Gait & Posture 41 (2015) 731–735

Contents lists available at ScienceDirect

Gait & Posture

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

Short Communication

Interpretation of postural control may change due to data processing techniques

Christopher K. Rhea [a,*], Adam W. Kiefer [b,c,d], W. Geoffrey Wright [e,f], Louisa D. Raisbeck [a], F. Jay Haran [g]

[a] Department of Kinesiology, University of North Carolina at Greensboro, Greensboro, NC, USA
[b] Division of Sports Medicine, Cincinnati Children's Hospital Medical Center, Cincinnati, OH, USA
[c] Department of Pediatrics, College of Medicine, University of Cincinnati, Cincinnati, OH, USA
[d] Center for Cognition, Action & Perception, Department of Psychology, University of Cincinnati, Cincinnati, OH, USA
[e] Department of Physical Therapy, Temple University, Philadelphia, PA, USA
[f] Department of Bioengineering, Temple University, Philadelphia, PA, USA
[g] Biomedical Research & Operations Department, Navy Experimental Diving Unit, Panama City Beach, FL, USA

ARTICLE INFO

Article history:
Received 24 July 2014
Received in revised form 16 November 2014
Accepted 9 January 2015

Keywords:
Center of pressure
Posture
Variability
Dynamics

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.

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

* Corresponding author at: 1408 Walker Avenue, Greensboro, NC 27412, USA. Tel.: +1 336 334 3023; fax: +1 336 334 3070.
E-mail address: ckrhea@uncg.edu (C.K. Rhea).

http://dx.doi.org/10.1016/j.gaitpost.2015.01.008
0966-6362/

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] $\times$ fil- 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.

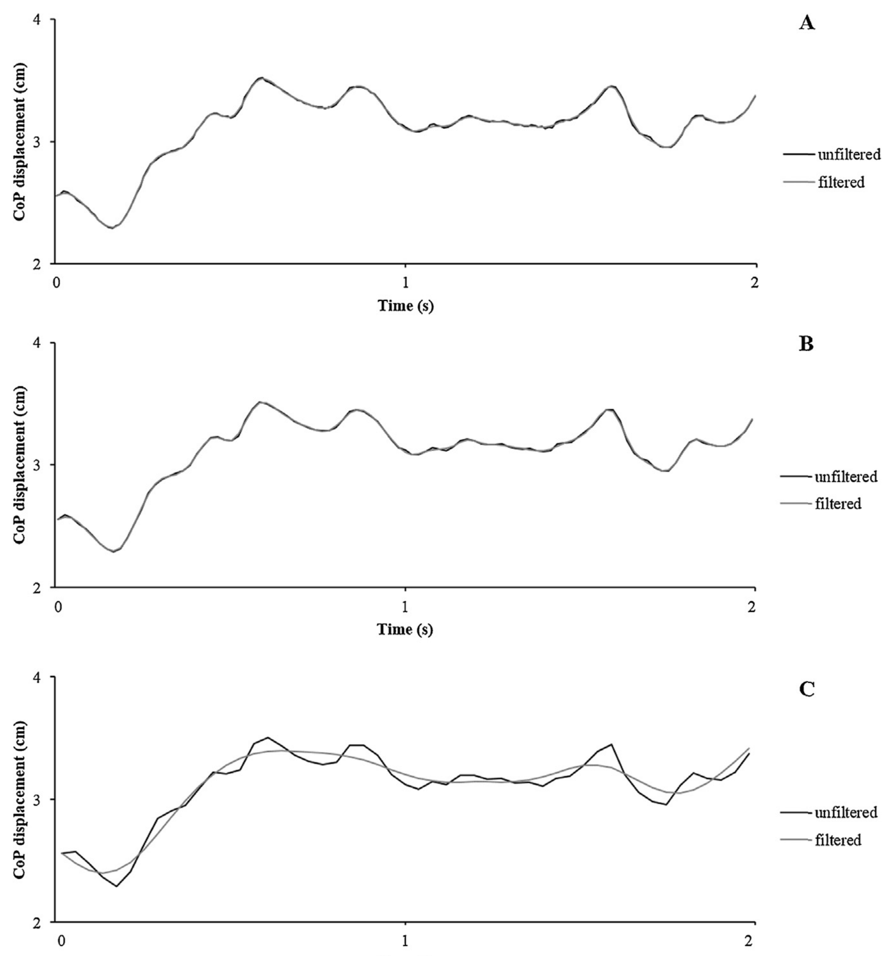

Fig. 1. A two second sample of the 60 s time series for center of pressure (CoP) displacement for the 100 Hz (A), 50 Hz (B) and 25 Hz (C) time series. The unfiltered data are shown with a black line and the filtered data are show with a gray line.