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Transitions in persistence of postural dynamics depend on the velocity and structure of postural perturbations

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Abstract
The sensorimotor system prefers sway velocity information when maintaining upright posture. Sway velocity has a unique characteristic of being persistent on a short time-scale and anti-persistent on a longer time-scale. The time where the transition from persistence to anti-persistence occurs provides information about how sway velocity is controlled. It is, however, not clear what factors affect shifts in this transition point. This research investigated postural responses to support surface movements of different temporal correlations and movement velocities. Participants stood on a force platform that was translated according to three different levels of temporal correlation. White noise had no correlation, pink noise had moderate correlation, and sine wave movements had very strong correlation. Each correlation structure was analyzed at five different average movement velocities (0.5, 1.0, 2.0, 3.0, and 4.0 cm·s^{-1}), as well as one trial of quiet stance. Center of pressure velocity was analyzed using fractal analysis to determine the transition from persistent to anti-persistent behavior, as well as the strength of persistence. As movement velocity increased, the time to transition became longer for the sine wave and shorter for the white and pink noise movements. Likewise, during the persistent time-scale, the sine wave resulted in the strongest correlation, while white and pink noise had weaker correlations. At the highest three movement velocities, the strength of persistence was lower for the white noise compared to pink noise movements. These results demonstrate that the predictability and velocity of support surface oscillations affect the time-scale threshold between persistent and anti-persistent postural responses. Consequently, whether a feedforward or feedback control is utilized for appropriate postural responses may also be determined by the predictability and velocity of environmental stimuli. The study provides new insight into flexibility and adaptability in postural control. This information has implications for the design of rehabilitative protocols in neuromuscular control.

Introduction

The control of upright stance is a fundamental aspect of motor control. Being able to maintain and successfully adapt posture is crucial to interacting with constantly changing and novel environments. The neuromuscular system plays a prominent role in the control of posture (Macpherson and Horak 2013). Information about the body's position and movement in space, and in relation to the environment, is gained through the somatosensory, visual, and vestibular systems (Macpherson and Horak 2013). The afferent sensory information is integrated and weighted in the central nervous system, and efferent motor potentials are elicited to maintain postural control. Understanding how the control of posture is modulated during changing environmental conditions is important to understand the flexibility and adaptability of postural control.

One way of changing the environmental conditions during the study of postural control is to move the support surface and analyze the response to those movements. Extensive work has been done with support surface translations, both using discrete and continuous translations (Buchanan and Horak 1999; Corna et al. 1999; Ko et al. 2013). Discrete translations provide a simulation of a slip or trip and then

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analyze the postural response, while continuous translations provide a constantly changing environment and analyze how the postural control system adapts to the new environment. Continuous support surface translations have mostly been performed using sinusoidal translations that vary in frequency and amplitude (Buchanan and Horak 2001; Corna et al. 1999; Nardone et al. 2000); however, research related to studies on adapting to complex signals is still limited. One previous study from the authors using complex support surface translations found that the structure of postural sway in healthy young subjects would trend towards the structure of the support surface movements (Rand et al. 2015). It was shown that when the complexity of the support surface movement was reduced, there was also a reduction in the complexity of postural sway (Rand et al. 2015).

One way to measure complexity is by looking at the fractal properties of a time series. The term fractal refers to the property of self-similarity, where different scales of observation result in similar properties. Fractals can be mathematically perfect such as the Koch snowflake, Cantor set, or the Sierpinski triangle. However, in nature fractals exist in a non-perfect form and instead have a statistical self-similarity (Mandelbrot 1982). Utilizing this concept in time series analysis allows the detection of self-similar patterns across different time-scales (Goldberger and West 1987). Fractal properties have been shown to be ubiquitous in time series of human action, including walking (Delignieres and Torre 2009; Hausdorff et al. 1996), reaction time (Van Orden et al. 2003, 2005), neuronal firing rates (Bhattacharya et al. 2005), team interaction dynamics (Gorman et al. 2010), and standing posture (Duarte and Zatsiorsky 2000; Rand et al. 2015), to name a few. Furthermore, fractal properties have been associated with adaptability (Gorman et al. 2010) and complexity (Bak and Paczuski 1995), with changes in fractal properties being associated with aging and disease (Goldberger et al. 2002; Stergiou and Decker 2011). It has been recognized in recent years that although there is adequate research demonstrating the ubiquitousness of fractal processes in human movement, what is lacking is experimentation that attempts to alter fractal processes through systematic manipulation of independent variables (Likens et al. 2015).

When analyzing the fractal properties of a time series, there are two main behaviors that can emerge, persistence and anti-persistence. In a persistent time series, increases are more likely to be followed by increases and decreases are more likely to be followed by decreases. An anti-persistent time series is one where increases are more likely to be followed by decreases, and decreases are more likely to be followed by increases. Biological processes can exhibit properties of both persistence and anti-persistence within the observed time-scales. This is thought to arise from the fact that biological systems tend to be bounded, so on some

time-scale increases will have to be followed by decreases (Liebovitch and Yang 1997). The work by Liebovitch and Yang used both biological data and models, and came to the conclusion that the transition from persistence to anti-persistence in biological systems most likely occurs due to a persistent random walk that is bounded. Furthermore, it has also been shown that when comparing position, velocity, and acceleration information about postural sway, the sensorimotor system prefers velocity information (Jeka et al. 2004). This makes center of pressure velocity (COP_{vel}) a sensitive variable to use when investigating changes in postural sway due to experimental manipulation.

The COP_{vel} characterizes a multifractal process that exhibits strong persistence on the short time-scale and anti-persistence on the longer time-scale (Delignieres et al. 2011). Starting at a point where the sway velocity is zero, the velocity will continue to increase (persistence) until a threshold is reached. If the threshold is passed, then the center of mass would be moving too fast to slow down and stop before reaching the boundaries of the base of support, and a fall may occur. Upon reaching the threshold, the sway velocity would start to decrease persistently in order to stop the sway and start moving in a different direction. This alternating between increasing and decreasing sway results in an anti-persistent behavior (Fig. 1). The time where the shift occurs between persistence and anti-persistence indicates the length of time the system allows increases or decreases in sway velocity before a transition occurs. While not demonstrated before, it is intuitive that support surface translation velocity would affect the time-scale threshold between persistent and anti-persistent postural responses.

Collins and De Luca showed that during quiet stance stabilogram, diffusion plots demonstrated distinct regions showing short- and long-term control mechanisms (Collins and De Luca 1993). Although this analysis was performed on COP position data, lack of an integration step in the algorithm makes the results comparable to performing fractal techniques such as detrended fluctuation analysis (DFA) to COP_{vel} data. For a complete comparison of the algorithmic differences, see Delignieres and colleagues (2003). The inference from the Collins and De Luca work was that the short-term persistent region was indicative of open-loop (feedforward) control which could be on a time-scale that did not allow the sensorimotor loops to effectively provide feedback, and the long-term anti-persistent region was indicative of closed-loop (feedback) control. However, it has been shown through a modeling study that stabilogram diffusion plots with two distinct regions can be obtained by varying time delays within a closed-loop system (Peterka 2000). This shows that feedforward control is not required to produce persistent and anti-persistent regions. Furthermore, Peterka's model (Peterka 2000) demonstrates that the stabilogram diffusion plots can be considered outside
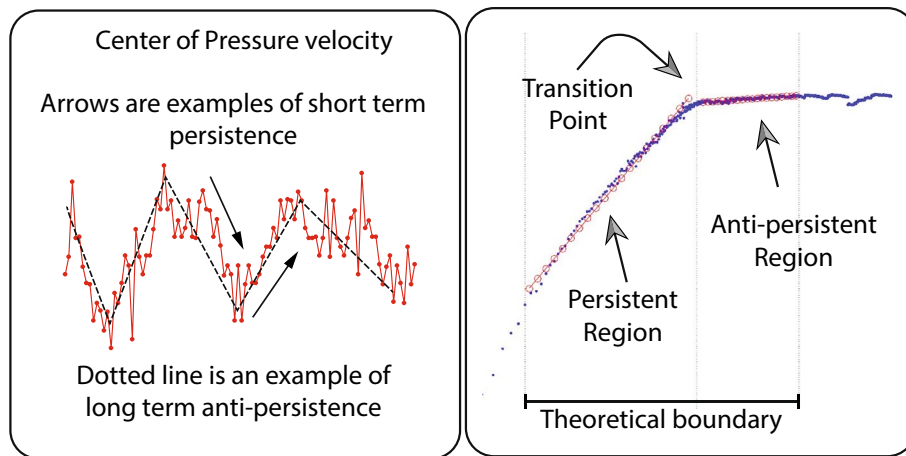
Fig. 1 Examples of center of pressure velocity time series and associated log/log plot. **a** Center of pressure velocity displays persistence on a short time-scale and anti-persistence on a longer time-scale. **b** Example of a log/log plot where root-mean-square fluctuation is on the *y*-axis and time-scale is on the x-axis. The transition point where the slope of the plot changes from > 0.5 to < 0.5 indicates the time-scale where the behavior shifts from persistent to anti-persistent. The slope of the linear regions indicates the strength of persistence and anti-persistence

of the context of fractal analysis. Only when the time series is approximated as a piecewise linear function and different time-scales are compared, does the analysis investigate the fractal relationship.

The goal of this research was to determine whether the commonly observed time-scale threshold between persistent and anti-persistent postural behavior was dependent on the velocity and/or structure of support surface oscillations. To reach our goal, we analyzed the postural responses to support surface translations ranging from predictable (sine wave) to unpredictable (white noise), as well as at different movement velocities ($0.5-4.0 \text{ cm·s}^{-1}$). A modified DFA algorithm was used to identify the time-scale where the COP_{vel} transitioned from a persistent to an anti-persistent behavior, and the strength of persistence. We hypothesized that as movement velocity increases, the time to transition of COP_{vel} and the strength of persistence will both decrease. We also hypothesized that the movements with weaker temporal correlations will result in shorter time to transition and weaker persistence.

Methods

Twenty healthy participants were recruited from the university campus (11M/9F, Age 24 ± 4 years, Height 175 ± 11 cm, Mass 76 ± 10 kg). Exclusion criteria included any lower limb dysfunction, and history of neuromuscular or orthopedic dysfunction. The Institutional Review Board at the University of Nebraska Medical Center approved all procedures and all participants provided informed consent.

The Neurocom® Balance Master® (Natus Medical Inc., Pleasanton, CA) was used to perform this research. The force platforms were translated in the AP direction and the resultant COP was recorded and converted to COP_{vel}. The translations had absolute average movement velocities ranging from 0.1 to 4.0 cm·s^{-1}, and different strengths of temporal persistence [no temporal persistence (white noise), moderate temporal persistence (pink noise), and strong temporal persistence (sine wave)]. The platform was translated at 10 Hz and all trials were 3 min in length. One trial was also conducted where there was no platform movement. This resulted in 19 trials in total and all trials were randomized. Participants stood in a side-by-side stance with the width of the feet normalized for height. This width was based on the Neurocom standard specifications, with the lateral calcanei separated by 22, 26, or 30 cm based on three height ranges (76–140, 141–165, and 166–203 cm, respectively).

All signals used to drive the platform translations were created using Matlab functions. The white noise signal was created using the built-in randn function and pink noise signals were created using a custom function that removed the high-frequency components from white noise to create a $1/f$ power spectrum. These signals were run through the DFA algorithm (Peng et al. 1995) with a scaling region of 16 data points to 200 data points and only accepted if they were within ± 0.02 of the theoretical α-value (0.5 for white noise and 1.0 for pink noise). Once the signal was accepted based on the α value, it was scaled for the six conditions. For the white and pink noise, this was done for 20 individual signals for each participant to have a unique signal that still contained the correct structure and scaling. The sine wave was also created in Matlab and scaled, but due to the periodicity

of a sine wave, there was no need to create individual sine waves for each participant. These signals were then printed to a text file and loaded into the Neurocom utilizing the researcher module.

Data processing

After data collection, the motor position of the Neurocom was exported and ran through the DFA algorithm to ensure that the temporal correlations of the output were similar to the input signal. Criteria was set at ± 0.05 from the theoretical α-value for white and pink noise signals. Due to limitations of the Neurocom, the signals that were generated at 0.1 cm·s^{-1} did not maintain the correct temporal correlations during the trials. These three trials were discarded for each participant and 16 trials were used for analysis. The COP in the anteroposterior direction was exported from the Neurocom and converted to COP$_{vel}$. These data were down sampled from 100 to 50 Hz and the first 5 s of each trial was removed to eliminate any startling effect from the start of the support surface translations. Two different analyses were conducted. Frequency response functions were calculated to explore the linear gain and phase responses to platform movements. A DFA based fractal analysis was used to determine the time to transition between persistent and anti-persistent behavior as well as the strength of the persistence within the persistent range.

The transfer function was calculated between the Neurocom's motor and the COP response. The transfer function is the ratio of the COP power spectrum and the stimulus power spectrum, and this describes the response gain (magnitude) and phase (timing) at different frequencies of the stimulus. The transfer function was estimated using the built-in Matlab function tfestimate, the magnitude of the transfer function is the gain and the angle of the transfer function is the phase. The power spectrum was binned into frequencies of 0.05 Hz and 100 values from 0.05 to 5 Hz were displayed.

The fractal analysis followed the procedures of DFA up to the point of plotting a log/log plot. These procedures are as follows: First, integrate the times series and divide into boxes of length n, where n will range from 3 to the length of the data/2. Detrend the boxes by subtracting a linear line of best fit and calculate the root-mean-square fluctuation of the remaining data. Average the root-mean-square fluctuations across the number of boxes. After performing this procedure for all box sizes, then plot these values on a log/log plot with box size (or number of data points) on the x-axis and root-mean-square fluctuation on the y-axis. The standard DFA algorithm would then determine the slope at a chosen scaling region and return the slope of the line as the α-value. An α value of 0–0.5 indicates an anti-persistent temporal correlation, an α value of 0.5 indicates a completely uncorrelated time series, or white noise, and increasing α values

beyond 0.5 indicate an increase in the strength of the temporal correlations. An α value of 1.0 indicates a time series that contains a pink noise structure, and an α-value 1.5 indicates a red noise structure (Brownian motion), or a random walk in the temporal evolution of the time series. In the modified algorithm used in this study, boundaries of lower and upper limits of the scaling region in the log/log plot were determined. This was based on a combination of previous work (Rand et al. 2015), theoretical boundaries (Damouras et al. 2010), and the specific data length. Using the ginput function in Matlab, a point was chosen on the log/log plot where the slope changed from greater than 0.5 to less than 0.5. Then, lower and upper boundaries for the short- and long-scaling regions were chosen. The point of transition was returned along with α values and upper and lower boundaries for the short and long regions. Figure 2 shows an example of the analysis for one subject across all conditions.

Statistical analysis

Two-way repeated-measures ANOVAs were used to determine the effect of temporal correlation and movement velocity on the time to transition and strength of short-term persistence of COP$_{vel}$. Tukey post hoc analyses were used to determine differences within groups. To compare all trials against quiet standing one-way repeated-measures ANOVAs were used with Dunnet's post hoc. All statistics were calculated using GraphPad Prism V6 (Graph Pad Software, La Jolla, CA). The frequency response function was calculated as exploratory analysis and was not put through any statistical testing.

Results

The two-way repeated-measures ANOVA of time to transition showed no effect of movement velocity ($F(4, 76) = 0.1209$, $p = 0.9812$), an effect of temporal correlation ($F(2, 38) = 103.2$, $p < 0.001$), and a movement velocity by temporal correlation interaction ($F(8, 152) = 4.382$, $p < 0.0001$). Post hoc showed that the time to transition was greater in the sine wave conditions compared to pink and white noise for all movement velocities (all $p < 0.0001$). The one-way ANOVA of time to transition was significant ($F(4.794, 91.08) = 23.16$, $p < 0.001$). Post hoc revealed several changes in time to transition compared to quiet stance. There was a decrease during pink noise at 0.5 cm·s^{-1}, as well as increases for sine wave and decreases for white and pink noise at 2.0, 3.0, and 4.0 cm·s^{-1}. These results are presented in Fig. 2. Mean differences and post hoc p values are presented in Table 1.

The two-way repeated-measures ANOVA of short-term persistence showed an effect of movement velocity ($F(4,

Fig. 2 Example of the log/log plots for one subject. The columns are white, pink, and sine wave stimulus and the rows are the different movement velocities. Solid vertical lines indicate the approximate transition point from persistence to anti-persistence and the time-scale of this line is displayed in seconds
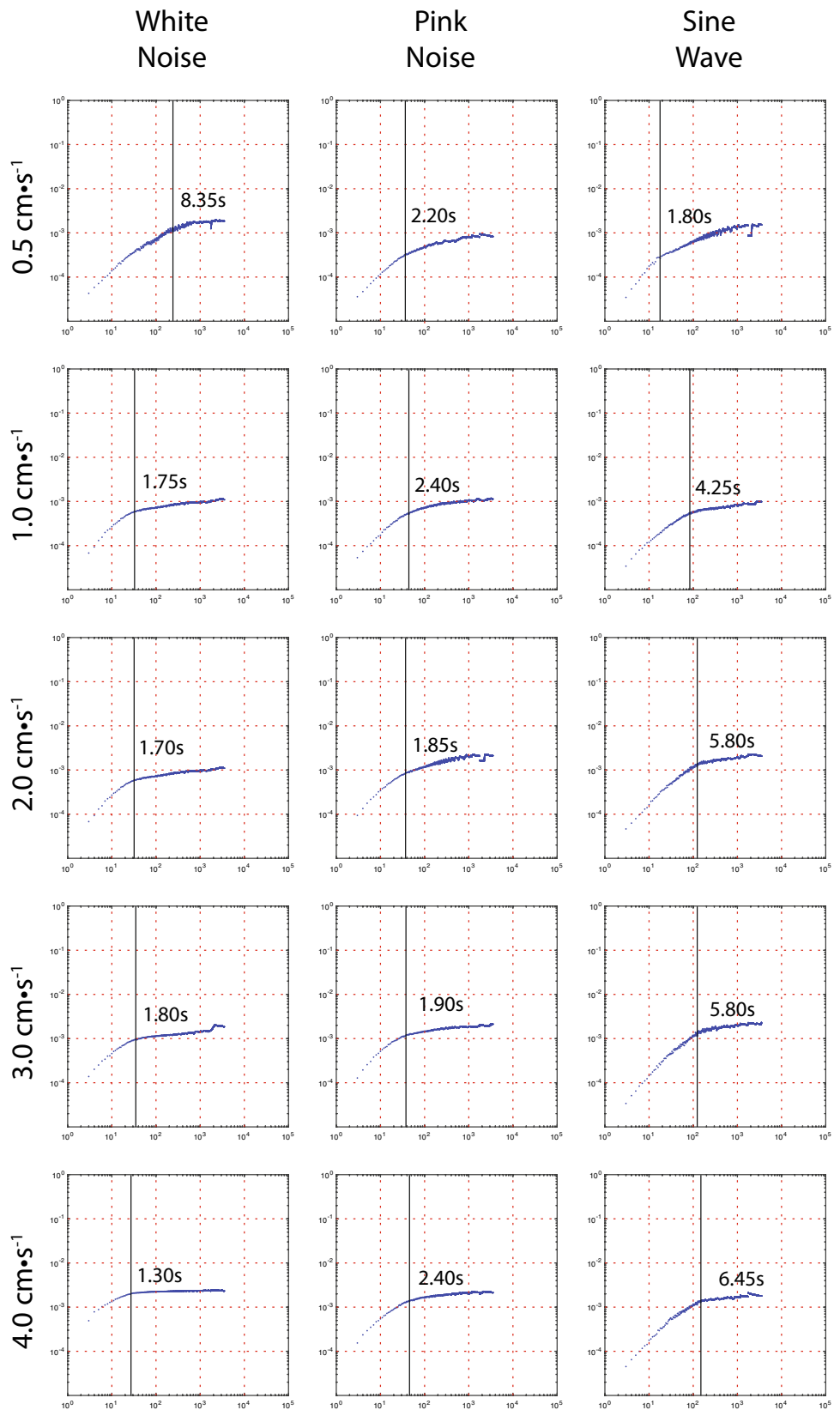
Table 1 Mean differences and associated *p* values for the comparisons between the temporal correlations (Tukey post-hoc), and comparisons to baseline standing (Dunnet's post hoc)

Velocity	Tukey post hoc	Time to transition		Short-term persistence	
		Mean difference	Adjusted *p* value	Mean difference	Adjusted *p* value
0.5 cm·s^{-1}	White vs. pink	0.66	0.1728	− 0.04	0.3042
	White vs. sine	− 1.92	**< 0.0001**	0.07	0.0617
	Pink vs. sine	− 2.58	**< 0.0001**	0.11	**0.0007**
1.0 cm·s^{-1}	White vs. pink	0.61	0.2198	− 0.06	0.0702
	White vs. sine	− 1.66	**< 0.0001**	− 0.09	**0.0074**
	Pink vs. sine	− 2.27	**< 0.0001**	− 0.02	0.6923
2.0 cm·s^{-1}	White vs. pink	0.19	0.6646	− 0.07	**0.0479**
	White vs. sine	− 3.24	**< 0.0001**	− 0.21	**< 0.0001**
	Pink vs. sine	− 3.43	**< 0.0001**	− 0.14	**< 0.0001**
3.0 cm·s^{-1}	White vs. pink	− 0.32	0.8615	− 0.08	**0.0146**
	White vs. sine	− 3.98	**< 0.0001**	− 0.17	**< 0.0001**
	Pink vs. sine	− 3.67	**< 0.0001**	− 0.09	**< 0.0001**
4.0 cm·s^{-1}	White vs. pink	0.46	0.4162	− 0.12	**0.0001**
	White vs. sine	− 3.55	**< 0.0001**	− 0.40	**< 0.0001**
	Pink vs. sine	− 4.01	**< 0.0001**	− 0.28	**< 0.0001**
	Dunnet's post hoc				
0.5 cm·s^{-1}	White noise	0.91	0.5355	− 0.05	0.6767
	Pink noise	1.57	**0.0358**	− 0.09	**0.0329**
	Sine wave	− 1.01	0.3501	0.01	0.9993
1.0 cm·s^{-1}	White noise	0.85	0.3387	0.02	0.9990
	Pink noise	1.46	0.0662	− 0.04	0.8099
	Sine wave	− 0.81	0.4032	− 0.07	0.1274
2.0 cm·s^{-1}	White noise	1.64	**0.0051**	0.08	0.2996
	Pink noise	1.83	**0.0027**	<0.01	0.9999
	Sine wave	− 1.60	**0.0029**	− 0.09	**0.0127**
3.0 cm·s^{-1}	White noise	1.97	**0.0012**	0.15	0.0805
	Pink noise	1.66	**0.0326**	0.07	0.5264
	Sine wave	− 2.01	**0.0013**	− 0.06	0.2195
4.0 cm·s^{-1}	White noise	1.66	**0.0348**	0.26	**< 0.0001**
	Pink noise	2.12	**0.0006**	0.14	**0.0283**
	Sine wave	− 1.90	**0.0027**	− 0.14	**0.0063**

All *p* values have been adjusted for multiple comparisons. All statistically significant differences are indicated in bold

76) $= 16.19$, $p < 0.0001$), an effect of temporal correlation ($F(2, 38) = 33.20$, $p < 0.0001$), and a movement velocity by temporal correlation interaction ($F(8, 152) = 19.93$, $p < 0.0001$). Post hoc revealed several differences in the strength of short-term persistence. Sine wave had weaker persistence than pink noise at 0.5 cm·s^{-1} and stronger persistence than white noise at 1.0 cm·s^{-1}. At movement velocities of 2.0, 3.0, and 4.0 cm·s^{-1}, there were differences between all three temporal correlations, with white noise being the weakest, sine wave being the strongest, and pink noise in the middle. The one-way ANOVA of short-term persistence was significant ($F(5.751, 109.3) = 20.54$, $p < 0.0001$). Post hoc revealed several changes in the strength of persistence. There

was an increase in pink noise at 0.5 cm·s^{-1}, an increase in sine wave at 2.0 and 4.0 cm·s^{-1}, and decreases for white and pink noise at 4.0 cm·s^{-1}. These results are presented in Fig. 3. Mean differences and post hoc *p* values are presented in Table 1.

The frequency response function for gain and phase showed clear differences between the noise signals and the periodic signal, with some slight differences between the white and pink noise (Fig. 4). At low frequencies (< 0.5 Hz), the pink noise gain was lower than white noise or sine wave, especially at the slower movement velocities. For all movement velocities, the white and pink noise gain peaked around the 0.75 Hz range and then slowly dropped until about the
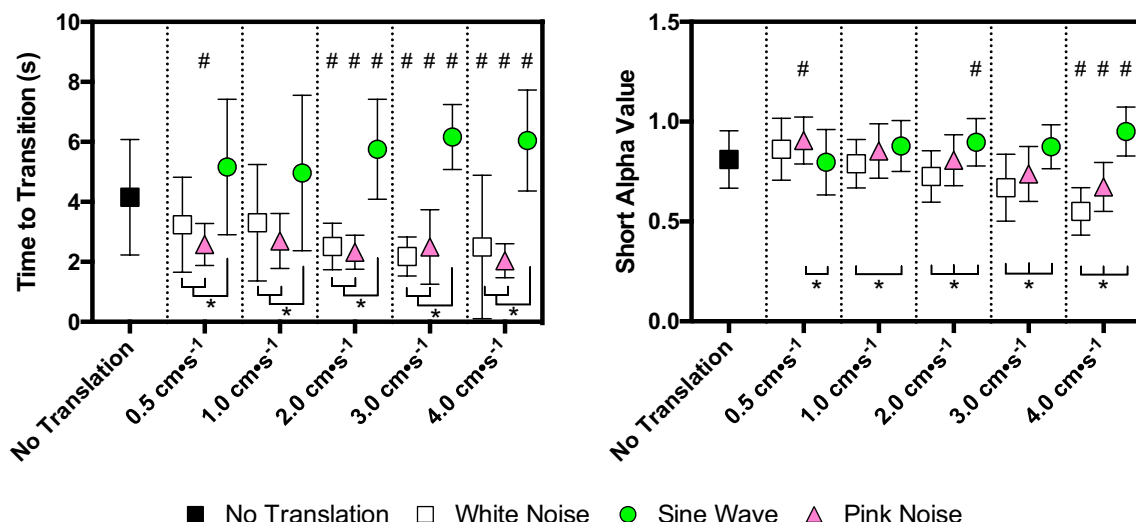
Fig. 3 Results for the time to transition and short-term persistence. #Difference compared to baseline, *difference between temporal correlations. **a** Compared to baseline standing, the time to transition was increased for sine wave and decreased for white and pink noise at all movement velocities 2 cm·s⁻¹ and greater. The white and pink noise signals had a shorter time to transition compared to the sine wave signal at all movement velocities. **b** Compared to baseline standing, the short-term persistence was stronger in the sine wave and weaker in the white and pink noise conditions at 4.0 cm·s⁻¹. At 2.0 cm·s⁻¹ and greater, there were differences in all three conditions, with white noise having the weakest persistence, sine wave the strongest, and pink noise in the middle. There were a few other significant differences noted on the figure, and all mean differences and exact *p* values are provided in Table 1
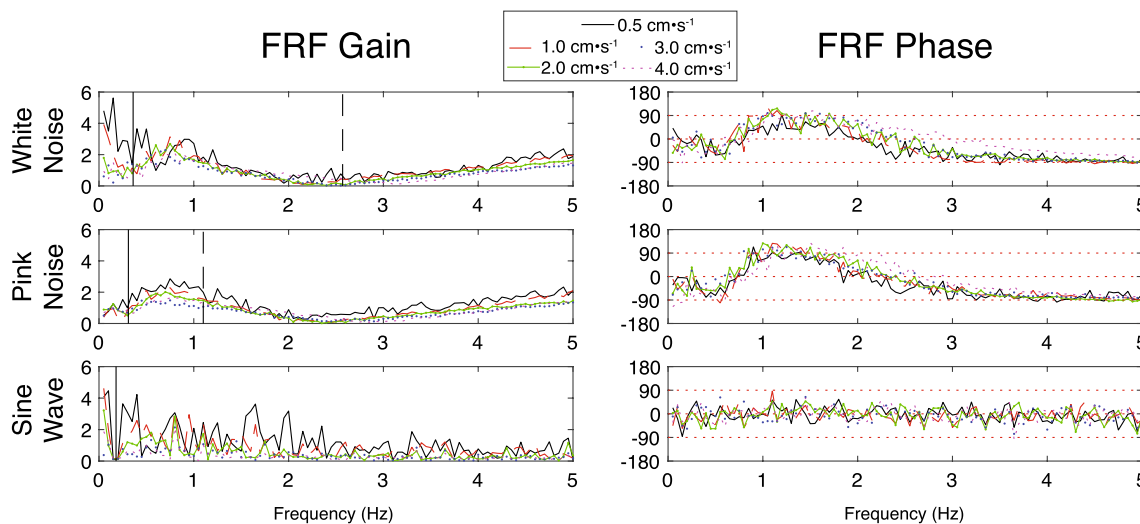

Fig. 4 Average frequency response function of all subjects for gain and phase changes across the three types of stimuli (white, pink, and sine) and different velocity conditions. Overall the gain was higher for lower velocity movements. White noise and pink noise had similar patterns for gain and phase; however, pink noise had lower gains for the three slowest movement velocities in the low frequency range. The solid vertical line in the white and pink noise graphs of gain shows the median frequency of the stimulus and dashed vertical line the mean frequency of the signal. Sine wave had a similar response across frequencies, with a very consistent response at the frequency of the stimulus (solid vertical line)

2.5 Hz range, after which it slowly increased again up to 5 Hz. The sine wave gain did not follow a specific pattern; however, at the frequency of the signal (0.18 Hz), the gain was almost 0, which indicates that the subjects were following the platform movement very well, this was true for all movement velocities and the variability of responses at this frequency was also very low (not shown). This indicates that all participants were following the platform movement at all velocities for the sine wave signal at this frequency. The phase also showed differences between the sine wave and noise signals. The sine wave had phases between −90° and 90°, but this fluctuated across all frequencies with no

specific pattern. The white and pink noise had a similar pattern, the phase was between $-90°$ and $0°$ up until around the 0.75 Hz range and then stayed between $0°$ and $90°$ until about 2 to 2.5 Hz, at which point it dropped back to the $-90°$ to $0°$ range and from 3 to 5 Hz it stayed close to $-90°$.

Discussion

We explored four main hypotheses within this study. Number one is that as movement velocity increases, the time to transition of COP_{vel} would decrease. This hypothesis was supported for the white and pink noise signals at movement velocities 2 cm·s^{-1} and greater, but the sine wave signal had an increased time to transition at velocities 2 cm·s^{-1} and greater. Second, we hypothesized that the strength of persistence would decrease as the movement velocity increased. This result was like the first hypothesis where the strength of persistence was decreased for the white and pink noise signals at 4 cm·s^{-1} but was increased in the sine wave condition at 4 cm·s^{-1}. Third, we hypothesized that movements with weaker temporal correlations would result in shorter time to transition of COP_{vel}. This was supported when comparing the sine wave to white and pink noise but not supported between the white and pink noise signals. Finally, we hypothesized that movements with weaker temporal correlations would result in weaker persistence. This hypothesis was supported for all movements 2 cm·s^{-1} and greater, with white noise showing the weakest persistence, pink noise in the middle, and sine wave showing the strongest persistence. Therefore, all our hypotheses were partially supported with some unexpected differences in the response to the sine wave input, which resulted in temporal correlation by movement velocity interactions.

COP_{vel} is a bounded system, since too large of a velocity will result in a fall. Furthermore, COP must alternate between increasing and decreasing velocities on a semi regular basis, which results in transition from persistence to anti-persistence at a specific time-scale (Delignieres et al. 2011; Liebovitch and Yang 1997). The time to transition indicates how long the system allows increases in velocity before decreases occur, or decreases in velocity before increases occur. During the short time-scale, before the time to transition, there will be some level of persistence. This is because COP_{vel} will continue to increase or decrease until it reaches its threshold and changes directions. The strength of persistence in this short region indicates how persistently the system increases or decreases velocity.

Predictable vs. unpredictable signals

There were clear differences in the sine wave and noise (white and pink) signals. The sine wave signal resulted in

longer time to transition as movement velocity increased, while the white and pink noise signals resulted in shorter time to transitions. At the same time, the strength of short-term persistence remained steady and even increased with the sine wave, while it decreased for the white and pink noise. In this case, the white and pink noise signals are not responding differently from each other, but both are responding differently from the sine wave signal. These differences could indicate a divergence in the way in which the central nervous system processes the different postural demands. It has been shown previously that support surface oscillations of different structures elicit characteristic postural responses (Rand et al. 2015).

The differences between the predictable and unpredictable signals may indicate the ability to utilize feedforward vs. feedback control. In the case of COP_{vel}, a feedforward mechanism would mean that the system can predict when the body needs to increase or decrease velocity to maintain balance. A feedback mechanism would mean the system must rely more on sensory input to determine when to increase or decrease velocity to maintain balance (Gahéry and Massion 1981; Macpherson and Horak 2013). Because the sine wave is a predictable signal and the noise signals are not as predictable, it would be logical to conclude that the system can utilize a feedforward mechanism during the sine wave condition more than in either of the noise conditions. Using measures of temporal correlation may be a unique way to understand how the system is utilizing feedforward or feedback mechanisms.

Differences in the strength of persistence

Even in the two noise signals, there were differences in the strength of persistence at all movement velocities 2 cm s^{-1} and greater. The white noise signal resulted in the weakest persistence, pink noise was stronger than white (although still weaker than baseline), and sine wave resulted in the strongest persistence. The strength of persistence in response to the three signals follows the same trend as the temporal correlation of the signal itself. This supports the previous findings that the temporal correlation of the environmental constraint drives the temporal correlation of the postural response (Rand et al. 2015). In the case of white noise movement, the feedback provided no useful information, because each movement of the support surface was randomly determined, the system could make no prediction about future movements based on the sensory feedback. However, with pink noise, there is a temporal persistence, meaning that the movements of the support surface have a relationship to the previous movements. This provides information that the system can use to determine whether it needs to increase or decrease velocity, which results in a stronger persistence of COP_{vel} for the pink noise movement. Therefore, although

both white and pink noise appear to result in a feedback mechanism being dominant, the useful information in the pink noise signal allows the system to maintain a stronger persistence in the COP$_{vel}$.

These data indicate that the central nervous system has different responses to sensory inputs that contain different strengths of temporal correlation. If information is perceived as very predictable, such as the sine wave, then a feedforward mechanism can remain dominant, which may reduce the computational load. If the information is unpredictable, such as in the white and pink noise conditions, then feedback processes may become more dominant, since the system cannot predict future movements as reliably. However, differences in the strength of persistence within these noise signals indicate that there may be a threshold where the system would transition from feedback to feedforward control. Testing signals that contain more persistence and, therefore, are more predictable, will be useful in determining where this threshold exists.

Frequency response function

The gain and phase of the transfer function both showed clear differences between the predictable and unpredictable signals. The sine wave stimulus resulted in a postural response that matched the input at the frequency of the movement, with no clear pattern across the rest of the frequencies. The white and pink noise stimuli resulted in similar COP responses, with increases in gain up to about 0.75 Hz and then decreases to around 2 Hz. There was also typically a higher gain at the lower platform velocities. These results are similar to a study comparing support surface tilts at different amplitudes and under different visual conditions (Asslander et al. 2015). This study used pseudo-random ternary sequences to drive the platform tilt at four different amplitudes. The gain pattern across frequencies was similar with increases up to around 0.5 Hz and then decreases until around 2 Hz. They also showed a lower gain with a greater amplitude of movement, similar to our results showing a lower gain with a larger velocity of movement. They hypothesized that this could be due to a tendency to compensate better for larger tilt stimuli; a similar mechanism may be present with support surface translations also. However, with lower amplitudes or velocities of movement, the natural sway tendency could also result in greater gains, and the biomechanical constraints may not allow large gains at higher movement velocities.

It should be noted that there are differing theoretical perspectives on whether the postural control system utilizes feedforward mechanisms, or if it can rely solely on feedback mechanisms. It has been proposed that the presence of two scaling regions indicated that the system used open-loop and closed-loop control strategies (Collins and De

Luca 1993). Subsequently, it was shown that similar results could be obtained by varying time delays within a closed-loop system (Peterka 2000). This shows that a feedforward, or closed-loop system, is not required to produce persistent and anti-persistent scaling regions and physical constraints could produce similar changes. However, it was also noted in that study that complex sensorimotor transformations could be implicated when the support surface perturbations are more complex such as in this study. In the current study, we are not proposing that the presence of two scaling regions is what indicates a shift towards feedforward control; instead, we are hypothesizing that the shift to a longer time to transition is what indicates a shift towards feedforward control in the predictable signals. There is also debate about how the term feedforward is used in the postural control literature (van der Kooij and de Vlugt 2007). A true feedforward system implies that the controller is independent from the system, but our sensorimotor system receives constant feedback which makes it difficult to determine if processes are happening in a true feedforward manner.

These findings could have implications for designing rehabilitative protocols. Training with a fixed pattern, such as a sine wave, will likely lead to fixed responses, and may not emulate real-life experiences. By being aware of the complexity of the task, it will be possible to design training protocols that contain complex structures resembling the task itself. Furthermore, assessing one's ability to transition from one behavior to another will give insight into the flexibility of the sensorimotor system. However, a better understanding of the neuronal processing involved in these findings will be required to fine tune these results to specific populations.

Future directions

Future studies could investigate whether the results of this study diminish, persist, or are exaggerated by aging or pathology. Another area of interest is to investigate our results with stimulus signals of other strengths of temporal correlation, such that a more distinct transition point can be determined where the system switches from reliance on feedback to feedforward mechanisms. A clearer picture regarding the transition point can also emerge through investigation on a wider range of velocities. Investigating stimulus signals from other sensory modalities will determine whether the observed responses are ubiquitous in nature. Finally, the utilization of neurophysiological measures such as brain activity measurements would provide greater insights into the underlying neuronal mechanisms.

In summary, we investigated two factors which could affect the transition point between persistent and anti-persistent behavior in postural dynamics. It was shown that both velocity and the predictability of support surface

oscillations affected this time-scale threshold. As velocity of support surface oscillations increased, the time to transition became longer for sinusoidal oscillations and shorter for both white and pink noise movements. In addition, during the persistent time-scale, the sine wave resulted in the strongest correlation, while white and pink noise had weaker correlations. At the highest movement velocity, the strength of persistence was lower for the white noise compared to pink noise movements. These findings point towards transitions between feedforward and feedback modes of postural responses based on the velocity and temporal structure of environmental constraints.

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