Interpretation of postural control may change due to data processing techniques

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Rhea, C.K., Kiefer, A.W., Wright, W.G., Raisbeck, L., & Haran, F.J. (2015). Interpretation of postural control may change due to data processing techniques. *Gait & Posture, 41(2)*, 731-735.

Made available courtesy of Elsevier: https://doi.org/10.1016/j.gaitpost.2015.01.008

Abstract:

Postural control is commonly assessed by quantifying center of pressure (CoP) variability during quiet stance. CoP data is traditionally filtered prior to analysis. However, some researchers suggest filtering may lead to undesirable consequences. Further, sampling frequency may also affect CoP analysis, as filtering CoP signals of different sampling frequencies may influence variability metrics. This study examined the influence of sampling frequency and filtering on metrics that index the magnitude and structure of variability in CoP displacement and velocity. Healthy adults ($N = 8$, 27.4 ± 2.6 years) balanced on their right foot for 60 s on a force plate. CoP data recorded at 100 Hz was then downsampled and/or filtered (2nd order dual-pass 10 Hz low-pass Butterworth) to create six different CoP time series for each participant: (1) original, (2) filtered, (3) downsampled to 50 Hz, (4) downsampled to 25 Hz, (5) downsampled to 50 Hz and filtered, and (6) down-sampled to 25 Hz and filtered. Data were then analyzed using four common variability metrics (standard deviation [SD], root mean square [RMS], detrended fluctuation analysis α [DFA α], and sample entropy [SampEn]). Data processing techniques did not influence the magnitude of variability (SD and RMS), but did influence the structure of variability (DFA α and SampEn) in CoP displacement. All metrics were influenced by data processing techniques in CoP velocity. Thus, when interpreting changes in CoP variability, one must be careful to identify how much change is driven by the neuromotor system and how much is a function of data processing technique.

Keywords: Center of pressure | Posture | Variability | Dynamics

Article:

1. Introduction

Upright stance is inherently unstable because two-thirds of the body's mass is located in the head/arms/trunk, creating an inverted pendulum effect [1]. Insight into how upright stance is

maintained has been garnered from computerized posturography, which can be used to quantify how the center of pressure (CoP) is moving during stance. Typically, a less variable CoP is considered a more stable system; a definition rooted in classic mechanical systems.

Research over the past three decades on human systems (e.g., postural control, gait, heart rate) suggests that increased variability may not be synonymous with dysfunctional (i.e., less stable) systems [2]. That is, some variability may actually serve a functional purpose [3]. Thus, researchers have begun to employ metrics that quantify both the magnitude (e.g., standard deviation [SD], root mean square [RMS]) and the structure (e.g., detrended fluctuation analysis alpha [DFA α], sample entropy [SampEn]) of a CoP time series to more fully characterize system variability [2], [4], [5].

While data acquisition guidelines have been published for CoP data collection [6], there is much variance in how data are processed after acquisition [7]. Prior to a variability analysis, traditional signal processing guidelines for human movement data, including postural control data, recommend that a signal is filtered to remove any artifacts unassociated with neuromotor control [8]. In biomechanics research, digital filters are often employed, which requires the selection of an order parameter (i.e., the desired smoothness of the data) and frequency threshold (i.e., point at which data above a certain frequency are removed). However, filtering the data may add a deterministic component to the signal, altering metrics that index the structure of variability within the signal [3], [9]. It is also possible that filtering the signal may remove parts of the signal (both deterministic and random) that are actually rooted in the postural control process [3], [10]. Thus, digital filtering of the data may influence estimates of dependent measures for the structure of variability. Accordingly, some researchers use non-filtered postural control signals [5], [9], [10], while others continue to filter the signal. Furthermore, there are a variety of sampling frequencies used for data collection, some of which have been shown to influence the structure of variability in postural control signals [4], and it is unclear how filtering signals at different sampling frequencies may influence metrics of postural control variability. Lastly, while variability in CoP displacement is a commonly measured postural control variable, it has been suggested that CoP velocity is the variable attended to by the neuromotor system to maintain upright stance [11], [12]. This study examined whether different sampling frequencies and/or filtering affect the magnitude and structure of variability in CoP displacement and velocity signals.

2. Methods

CoP data from healthy adults (N = 8; 27.4 ± 2.6 years; 1.73 ± 0.08 m; 71.9 ± 9.6 kg) who participated in a recently published study [5] were reanalyzed for this paper. Participants stood on their dominant limb for 60 s with eyes open while their CoP displacement was collected at 100 Hz with a force platform (AMTI, Watertown, MA). Only anterior–posterior (AP) data were analyzed for this paper. Filtering (dual pass 2nd order 10 Hz low-pass Butterworth) and downsampling techniques were then applied to create six different CoP time series for each participant: (1) original, (2) filtered, (3) downsampled to 50 Hz, (4) downsampled to 25 Hz, (5) downsampled to 50 Hz and filtered, and (6) downsampled to 25 Hz and filtered. Time series were then analyzed using four common variability metrics (SD, RMS, DFA α, and SampEn [m = 2, r = .15]). The methods for DFA and SampEn have been previously

published [13], [14] separate 3 × 2 (sampling frequency [100, 50 or 25 Hz] × filtering [not filtered or filtered]) repeated measures analyses of variance (ANOVAs) were used for each variability metric to examine the main effect of sampling frequency or filtering, as well as their interaction. Statistical significance was set at $p \leq .05$. Bonferroni corrected paired *t*-test was used as post hoc tests when appropriate.

3. Results

Two seconds of each 60 s time series are presented in Fig. 1 (CoP displacement) and Fig. 2 (CoP velocity) to show the qualitatively different characteristics in each time series. The values for 3 × 2 repeated measures AVOVA and the post hoc findings are presented in Table 1. The main effects and interactions can be visually observed in Fig. 3.

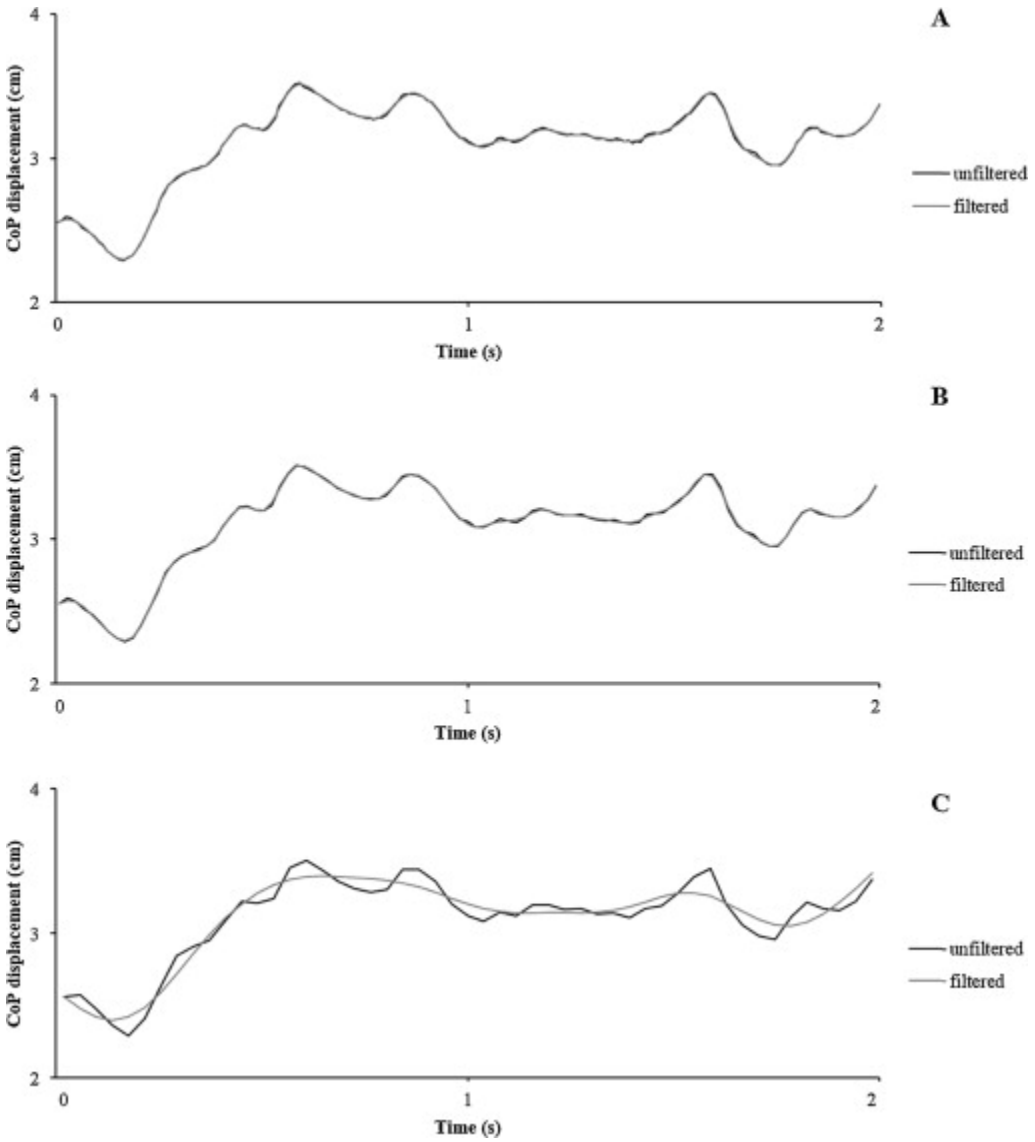

Figure 1. A two second sample of the 60 s time series for center of pressure (CoP) displacement for the 100 Hz (A), 50 Hz (B) and 25 Hz (C) time series. The unfiltered data are shown with a black line and the filtered data are show with a gray line.

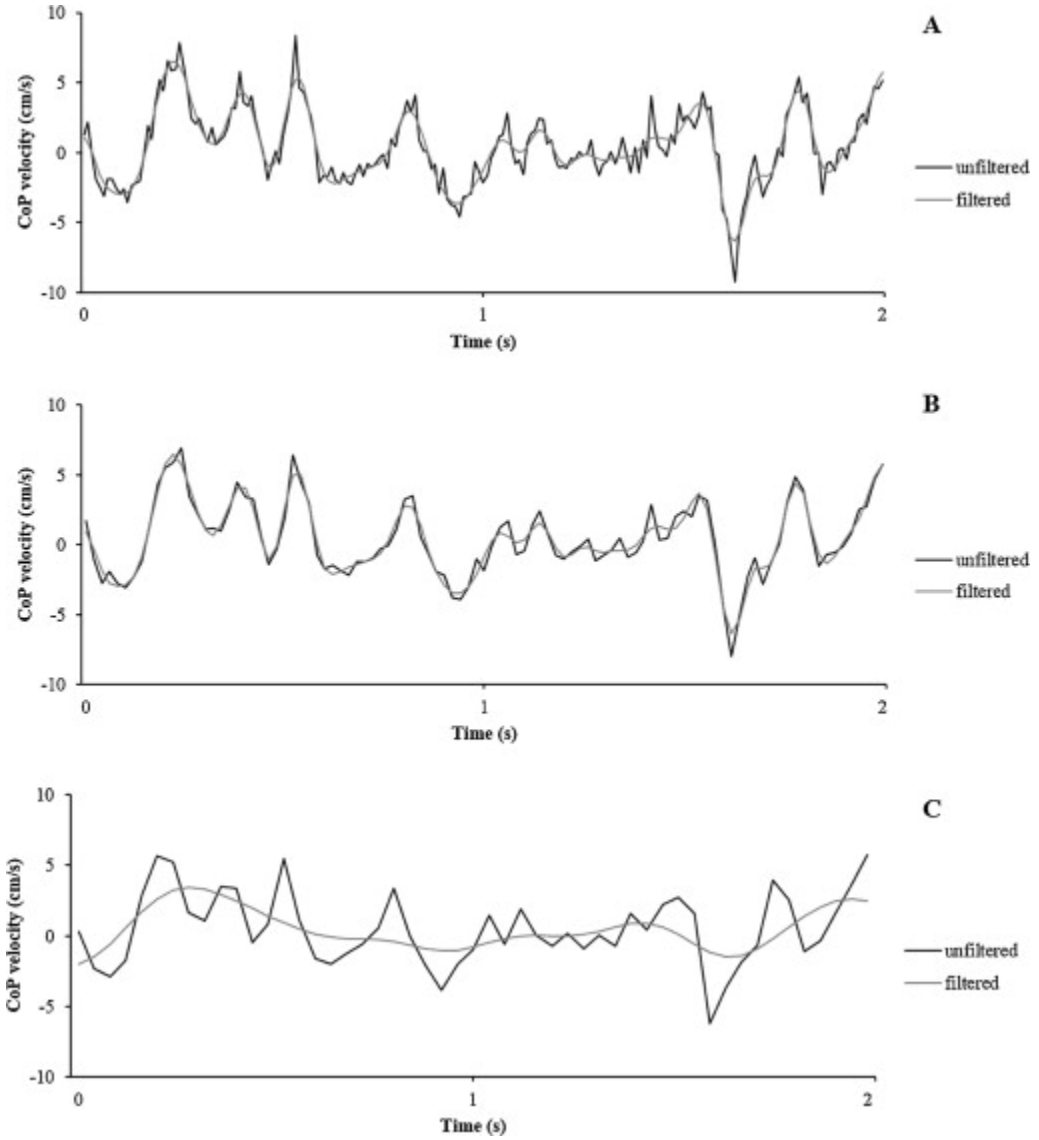

Figure 2. A two second sample of the 60 s time series for center of pressure (CoP) velocity for the 100 Hz (A), 50 Hz (B) and 25 Hz (C) time series. The unfiltered data are shown with a black line and the filtered data are show with a gray line.

4. Discussion

Three main themes were observed across the data processing techniques: (1) CoP velocity metrics are more affected than CoP displacement metrics, (2) structure of variability metrics are more sensitive than magnitude of variability metrics, and (3) filtering the data produced the largest differences in the structure of variability metrics of the CoP velocity time series. Specific to the last point, downsampling had a rather linear effect on the structure of variability metrics, while combing downsampling with filtering led to a curvilinear effect. The findings support an earlier suggestion that filtering CoP data alters variability characteristics of the time series [9]. Given that changes in the variability metrics were observed in CoP velocity, and that CoP velocity is likely to serve as a control variable to maintain upright stance [11], [12], these

findings are consistent with a previous assertion that certain data processing techniques may remove components of the CoP time series related to the postural control process [10].

Table 1. Statistical values for each metric and factor. Post hoc results are listed below the table.

Metric	Factor	df	*F*	*p*-Value	Partial eta squared
SD of CoP displacement[a]	Sampling frequency	2,14	2.65	.11	.28
	Filtering	1,7	4.61	.07	.40
	Sampling frequency × filtering	2,14	0.87	.44	.11
RMS of CoP displacement[b]	Sampling frequency	2,14	8.15	<.01	.54
	Filtering	1,7	8.52	.02	.55
	Sampling frequency × filtering	2,14	7.74	<.01	.53
DFA α of CoP displacement[c]	Sampling frequency	2,14	135.09	<.01	.95
	Filtering	1,7	139.24	<.01	.95
	Sampling frequency × filtering	2,14	114.12	<.01	.94
SampEn of CoP displacement[d]	Sampling frequency	2,14	356.39	<.01	.98
	Filtering	1,7	35.12	<.01	.83
	Sampling frequency × filtering	2,14	46.37	<.01	.87
SD of CoP velocity[e]	Sampling frequency	2,14	94.23	<.01	.93
	Filtering	1,7	77.09	<.01	.92
	Sampling frequency × filtering	2,14	100.00	<.01	.94
RMS of CoP velocity[f]	Sampling frequency	2,14	94.36	<.01	.93
	Filtering	1,7	77.10	<.01	.92
	Sampling frequency × filtering	2,14	99.89	<.01	.94
DFA α of CoP velocity[g]	Sampling frequency	2,14	57.36	<.01	.89
	Filtering	1,7	384.90	<.01	.98
	Sampling frequency × filtering	2,14	276.87	<.01	.98
SampEn of CoP velocity[h]	Sampling frequency	2,14	49.00	<.01	.88
	Filtering	1,7	2007.02	<.01	.99
	Sampling frequency × filtering	2,14	71.64	<.01	.91

[a] No significant differences.

[b] Although a sampling frequency × filtering interaction is reported, no differences were observed between conditions after accounting for the Bonferroni correction.

[c] All conditions significantly different from each other except downsampled (50 Hz) vs. downsampled (25 Hz) and filtered.

[d] All conditions significantly different from each other except original (100 Hz) vs. filtered (100 Hz).

[e] All conditions significantly different from each other except filtered (100 Hz) vs. downsampled (25 Hz) and downsampled (25 Hz) vs. downsampled (50 Hz) and filtered.

[f] All conditions significantly different from each other except filtered (100 Hz) vs. downsampled (25 Hz) and downsampled (25 Hz) vs. downsampled (50 Hz) and filtered.

[g] All condition significantly different from each other except original (100 Hz) vs. downsampled (25 Hz) and filtered and filtered (100 Hz) vs. downsampled (25 Hz) and filtered.

[h] All conditions significantly different from each other except original (100 Hz) vs. downsampled (50 Hz) and filtered (100 Hz) vs. downsampled (25 Hz) and filtered.

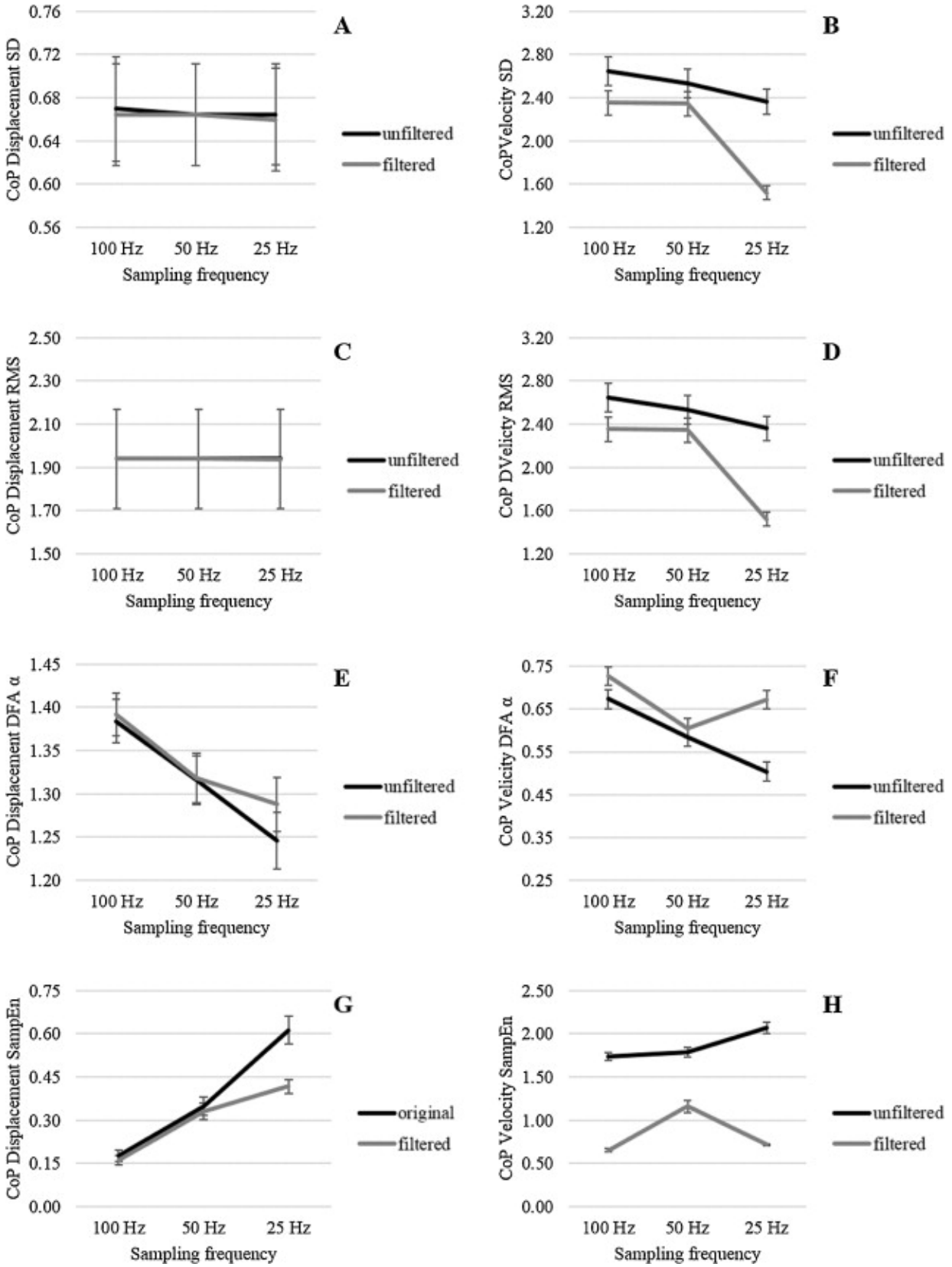

Figure 3. Mean values for SD (A and B), RMS (C and D), DFA α (E and F), and SampEn (G and H) for CoP displacement and CoP velocity. The error bars are standard error.

Previous work has suggested that 100 Hz is suitable to appropriately characterize CoP variability [5], [6], [7], [15]. Our data show that lower sampling frequencies (50 Hz and 25 Hz) in CoP displacement and velocity led to lower DFA α and higher SampEn values, consistent with previous work [4]. The combination of these directionalities is typically interpreted as a move toward a less-structured signal. A DFA α value of 0.5 reflects a randomly organized time series. Healthy adults exhibit an underlying structure in their CoP variability (DFA $\alpha > 0.5$), but typically shift toward a more random, less-structured pattern after natural aging or disease [2]. Thus, our data show that a healthy adult may present with a normal variability pattern (DFA $\alpha = 0.67$) if their CoP velocity was collected at 100 Hz, but that same person may be classified as having an unstructured, random pattern (DFA $\alpha = 0.50$) if their CoP velocity was collected at 25 Hz (Fig. 3). This observation is corroborated by increases in SampEn as a function of lower sampling frequencies in CoP velocity. It should be noted that many studies look for relative directional changes between groups or conditions to identify neuromotor functional ability (i.e., older adults typically present with a lower DFA α relative to younger adults). However, as more data from studies using nonlinear techniques become available, there will be an opportunity to develop normative data along with cutoff scores to indicate when a person is at risk of injury due to neuromotor dysfunction. Thus, it is important to not only have a strong understanding of how data processing may influence nonlinear analyses within each study, but also to report the specific data processing techniques used so that those developing normative data in the future can be better informed. Lastly, we note that similar DFA α values are observed in CoP velocity when comparing the original data collected at 100 Hz (0.67 ± 0.07) to the downsampled (25 Hz) and filtered data (0.67 ± 0.06). Thus, while downsampling reduces the underlying structure in the time series, filtering artificially adds structure back into the time series, leading to a DFA α value that is similar to the original data, even though the time series are qualitatively different (Fig. 2A and F). In summary, these results suggest care must be taken when attempting to make interpretations about the postural neuromotor system from downsampled and/or filtered CoP data.

Acknowledgement

Manuscript preparation was funded by the US Navy (W91CRB-11-D-0001; subcontract P010202825) to Christopher Rhea.

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