To further test this interpretation and to decipher the role of the ACF and PDF of the pacing signals for sensorimotor synchronization, the next logical experimental step is to include a pacing trial which combines both pink noise and a uniform distribution.

Therefore, the purpose of the present study was to investigate the isolated and combined effect of ACF and PDF of the pacing signals on the temporal structure of the stride-to-stride time intervals during visually guided paced overground walking. To accomplish this purpose, we included four paced walking trials with the following pacing signals: 1) pink noise with Gaussian distribution (PG), 2) pink noise with uniform distribution (PU), 3) white noise with Gaussian distribution (WG) and 4) white noise with uniform distribution (WU); in addition to a SPW trial. DFA scaling exponent was used to quantify the temporal structure of the variability of the stride-to-stride time intervals. We hypothesized that 1) the scaling exponent would be highest and close to 1.0 during the PG trial, 2) that the inclusion of either white noise pattern (WG and WU trial) or uniform distribution (PU and WU trials) in the pacing signals would decrease the scaling exponent compared to the PG trial and 3) that the scaling exponent during the trial with combined use of white noise pattern and uniform distribution (WU) in the pacing signal would be lower than the three other trials and close to 0.5.

2. Methods

2.1. Participants

Ten healthy young adults (3 females, 7 males; age = 25 ± 3.8 years;

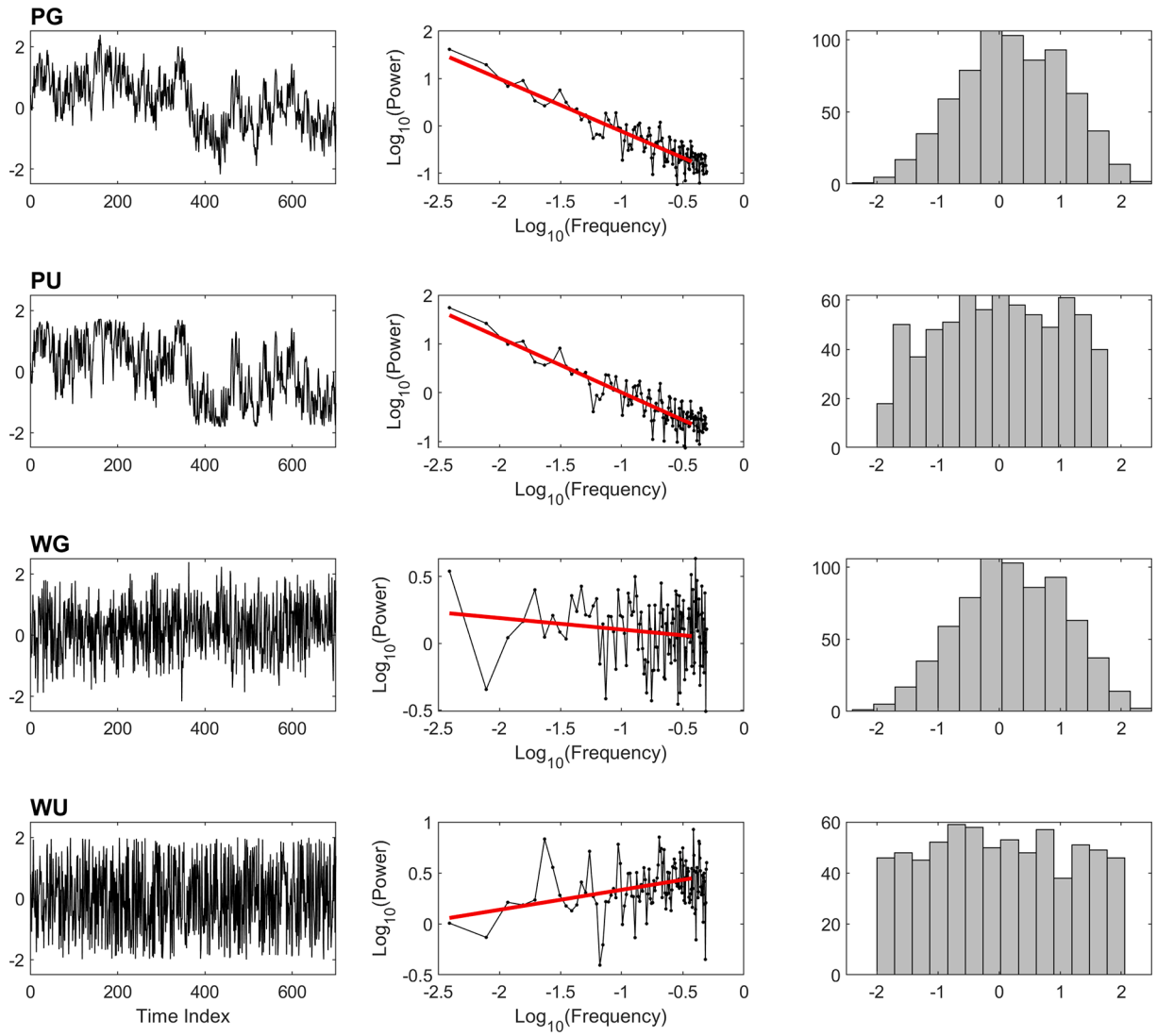

Fig. 1. Examples of the four pacing signals Gaussian pink noise (top row), uniform pink noise (second row), Gaussian white noise (third row) and uniform white noise (bottom row) with corresponding power spectral density (second column) and probability distribution (third column).

body mass = 80.2 ± 16.1 kg; height = 1.78 ± 0.12 m) with no neurological or musculoskeletal disorders participated in this study. All participants provided informed written consent prior to participation. The study protocol was approved by the University of Nebraska Medical Center Institutional Review Board, and the study was carried out in accordance with the approved guidelines.

2.2. Experimental protocol

Upon arrival to the laboratory, the participants were informed of the experimental protocol and footswitch sensors sampling at 1500 Hz (Noraxon, Scottsdale, AZ, USA) were placed under both heels for heel strike identification. This sampling frequency ensured a heel strike event detection precision of more than 1 ms.

The participants completed five overground walking trials on an indoor 1/8th mile long track separated by at least 5 min of rest between the trials and where each trial included a minimum of 700 strides (approximately 13 min duration). First, the participants completed a SPW trial followed by the four paced trials PG, PU, WG and WU in randomized order. During the paced trials, the participants received visual cues through worn non-prescription glasses with an attached mini HDMI screen (Vufine+, Sunnyvale, CA, USA). The visual cue was a horizontal bar which moved vertically between two stationary bars (Fig. 2). The participants were instructed to synchronize their right heel strike to the moving bar reaching the stationary top bar and their left heel strike to the moving bar reaching the bottom stationary bar (Fig. 2). The timing of the moving bar was scaled to the mean and standard deviation of the stride-to-stride time intervals recorded during the SPW trial for each participant. The four pacing signals displayed to the participants were generated in using custom made scripts in MATLAB (MathWorks Inc. Natrick, MA). The PG signal was created in an iterative fashion by first simulating PG from an algorithm documented in Supplementary Material in a file named 'pinkNoise.m'). Next, the noise was checked using DFA to ensure it had an α close to 1. If not, then the process repeated until convergence was met ($0.996 < \alpha < 1.004$). WG was also created in an iterative fashion by randomly permuting the PG signal until DFA measured $0.496 < \alpha < 0.504$. In this way, the two signals contained the exact same values – and consequently identical PDF – but differed in ACF. WU was generated using the 'rand' function in MATLAB but also in an iterative fashion, checking for the same convergence criteria as WG. Lastly, PU signal was constructed by re-ordering WU to have the same rank ordering as the PG signal. This process is documented in Supplementary Material in a file named 'GeneratedNoiseTS.m'. The maximal and minimum of the DFA alpha values of each pacing signals are presented in Table 1. The present study used visual cues following the conclusion based on previous

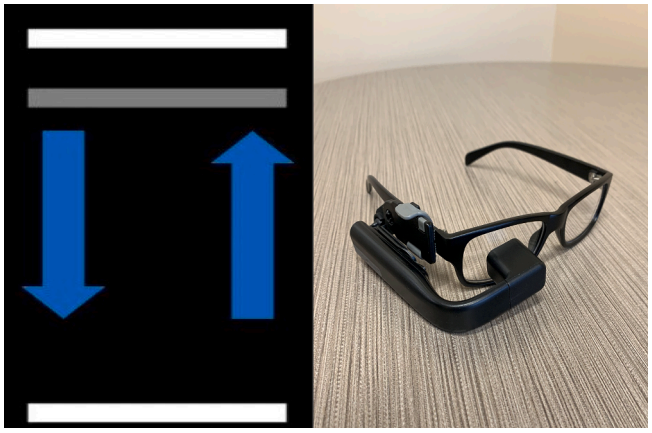

Fig. 2. The participants wore glasses with an HDMI display attachment (right picture). This display was placed only on the right side and allowed participants to view the visual pacing signal while simultaneously being unobtrusive to their normal vision. The continuous visual stimulus viewed by participants consisted of a grey bar moved from top to bottom (left picture). The participants were instructed to match the heel strikes of their right foot to the top and left heel strikes with the bottom of the bar's path. The blue arrows present on the figure are only illustrative of the bar's movement direction.

Table 1
Maximum and Minimum values of α for all pacing signal conditions.

	PG	PU	WG	WU
Max α Value	1.03	0.99	0.51	0.52
Min α Value	0.92	0.77	0.42	0.45

observations from our lab of visual cues being superior to auditory cues during paced treadmill walking [39].

2.3. Data analysis

Stride-to-stride time intervals were calculated as the time between two consecutive heel strikes of the same foot. The initial and final 50 strides were discarded from the stride-to-stride time intervals time series from the paced walking trials prior to further analysis to avoid any transient effect related to visual stimulus familiarization. The length of the analyzed time series (n = 600 strides) were in agreement with previous recommendations for DFA calculations [5].

DFA was used to quantify the temporal structure of the stride-to-stride time interval variability during the five trials [9]. DFA includes several calculation steps. First, the time series is integrated by calculating the cumulative sum of the deviations around the mean (Equation (1)).

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

Second, the time series is divided into windows of equal length, *n* and a least square line is fitted to each window. Third, the *y* coordinate of the straight-line segments, $y_n(k)$, is used to detrend the time series, y(k), after which the root mean square fluctuation is calculated (equation (2)).

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

This procedure is repeated across the entire time series to assess the relationship between the average fluctuation, *F(n)*, as a function of window size *n*. To characterize the fluctuations, a scaling exponent is calculated as the slope of the linear relationship between log*F(n)* and log*n* [18]. The present study used an average evenly-spaced DFA algorithm as recommended by Almurad and Deligniéres [1]. A box size range of [16, N/9] and a scaling region of 10–30 were used for the DFA in the present study.

2.4. Statistics

To test if the stride-to-stride time intervals deviated from a Gaussian distribution, a one-sample Kolmogorov-Smirnov test was applied. A potential limitation of comparing distributions with KS test is that it only compares the one value, the maximum distance between respective cumulative distributions. In search of convergent validity, we also fit a normal distribution to each time series using a maximum likelihood approach. Subsequently, we compared the deviances (deviance = -2 × loglikelihood) to determine if normality depended on experimental conditions.

To investigate if the probability distributions of the stride-to-stride time intervals and the corresponding visual cues during each trial were similar, a two-sample Kolmogorov-Smirnov test was applied. This test quantifies the difference in probability distribution between the two investigated signals and returns a D-value. D-values below the critical D-limit (with a level of significance set at 0.05) indicate that the two signals had similar probability distribution. Additionally, the D-value was used as a proxy measure of the cue-matching performance i.e., how well the footsteps were timed to the visual cues. Greater cue-matching performance was characterized by low D-values.

The present study adopted a Bayesian analytical approach which is briefly described below (for details see references [16,26,27,40]). A two-way Bayesian repeated measure ANOVA was applied to investigate the effect of the different cue signals on the D-values from the one-sample and two-sample Kolmogorov-Smirnov tests and the scaling exponent of the stride-to-stride time intervals. The present study used an objective Bayesian ANOVA with default Cauchy priors which entailed the computing and interpreting the Bayes Factor (BF_{10}) as an alternative to the traditional p-value often reported in frequentist statistics. The BF_{10} is a ratio representing the information in favor of the alternative hypothesis relative to the null hypothesis. To interpret the BF_{10}, the following intervals were related to the strength of the evidence in favor of the alternative hypothesis: $BF_{10} = 1 – 3$ 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} greater than 100 represents decisive evidence. The following intervals of the BF_{10} were related to the strength of the evidence in favor of the null hypothesis: $BF_{10} = 1/3 – 1$ 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 [42]. $BF_{10} = 1$ represent no evidence in favor of either of the two hypothesis. We do note that the above categories are not to be taken as absolute, nor are they to be used to make dichotomous decisions or absence about an effect. Instead, the above categories are meant to provide researchers with a vocabulary to describe the strength of empirical results. Between-trial differences in D-values and scaling exponents were investigated using post hoc tests with the posterior odds corrected for multiple comparisons [41]. All statistical analyses were performed in JASP (JASP Team, 2021).

3. Results

The data from the PU trial of two participants were excluded due to equipment failures.

3.1. Scaling exponent of the visual cues

The scaling exponents of the four pacing signals PG, PU, WG and WU were 0.97 ± 0.03, 0.93 ± 0.06, 0.45 ± 0.16 and 0.43 ± 0.15, respectively.

3.2. Scaling exponent of the stride-to-stride time intervals

There was substantial evidence for including both main effects of ACF and PDF ($BF_{10} = 4.72$) on the scaling exponent of the stride-to-stride time intervals and there was anecdotal evidence against including an interaction ($BF_{10} = 0.431$; Fig. 3). There was decisive evidence ($BF_{10} = 3.99 \times 10^5$) suggesting that the stride-to-stride time intervals during trials with pink noise as pacing signal returned higher scaling exponents compared to the white noise trials regardless of the PDF. There was limited evidence ($BF_{10} = 2.12$) suggesting that the stride-to-stride time intervals during trial with a Gaussian distribution of the cues returned higher scaling exponent compared to the uniform distribution trials regardless of the ACF.

The scaling exponent stride-to-stride time intervals was 10.15 % lower compared to the scaling exponent of the corresponding pacing signal during the PG trial, 9.13 % lower during the PU trial, 24.96 % higher during the WG trial and 13.41 % higher during the WU trial.

3.3. Normality distribution of stride-to-stride time intervals

There was substantial evidence for including both main effects for ACF and PDF as well as their interaction effect ($BF_{10} = 7.71$) on the D-value from the one-sample KS test (Fig. 4). The interaction revealed that there was strong evidence ($BF_{10} = 10.12$) suggesting a higher D-value during the WU trial compared to the PU trial. The was not enough evidence ($BF_{10} = 1.53$) to make conclusions about the difference between the PG and WG trials.

Based on maximum likelihood estimation, there was substantial evidence for only including effect of ACF on deviances ($BF_{10} = 3.26$). That is, regardless of PDF, results from maximum likelihood estimation suggested that stride intervals produced during white noise conditions were better fit by Gaussian distribution than a uniform distribution ($BF_{10} = 2201.98$).

3.4. Cue-matching performance

There was substantial evidence ($BF_{10} = 7.1$) that the effect on the D-value from the two-sample KS test was attributable to the ACF alone. That is, there was substantial evidence against a main effect of PDF ($BF_{10} = 0.39$), but there was insufficient evidence to determine the presence of an interaction ($BF_{10} = 0.18$; Fig. 5), potentially suggesting the need for a larger data set. There was very strong evidence ($BF_{10} = 61.51$) suggesting that the D-value was larger during trials with white noise as the pacing signal compared to pink noise trials regardless of the PDF.

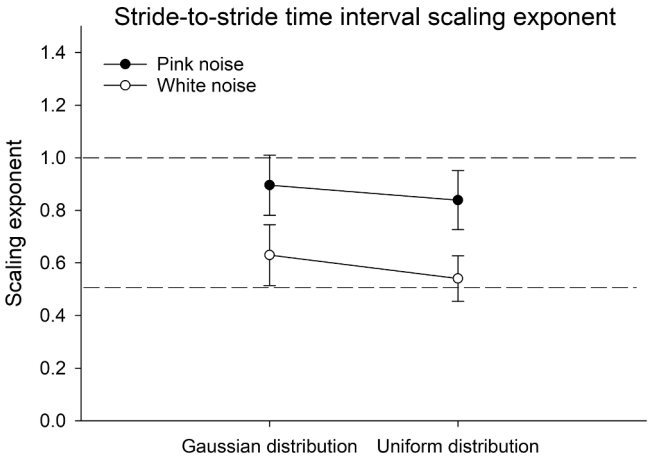

Fig. 3. Mean ± SD of scaling exponent of the stride-to-stride time intervals for the four pacing trials with the two noise types (pink and white) and two probability distributions (Gaussian and uniform). The scaling exponent increased as a function of both noise type and probability distribution with pink noise and Gaussian distribution having higher scaling exponents.

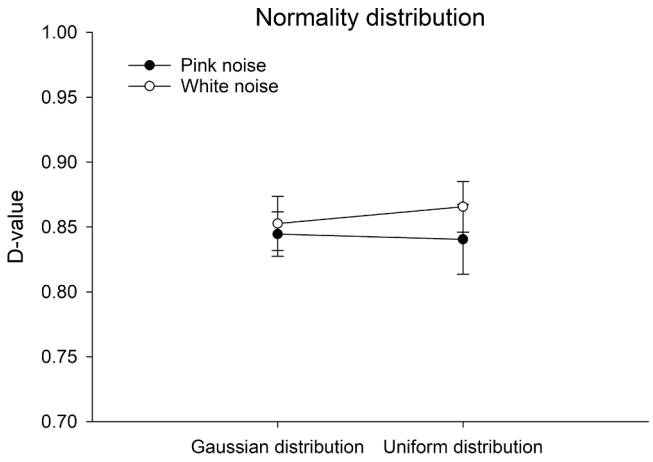

Fig. 4. Mean ± SD of the D-value from the one-sample KS test for normality distribution in the stride-to-stride time intervals for the four pacing trials with the two noise types (pink and white) and two probability distributions (Gaussian and uniform). The D-value was higher during the WU trial compared to the PU trial.

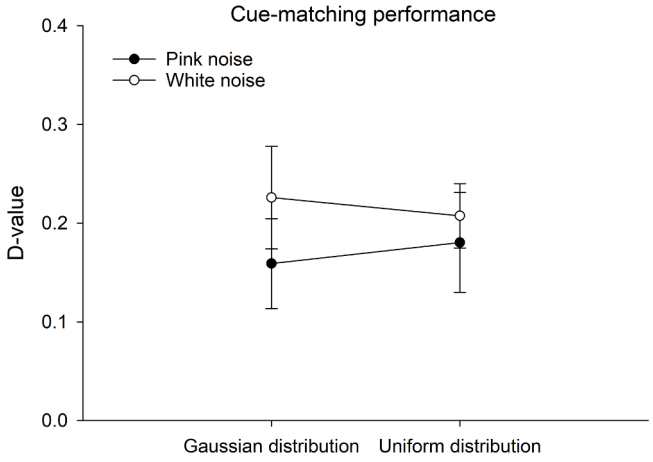

Fig. 5. Mean ± SD of the D-value from the two-sample KS test for cue-matching performance during the four pacing trials with the two noise types (pink and white) and two probability distributions (Gaussian and uniform). The D-value was higher during the white noise trials compared to the pink noise trials.

4. Discussion

The purpose of the present study was to investigate the isolated and combined effect of ACF and PDF of the pacing signals on the temporal structure of the stride-to-stride time intervals during visually guided paced overground walking. This was achieved by including four pacing trials where the pacing signals were combinations 1) of pink and white noise signals which represent two qualitatively different ACFs, and 2) Gaussian and uniform distributions, which represent two qualitatively different PDFs. Temporal structure of the stride-to-stride time intervals was quantified by the DFA scaling exponent. We hypothesized that 1) the scaling exponent would be highest and close to 1.0 during the PG trial, 2) that the inclusion of either white noise pattern (WG and WU trial) or uniform distribution (PU and WU trials) in the pacing signals would decrease the scaling exponent compared to the PG trial and 3) that the scaling exponent during the trial with combined use of white noise pattern and uniform distribution (WU) in the pacing signal would

be lower than the three other trials and close to 0.5.

4.1. Hypothesis 1: Scaling exponent close to 1 during the PG trial

The first hypothesis was supported as the scaling exponent of the stride-to-stride time intervals during the PG trial was 0.90 and higher than the three other pacing trials. This is in line with several previous studies from our laboratory using both visual and auditory cues as pacing signals [11–13,20,37,39]. It suggests that paced walking with a pink noise signal with a Gaussian distribution results in statistical persistence, consistent with the natural variability of the stride-to-stride time intervals.

It is well-established in the literature that the DFA scaling exponent of the variability of the stride-to-stride time intervals is close to 1 during SPW in healthy young individuals [8,9,33,34]. Furthermore, the scaling exponent of the stride-to-stride time intervals is reduced towards 0.5 in older individuals and patients of various disorders [7,10,22]. This indicates that the healthy natural variability of the stride-to-stride time intervals possesses strong statistical persistence, but that age and disorders can alter the temporal structure of the stride-to-stride time intervals towards uncorrelated noise. According to the OMVH, the movement of healthy individuals are characterized by an optimal combination of moderate predictability and high complexity. Changes to the sensorimotor system following aging or disorders are believed to move the individuals away from the optimal state towards either a state of low predictability and low complexity or high predictability and low complexity [30,31]. Equally, walking at speeds above or below the SPW constitutes non-optimal conditions where stride-to-stride time intervals fluctuations and lower limb segment movements have different temporal structure compared to that during SPW [4,19]. Hence, the SPW in healthy young individuals constitutes an optimal condition, where the stride-to-stride intervals produce high complexity and moderate level of predictability as predicted by OMVH. The results of the present study suggest that paced walking to a Gaussian distributed pink noise signal constituted an equally optimal walking condition as SPW. Interestingly, we recently provided evidence suggesting that paced walking with pink noise signals can restore the temporal structure of the stride-to-stride time intervals of older adults and retain the restored values after the paced signal was removed [13,21]. This indicates that paced walking with pink noise as the pacing signals could have a strong impact as a gait rehabilitation tool.

4.2. Hypothesis 2: Reduced scaling exponents during the PU, WG and WU trials

The second hypothesis was supported for the WG and WU trials as there was decisive evidence of a lower scaling exponent during the trials with white noise when compared to the trials with pink noise as pacing signals. Furthermore, it was partly supported for the PU trial, as there was limited evidence of lower scaling exponent during trials with uniform distributed pacing signals compared to the trials with Gaussian distributed pacing signals. These results support our recent study, where we observed that walking paced with either shuffled pink noise with a Gaussian distribution, white noise with a Gaussian distribution, or white noise with a uniform distribution resulted in lower scaling exponent of the stride-to-stride time intervals when compared to paced walking with pink noise with a Gaussian distribution as pacing signal and SPW [20]. Taken together, the present and previous studies provide compelling evidence that both the ACF and the PDF of the pacing signal affect the temporal structure of the stride-to-stride time intervals [20]. The effect of the ACF on the temporal structure of the stride-to-stride time intervals has been presented previously in studies using either auditory or visual pacing cues [11,12,15,24,28,32,37,39]; however, the observed effect of the PDF has to our knowledge not been reported previously. Noteworthy, the results of the present study favored an exclusion of the interaction between the two independent parameters suggesting that ACF and PDF have independent effects on the scaling exponent of the stride-to-stride time intervals.

From the initial OMVH perspective, the pink noise pacing signal represents sensory input with high complexity and moderate predictability and the white noise pacing signal represents sensory input with low complexity and low predictability [30,31]. Our previous findings in combination with the current results suggest the need to reevaluate these assumptions [20]. In pacing signals with a uniform distribution, all values are equally likely to occur which increases the complexity of the signals due to higher distributional entropy compared to the signals with a Gaussian distribution. Thus, the pacing signal used in the PG trial has lower complexity compared to the pacing signal used in the PU trial but the same moderate predictability. The pacing signal in the WG trial has also lower complexity compared to the pacing signal in the WU trial but the same low predictability. The altered complexity and predictability of the pacing signal in the PU, WG and WU trials compared to the PG trial led to a reduction in the scaling exponent of the stride-to-stride time intervals suggesting an impaired sensorimotor synchronization process. Thus, the sensorimotor system appears to have an affinity towards sensory input with temporal structure similar to pink noise and a Gaussian probability distribution. Based on the results of the present study, gait rehabilitation with paced walking should use pink noise signals with a Gaussian distribution compared to alternative signals.

It is noteworthy that the present study only included Gaussian and uniform distributions for the pacing signals. These were chosen as they represent two distinctly different distributions with different distributional entropy. The effect of other distributions with more similar distributional entropy should be investigated in future studies. Furthermore, future studies should aim at establishing reliable and valid methods for quantifying this distributional entropy.

4.3. Hypothesis 3: Scaling exponent close to 0.5 during the WU trial

The third hypothesis was also supported as the scaling exponent of the stride-to-stride time intervals during the WU trial was, on average, 0.54 and lower than during the three other trials. This indicates that the temporal structure of the stride-to-stride time intervals during the WU trial resembled uncorrelated noise where each stride time was uncorrelated to the stride time of previously completed strides. This bolsters our previous observations and suggests that the combination of white noise and uniform distribution in the pacing signals challenge the sensorimotor synchronization process and removes the temporal correlation which normally exists in the natural variability of stride-to-stride time intervals [20]. Thus, the presence of temporal structure in the sensory input during paced walking is crucial for the generation of the temporal structure of the variability of the stride-to-stride time intervals.

Humans can walk energetically favorable and stable (i.e., without falling) in many surroundings and on different surfaces, and while performing competing cognitive tasks (e.g., mobile phone talking or texting) [14,36]. This is only possible due to a flexible motor control system which is capable of solving the task of walking in a number of ways, while still being energy efficient, stable and adaptive [36]. Thus, several internal and external sensory systems can be used to control walking including the vision, hearing, proprioception and vestibular system [6,35]. Excluding one of the sensory inputs does not hinder the motor control of stable walking. For example, the flexibility of the motor control system enables walking with eyes closed, without falling – walkers simply adopt a more cautious strategy [23]. In the present study, the visual input was manipulated by altering the temporal pattern of the cues which affected the temporal structure of the variability of the stride-to-stride time intervals. This suggests that not only spatial information about obstacles, distances to obstacles, or different surfaces influences the stride-to-stride time but also the temporal rate and order of the visual information.

4.4. Stride-to-stride time interval normality distribution and cue-matching performance

The use of pacing signals with Gaussian distribution did not affect the normality of the stride-to-stride time intervals quantified by the one-sample KS test regardless of the noise type. However, the D-value during the PU trial was lower compared to during the WU trials, indicating that the stride-to-stride time interval deviated more from a normal distribution compared when the participants were instructed to synchronize their steps to a pacing signal with white noise pattern and uniform distribution. Thus, the present study replicate the results of our previous study and suggests that the effect of the different noise types on the normality of the stride-to-stride time intervals were only evident when combined with a uniform distribution of the pacing signals [20]. In contrast, the somewhat conflicting evidence from distribution fits based on maximum likelihood suggests that white noise pacing signals were generally better fit by a Gaussian distribution than a uniform distribution. However, we also note that, in most cases, a Gaussian distribution as a better fit for stride intervals produced with white noise pacing signals than those produced with uniform distributions. Clearly, more research will be needed to fully distinguish causal influences of ACFs and PDFs on stride interval distributions.

Interestingly, the results of the cue-matching performance indicated that it was easier for the participants to match their footsteps to the pacing signals with a pink noise pattern compared to a white noise pattern. This was also observed in our previous study and suggests an affinity to the temporal pattern of the pink noise pacing signals for sensorimotor synchronization [20]. The results did not indicate that the underlying probability distribution influenced the cue-matching performance. This could suggest that the ability to match movement to an external visual cue relies on the temporal structure of the cues and not on the likelihood of receiving a given cue.

5. Conclusion

In the present study, we observed that the ACF and PDF of pacing signals have individual effects on the temporal structure of the stride-to-stride time intervals during visual guided paced walking. The temporal structure of the stride-to-stride time intervals was quantified by the DFA scaling exponent and resembled the temporal pattern of the pacing signal. Thus, pacing signals with a pink noise pattern resulted in a scaling exponent of the stride-to-stride time intervals close to 1 which corresponds to that observed when young healthy adults walk un-paced at a self-selected speed. Pacing signals with a white noise pattern resulted in a scaling exponent close to 0.5, which is often observed in older adults and individuals with impaired gait. Changing the probability distribution of the pacing signals from Gaussian to uniform also reduced the scaling exponent of the stride-to-stride time intervals. Together, these results suggest that the sensorimotor system in healthy young individuals has an affinity towards external cues with a pink noise pattern and a Gaussian probability distribution during paced walking. Furthermore, the pacing signals with low predictability (e.g. white noise) or high distributional complexity (uniform distribution) challenged the sensorimotor system which led to a deviations from a normal distribution of the stride-to-stride time intervals and poorer footstep-visual cue matching performance compared to the trials with the pink noise and Gaussian distributed (high complexity and moderate predictability) pacing signal. The results of the present study should be taking into consideration when using paced walking as a rehabilitation tool.

6. Availability of data, material and code

Data and code will be made available on reasonable request.

CRediT authorship contribution statement

All authors contributed to conceptualizing the experiment. PR contributed to drafting, editing, and revising the manuscript as well as figure generation. JS contributed to time series and statistical analyses, writing code, and editing the manuscript. NS contributed to editing and revising the manuscript. AL contributed to drafting, editing, and revising the manuscript as well as performing statistical analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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