A new measure of the CoP trajectory in postural sway: Dynamics of heading change

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Abstract:

The maintenance of upright stance requires the simultaneous control of posture in both the anterior–posterior (AP) and medial–lateral (ML) dimensions. Postural sway is typically measured by quantifying the movement of the center of pressure (CoP) in the AP and ML dimensions independently. Metrics such as path length and 95% ellipse area have been developed to take into account movement in both the AP and ML directions, but these metrics only quantify the magnitude of the CoP movement. The movement of the CoP is technically a vector quantity with both magnitude and direction characteristics. The direction of displacement, or heading, of the CoP may provide further insight into the control of posture. Accordingly, we present a novel variable that describes the rate of change in direction of CoP displacement in two dimensions, the *heading change* ($\Delta\phi$), which is derived from the CoP *heading* (ϕ). We then compared the standard deviation (SD) and the dynamic structure characterized by sample entropy (SampEn) of the heading change time series to previously examined metrics presented in the literature (SD and SampEn of the AP and ML time series, path length, SD and SampEn of the CoP resultant magnitude time series) during a 60 s single-leg stance performed by healthy participants and patients with a ruptured anterior cruciate ligament (ACL) prior to surgical intervention. Patients with an ACL rupture exhibited a different dynamic structure in $\Delta\phi$compared to healthy controls, $t(14) = 2.44$, $p = 0.029$, whereas none of the other metrics differed between groups (all $p > 0.05$). The novelty and utility of $\Delta\phi$ is that it characterizes directional changes of the CoP, whereas previously documented postural control analyses describe only changes in magnitude.

Keywords: Posture | Dynamics | Sample entropy | Balance

Article:

1. Introduction

Upright posture is an inherently unstable position, yet healthy humans are able to effortlessly control posture to avoid falls and potential injury. Tasks such as seated posture, standing quietly upright in uni- or bi-pedal stance, dynamic stance, and stance during dual-tasks have provided valuable information about the dynamics of postural sway and nervous system adaptation [1]; [2]; [3]; [4]; [5]; [6].

A common method for the characterization of postural sway is to quantify the displacement of the center of pressure (CoP) over time. The trajectory of the CoP in the ground plane is typically recorded with a force platform, which provides a time series of the CoP position in the anterior–posterior (AP) and medial–lateral (ML) dimensions. AP and ML time series exhibit different patterns of postural behavior [7], which supports the practice of analyzing CoP displacement in each dimension independently. To analyze movement in these dimensions, a number of analysis techniques have been developed to quantify CoP behavior in both the time and frequency domains [8]; [9]; [10]. Researchers have expanded on that work and much progress has been made to understand how CoP behavior evolves over time (i.e., the dynamics of the behavior) (see [9]; [11] for a review). Analyses that index both global (i.e., acceleration profiles [12] and principle components analysis [13]) and fine-grained (i.e., the largest Lyapunov exponent [5], fractal patterns [14], and signal complexity [15]) changes in CoP behavior collectively provide insight into how posture is controlled in a variety of contexts.

The majority of these analyses typically examine movement independently for both the AP and ML dimensions. However, a case can be made to avoid the separation of the CoP trajectory into two independent dimensions for subsequent analyses. Specifically, the inherent instability of upright posture requires AP and ML sway to be controlled simultaneously to avoid a loss of balance. While different patterns in the AP and ML dimensions may be observed, it is their combination that perhaps better provides a window into postural control processes. This recognition has caused a number of researchers to explore the resultant vector of the distance traveled in the combined AP and ML directions [16]; [17]; [18]; [19], as this allows for a more parsimonious description of postural sway.

The basis of the CoP resultant vector is the magnitude and direction components of the CoP behavior. The impetus for this paper is that much research has only focused on the magnitude component of the CoP resultant vector and subsequently neglected the direction component [17]; [18]; [19]. The magnitude component is an informative variable that quantifies how far the CoP travels from moment-to-moment, with large deviations in the magnitude component indicative of postural instability due to neuromotor control properties [17]; [18]; [19] or anthropometric factors [20]; [21]; [22]. However, it is also conceptually feasible for the CoP resultant vector magnitude to vary in small increments with each increment moving in a vastly different direction. In such a scenario, abrupt changes in the direction of the CoP resultant vector may also reflect postural instability that might be masked if the analysis only focused on the magnitude component. Furthermore, large deviations in both magnitude and direction would likely indicate even greater postural instability, so considering both components of the CoP resultant vector would potentially provide more holistic insight into postural control. Thus, the novelty of our approach is to quantify the direction component of the CoP dynamics which has, to our knowledge, been neglected in the literature despite its potential relationship to the control of posture. In the next section we outline how the magnitude component of the resultant vector is quantified, and also introduce our novel computational approach to quantify the direction component.

There are several traditional metrics that characterize the magnitude of the resultant vector throughout a balance trial, such as quantifying 95% of the total area covered in the AP and ML directions using an ellipse fit to the data or calculating the CoP resultant velocity from the AP and ML velocity time series. Another common metric is *path length*, and it quantifies the magnitude of the two-dimensional (AP and ML) displacement of the CoP based on the total distance traveled [4]—a larger value of total path length is thought to represent lesser postural stability. However, the control of posture is a dynamic process that evolves throughout the task and over time. While two people may exhibit the same path length over 60 s, the nature in which their posture is controlled likely varies from person to person (e.g., many small changes in displacement vs. very few, but larger changes in displacement). In this example, the dynamic character (moment-to-moment changes) of the posture behavior would not be reflected in the total path length. Consequently, metrics have been developed to examine the dynamics of the path length that characterize the change in the magnitude of the resultant displacement vector over multiple time scales (diffusion coefficient), the magnitude of the non-stationarity of the resultant displacement dynamics (drift coefficient), and the regularity of the magnitude of the resultant displacement time series (SampEn) [16]; [17]; [18]; [19]; however, these analyses are also limited given their focus on the magnitude component of the CoP resultant vector and their inattention to the direction component. Thus, it is plausible that further insight into the control of posture could be gained from a characterization of direction component of the CoP resultant vector.

We present a novel variable that describes the rate of change in direction of CoP displacement in the combined AP and ML dimensions, the *heading change* ($\Delta\phi$), which is derived from the CoP *heading* (ϕ). The term *heading* has been used to describe an individual's direction of travel during locomotion, for example [23], and we borrow from this literature to analogously refer to the direction of travel of the CoP in standing posture. We elected to focus on $\Delta\phi$ primarily due to our interest in the potential control strategy. The $\Delta\phi$ variable quantifies the change in direction of the CoP from moment-to-moment, providing a way to index CoP variability. A typical summary statistic to examine CoP variability is standard deviation (SD), which defines the amount of variability in the CoP behavior. However, behavior in pathological and other naturally or artificially constrained systems can exhibit a similar amount of variability as less constrained, healthy systems [24]; [25]. Thus, it is also important to examine the structure of variability, which quantifies repeating patterns as the behavior unfolds, potentially identifying different control strategies. Structure of variability analyses has been used to characterize adaptive and maladaptive systems, which originated in the cardiac dynamics literature [24]; [26]; [27]; [28]. These analyses now have been extended to a variety of other physiological and behavioral systems, including postural control, to help explain their functional properties [2]; [3]; [5]; [11]; [17]; [18]; [19]; [29]; [30]. While many different dynamic properties can be extracted to examine a system's functional characteristics, the sample entropy (SampEn) metric [31] was selected for this experiment. SampEn is a measure of regularity and it has been suggested that too much regularity in postural control (i.e., a low SampEn number, indicating an overly constrained system) would reflect maladaptive behavior [11]; [19], potentially leading to an increased risk of falling.

The purpose of this experiment was to determine whether a healthy population and a clinical population with an anterior cruciate ligament (ACL) rupture prior to surgical intervention differed in CoP behavior as characterized by the new $\Delta\phi$ metric. Previous research focused on the dynamics of postural control in an ACL deficient or ACL reconstructed (ACLR) population used wavelet analysis, SampEn, and recurrence quantification analysis to examine CoP magnitude changes relative to healthy controls [32]; [33]; [34]. However, these papers only focused on the CoP in the AP and/or ML dimensions. Analyzing the dynamics of the resultant CoP vector after an ACL injury, and specifically the direction component of the vector, represents a novel contribution to the literature. To provide a comprehensive evaluation of our new metric, we included the following analyses: path length (sum of resultant vector magnitudes), amount of variability (standard deviation, SD) of the resultant vector magnitude and direction, and structure of variability (SampEn) of the resultant vector magnitude and direction. We hypothesized that metrics that capture the overall CoP behavior (path length and SD) would not exhibit group differences. We also hypothesized that SampEn of the CoP resultant magnitude would not be different between our groups given that previous research has demonstrated no significant differences between patients after ACLR and healthy controls [32]. However, given that the CoP resultant direction characterizes a different component of the vector that could relate to postural instability, we further hypothesized that SampEn of $\Delta\phi$ would differ between groups.

2. Methods

All procedures were approved by the institution's IRB. Eight healthy adults (3 females and 5 males; age: 27.4 ± 2.6 years; height: 1.73 ± 0.08 m; weight: 71.9 ± 9.6 kg) and eight patients with a ruptured ACL in their right knee prior to surgical reconstruction (5 females and 3 males; age: 25.9 ± 6.3 years; height: 1.72 ± 0.14 m; weight: 70.5 ± 17.1 kg, time since injury: 4.9 ± 2.5 weeks) balanced on their involved leg (i.e., ACL ruptured side) with eyes open for 60 s. CoP displacement in the AP and ML directions was recorded at 100 Hz[1] with a force platform (AMTI, Watertown, MA) [35].

A total of nine variables were calculated from the CoP data. Four of the nine variables were calculated on the independent AP and ML time series (i.e., SD-AP, SD-ML, SampEn-AP, and SampEn-ML) and the remaining five variables were calculated from the resultant vector created from the combined AP and ML time series (i.e., path length, SD resultant magnitude, SD resultant direction, SampEn resultant magnitude, and SampEn resultant direction). For the latter, a resultant vector time series was created and separated into a magnitude component time series

[1] Post hoc analyses showed that down-sampling to 25 or 50 Hz was not sufficient to pick up the CoP dynamics of interest. Thus, it is recommended that 100 Hz is an appropriate sampling frequency for the CoP $\Delta\phi$ variable, and this is also the suggested sampling frequency for other CoP dynamics analyses [35]. Likewise, filtering dampened the dynamic characteristics of the CoP data, so it is suggested that unfiltered CoP data should be used for the CoP $\Delta\phi$ analysis. Alternatively, a nonlinear filter has been employed in previous research to avoid altering the dynamics of the original signal [5].

and a direction component time series prior to analysis. Path length (the fifth variable) was calculated by summing the magnitude of the distance change of the CoP at every time step with the following equation:

$$\text{Path length} = \sum_{i=1}^{N=1} \sqrt{(\text{AP}_{i+1} - \text{AP}_i)^2 + (\text{ML}_{i+1} - \text{ML}_i)^2} \qquad (1)$$

where N is the number of data points in the CoP displacement time series and i is each successive data point. The last four variables were calculated by quantifying the SD and SampEn of the CoP resultant vector magnitude and direction time series. While the magnitude of the CoP resultant vector has been previously examined [17]; [18]; [19], this paper presents a new variable that characterizes the CoP resultant direction (ϕ).

ϕ was calculated by determining the direction of displacement between two successive CoP positions. Specifically, the two argument variant of the arctangent function was used (commonly expressed in computer languages as atan2). This function is capable of discriminating between two diametrically opposite directions and returns values that range from $-\pi$ to π. To map values onto the traditional unit circle's range of 0 to 2π, a constant of 2π must be added to the negative values. We converted the function's output from radians to degrees by multiplying by $180°/\pi$. It is important to note that the function atan2(y,x) specifies that the x-coordinate is on the horizontal (ML) axis. Thus, we used the following equation to calculate the CoP heading:

$$\phi_i = \tan^{-1}(y, x) \qquad (2)$$

where y is the difference in successive AP positions ($\text{AP}i_{+1} - \text{AP}i$) and x is the difference in successive ML positions ($\text{ML}i_{+1} - \text{ML}i$). This allowed us to define movement along the horizontal axis as ML displacement, as shown in Fig. 1.

Lastly, $\Delta\phi$ was used to quantify the displacement magnitude of ϕ from moment-to-moment (Fig. 1). The circ_dist.m function within the Circular Statistics Toolbox for Matlab [36] was used to create a time series that indexed the angular displacement between successive ϕ points, denoted as $\Delta\phi$. Since counterclockwise movement around a traditional unit circle is denoted as positive angular displacement, a positive $\Delta\phi$ indicates a counterclockwise movement in ϕ, whereas a negative $\Delta\phi$ value indicates that ϕ moved in the clockwise direction. This distinction bounded each $\Delta\phi$ data point between $-180°$ and $180°$ (Fig. 1; Fig. 2), as this allows $\Delta\phi$ to rotate a full 360° from moment-to-moment. Any movement outside that range requires the CoP trajectory to loop back on itself (either clockwise or counter clockwise) in between sampled points. Given the relatively high sampling rate (100 Hz), a nearly full rotation of the CoP in 1/100 of a second is unlikely. Previous work has shown that 95% of the power in the CoP magnitude displacement time series is less than 2 Hz in healthy subjects [37]; [38]; [39], so the sampling rate in the current analysis was high enough to capture the actual phenomena of the CoP trajectory.

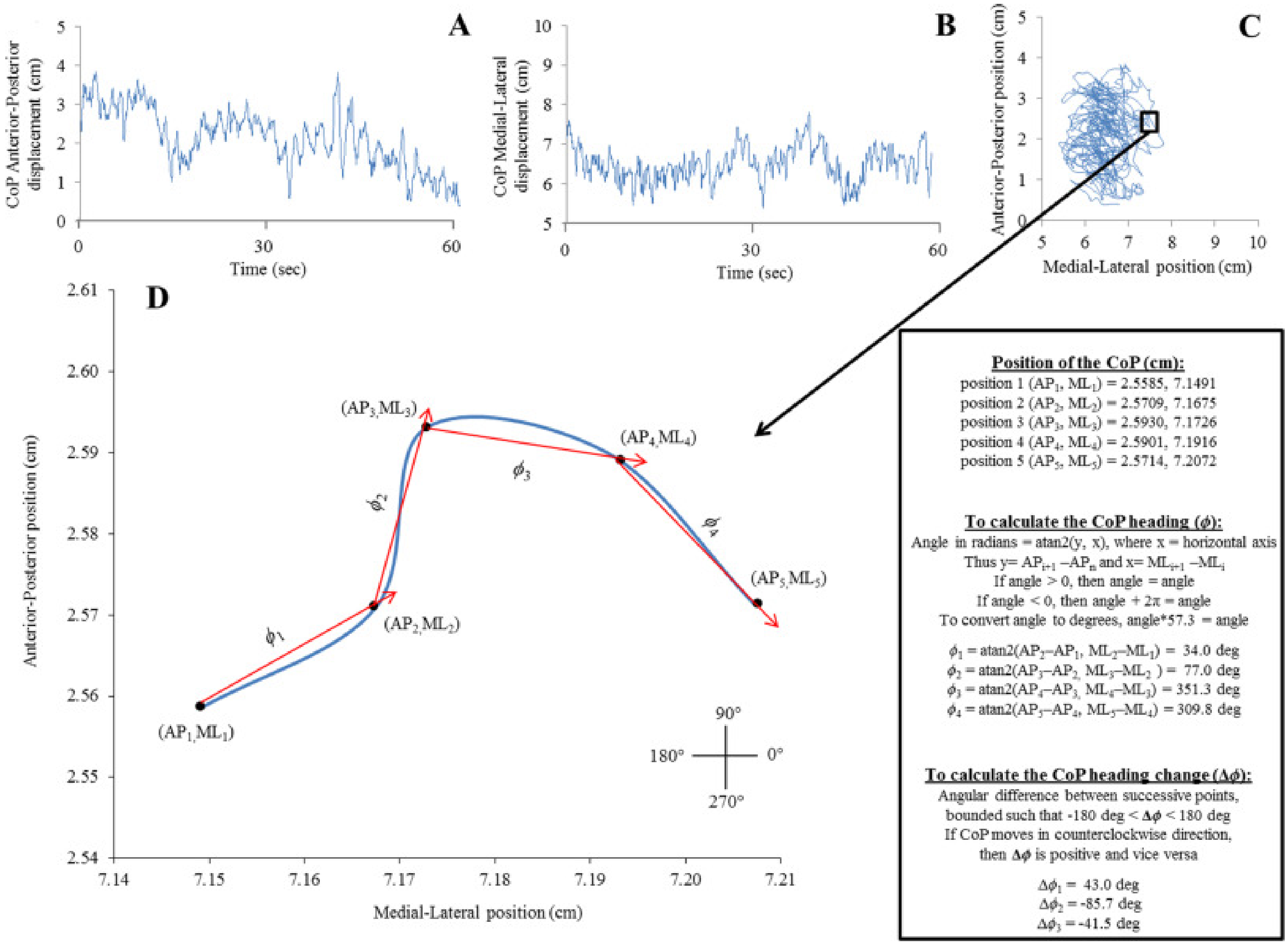

Fig. 1. Sample data from one 60 s trial of single-leg stance in a healthy participant. CoP displacement in the anterior–posterior (A) and medial–lateral (B) directions over the entire 60 s task, and the resulting top-down view of the CoP displacement over the entire 60 s task (C) are shown. The first five data points in the anterior–posterior and medial–lateral time series are shown to illustrate the calculation of the CoP heading (ϕ) and CoP heading change ($\Delta\phi$) (D).

Matlab (Mathworks, Inc., Natick, MA) scripts were used to calculate all CoP variables. SD of $\Delta\phi$ was calculated using the circ_std.m function in the Circular Statistics Toolbox for Matlab [36]. The details of the SampEn algorithm have been published elsewhere [40]. In short, SampEn calculates the conditional probability of repeating patterns in the time series. First, a template of defined length (*m*) is created from the first few data points in the time series. The template is then compared to successive data points in the time series and a match is counted if it is within a defined threshold (*r*) of the template. The SampEn algorithm is computationally similar to the preceding Approximate Entropy algorithm, except self-matches to the template are not counted in the conditional probability equation. SampEn typically ranges from 0 to 2 in human physiological systems, with lower values indicating more regularity in the dynamics. To employ the SampEn algorithm, the parameters *m* (template length) and *r* (tolerance level) must be defined. A guideline to select *m* and *r* was first developed to examine the SampEn of cardiac dynamics [40], and this has been used previously to examine dynamics of the CoP in other posture tasks [19]; [41]. As per these guidelines, a variety of m and r value combinations were examined to determine the set of values that lead to the lowest acceptable variance. An efficiency metric was derived from the maximum relative error of SampEn and of the conditional probability to determine the largest value of m and r that could be used obtain reliable data at the 95% confidence interval level. For our data set, we examined a range of m values from 2 to 10 and r values from 0.01 to 0.60. The values of m = 3 data points, $r = 0.3 \times$ SD of the $\Delta\phi$ time series (relative threshold) were selected for the CoP resultant magnitude and direction time series using this method. The same method was used to select values of m = 3 and $r = 0.07 \times$ SD for the independent analysis of both the AP and ML time series. Additionally, detrended fluctuation analysis (DFA) was used to index the presence of long-range correlations in the $\Delta\phi$ time series [42]. Since $\Delta\phi$is an angular variable, the Watson-Williams test was used to examine group differences in the SD of $\Delta\phi$. All other CoP variables were ratio variables, so an independent samples t-test was used to compare the ACL deficient group to the healthy group.

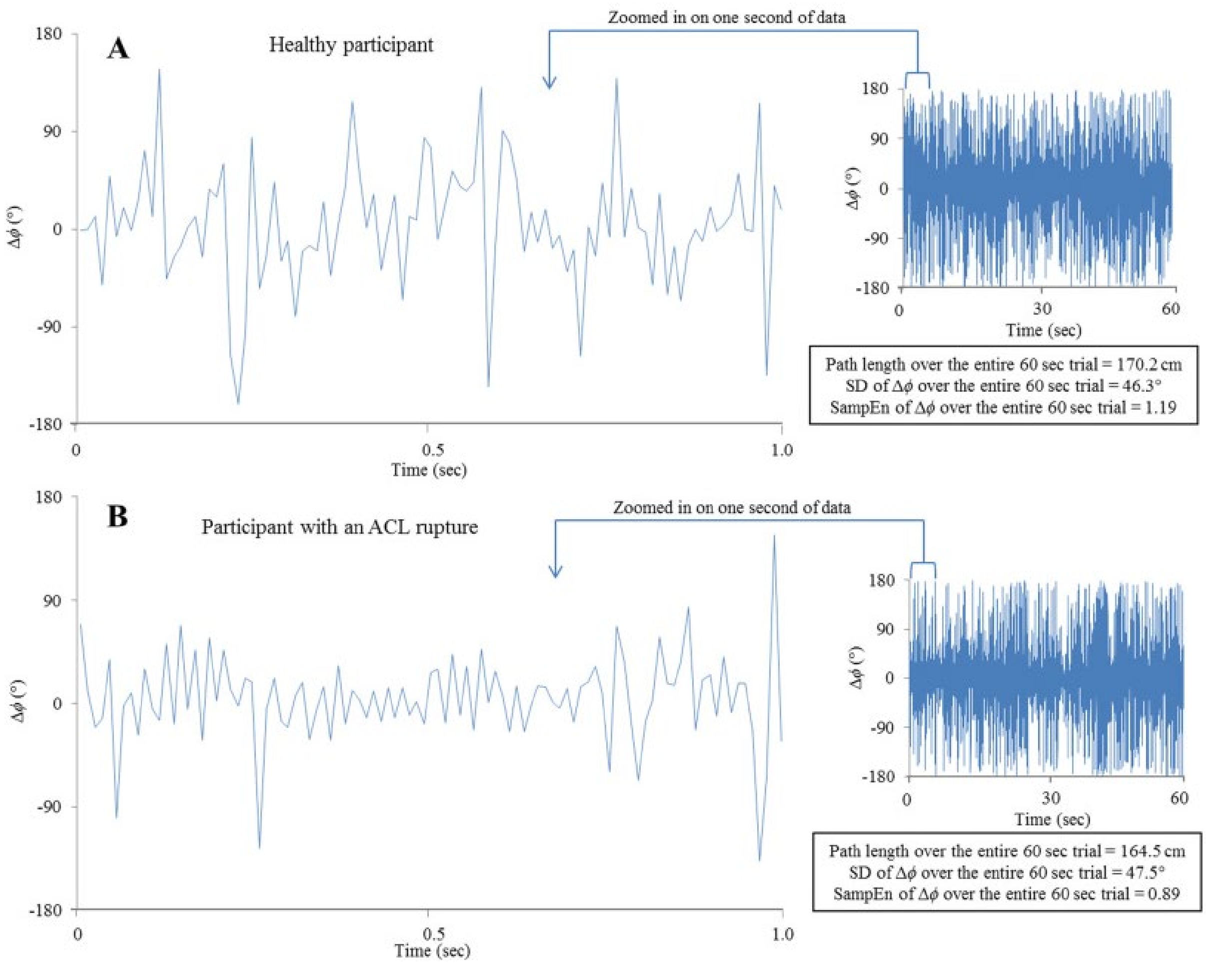

Fig. 2. An example of the CoP heading change ($\Delta\phi$) time series over 1 s for both a healthy participant (A) and an ACL-ruptured participant (B). Notice the relatively more regular $\Delta\phi$ time series in the ACL-ruptured patient, leading to the lower SampEn value over the 60 s trial.

3. Results

3.1. Preliminary results

DFA was run on the $\Delta\phi$ time series for all participants and it was confirmed that long-range correlations were not present; indicating that a time delay parameter did not need to be included in the SampEn algorithm. Furthermore, no group differences were observed between the patients with an ACL rupture (DFA $\alpha = 0.48 \pm 0.03$) and the controls (DFA $\alpha = 0.49 \pm 0.02$), $t(14) = -0.76$, $p = 0.46$.

3.2. AP and ML time series

Table 1 shows the SD and SampEn of the AP and ML time series for each participant. Table 2 contains the inferential statistics. No differences between groups were observed for any of the dependent measures (all $p > 0.05$).

Table 1. Analyses for the CoP AP and ML directions.

	SD AP (cm)	**SD ML (cm)**	**SampEn AP**	**SampEn ML**
Healthy participants				
1	0.75	0.44	0.39	0.37
2	0.89	0.46	0.32	0.35
3	0.56	0.33	0.29	0.43
4	0.80	0.55	0.43	0.35
5	0.54	0.37	0.25	0.41
6	0.53	0.41	0.40	0.39
7	0.63	0.43	0.34	0.38
8	0.63	0.33	0.29	0.39
Mean	0.67	0.42	0.34	0.38
SD	0.13	0.07	0.06	0.03
ACL deficient participants				
1	0.66	0.35	0.28	0.48
2	0.73	0.40	0.24	0.40
3	1.30	0.56	0.38	0.28
4	0.44	0.40	0.33	0.39
5	0.76	0.41	0.45	0.37
6	0.66	0.43	0.42	0.39
7	0.79	0.52	0.37	0.36
8	0.40	0.19	0.28	0.44
Mean	0.72	0.41	0.35	0.39
SD	0.28	0.11	0.07	0.06

SD = standard deviation; SampEn = sample entropy; AP = anterior–posterior; ML = medial–lateral.

Table 2. Statistics for each analysis.

Variable	t	df	p-value
SD AP	−0.47	14	0.643
SD ML	0.16	14	0.876
SampEn AP	−0.15	14	0.886
SampEn ML	−0.22	14	0.831
PL	−0.96	14	0.352
SD resultant magnitude	−1.39	14	0.186
SD resultant direction[a]	0.85	14	0.410
SampEn resultant magnitude	1.74	14	0.103
SampEn resultant direction	2.44	14	0.029

SD = standard deviation; AP = anterior–posterior; ML = medial–lateral; SampEn = sample entropy; PL = path length.
[a] All variables were analyzed using an independent samples *t*-test with the exception of SD resultant direction, which required a Waston–Williams *t*-test from circular statistics.

3.3. Resultant time series

Table 3 shows the path length for each participant, along with SD and SampEn of the CoP resultant magnitude and direction time series for each participant. Table 2 shows the associated statistics. Only SampEn of CoP resultant direction time series ($\Delta\phi$ showed a difference between groups, with the ACL deficient group exhibiting a lower value (0.92 ± 0.12) compared to the healthy group (1.08 ± 0.14).[2]

Table 3. Analyses for the CoP resultant vector.

	PL (cm)	SD magnitude (cm)	SD direction (cm)	SampEn magnitude	SampEn direction*
Healthy participants					
1	162.0	0.018	41.5	1.07	0.99
2	153.4	0.017	42.4	1.10	1.15
3	168.5	0.020	49.3	1.04	0.95
4	201.3	0.023	40.3	0.99	1.10
5	177.7	0.018	48.8	1.34	1.32
6	170.2	0.019	46.3	1.12	1.19
7	207.3	0.027	39.4	0.76	0.95
8	141.8	0.016	44.6	1.06	0.97

[2] To confirm that the SampEn findings of $\Delta\phi$ were not a function of artificial noise in the time series, we randomly shuffled the $\Delta\phi$ time series to create a surrogate $\Delta\phi$ time series for each participant. SampEn for the surrogate $\Delta\phi$ time series was 1.48 ± 0.06 for the healthy participants and 1.44 ± 0.11 for the patients with an ACL rupture, $t(14)$ = 0.73, p = 0.48, suggesting that SampEn of the original $\Delta\phi$ time series is capturing a true biological phenomenon.

	PL (cm)	SD magnitude (cm)	SD direction (cm)	SampEn magnitude	SampEn direction*
Mean	172.8	0.020	44.1	1.06	1.08
SD	22.4	0.004	3.8	0.16	0.14
ACL deficient participants					
1	187.4	0.021	48.9	1.18	1.02
2	180.8	0.021	40.8	0.98	0.87
3	309.5	0.049	38.4	0.50	0.72
4	170.7	0.022	48.9	1.00	1.03
5	164.5	0.021	47.5	0.93	0.89
6	233.7	0.029	34.9	0.79	0.81
7	223.4	0.030	36.8	0.76	1.03
8	93.4	0.011	50.6	1.04	1.01
Mean	195.4	0.025	43.4	0.90	0.92
SD	62.7	0.011	6.3	0.21	0.12

PL = path length; SD = standard deviation; SampEn = sample entropy.
* Significant difference between the healthy and ACL deficient group ($p = 0.029$).

4. Discussion

This paper introduces $\Delta\phi$ as a novel variable to index the moment-to-moment change in direction of the CoP collectively across two dimensions. By measuring the angle between two successive positions of the CoP, the variable ϕ was derived from movement in the AP and ML dimensions. This variable meets the challenge of using a single metric to quantify changes in both the AP and ML directions concurrently. Previous measures that index the resultant (combination of the AP and ML directions) of the CoP movement, such as path length, sway area, and 95% confidence ellipse area, quantified the magnitude of displacement. However, the CoP resultant trajectory exhibits vector characteristics that vary with respect to both magnitude and direction. Examining only the characteristics of the magnitude component may mask postural instability. For example, it is feasible for the CoP to zig–zag over a five sample window. In this case, the CoP resultant magnitude (distance traveled by the CoP) could be identical over the five samples, but the CoP resultant direction would be vastly different at every time point. Thus, postural instability may be more accurately indexed when considering both magnitude and direction components of the CoP resultant vector.

The findings show that different strategies can be used to produce the same overall behavior. While no difference in CoP behavior was observed between groups with magnitude derived metrics, SampEn of $\Delta\phi$ was lower for the patients with an ACL rupture, which indicates more regular postural dynamics. This is congruent with previous work that examined the COP dynamics in ACLR patients and showed no differences in SampEn of the AP time series [32]. That research group also observed an increase in SD of the AP time series relative to healthy participants, however, and this was a finding that was not supported by the current data. Since patients with an ACL rupture exhibit proprioceptive degradation [43], it could be assumed that less regular control of posture would emerge. However, patients with a ruptured ACL are also known to exhibit muscular co-contraction around the knee, which is thought to protect the knee joint from further injury by off-loading forces from the remaining connective tissue to the musculature around the knee [44]; [45]; [46]; [47]. This protective mechanism leads to more regular movement of the CoP, which diminishes functional ability by reducing the ability to adapt to postural fluctuations. Fig. 2 shows a qualitatively different $\Delta\phi$ pattern over 1 s for the healthy participant compared to the patient with the ACL rupture. As shown on the figure, the overall behavior of the CoP, as indexed by path length and SD of $\Delta\phi$ was not different between the two participants. However, the qualitative difference in behavior between groups was identified by the SampEn analysis. This indicates the potential adoption of different control strategies between groups.

A change in the structure of variability (SampEn) in the behavior without a corresponding change in the amount of variability (SD) is not an uncommon finding in pathological populations, or during constrained tasks [24]; [25], and is typically interpreted as a reorganization of the system in response to imposed internal or external constraints. It could be argued that the non-regular (i.e., complex) behavior exhibited by the healthy controls reflects their ability to produce adaptive behavior. That is, by not being locked into a particular behavior, the individual has the flexible control needed to adjust their CoP to respond to perturbations. Conversely, patients with an ACL rupture exhibited more regularity in their $\Delta\phi$ behavior, as most values hovered around 0°, and this indicates relatively little change in the direction of their CoP from a moment-to-moment basis. This behavior is typically interpreted in the dynamics literature as maladaptive, given it may be difficult for the participant to adjust their behavior to respond to perturbations. Since the regular (i.e., non-complex) behavior has not allowed the patient to fully explore their boundaries of postural control, a perturbation may threaten their stability. Thus, the reduced SampEn values in the $\Delta\phi$ time series are congruent with previous research showing that natural or artificial constraints can lead to a deviation away from the healthy complexity (i.e., adaptive behavior) exhibited by young healthy adults [11]; [25] and that decreased entropy is observed in the dynamics of movement patterns in patients with an ACL rupture [48]; [49]; [50].

We contend that CoP heading captures the phenomena related to the postural control process. That is, upright stance is not controlled via an AP and ML grid within the neuromotor system. Rather, the CoP location is altered within a short time-lag in response to changes in the center of mass location, which can also move in multiple directions at once (e.g., forward and to the right). Separating postural control analyses into AP and ML distinctions may mask changes to the behavior. Similarly, our data show that analyses focusing on magnitude changes to the resultant vector may also mask changes to the behavior, as a series of small and large changes in CoP position could look quantitatively similar to a series of medium changes in CoP position. CoP heading indexes a component of the resultant vector that, until now, has been neglected in the literature. CoP heading was shown to be more sensitive to changes in postural control relative to analyses focused on AP, ML, or resultant magnitude behavior. It is plausible that CoP heading may index postural stability processes rooted in proprioceptive sensitivity or reaction time. However, these postulates warrant further investigation.

One limitation to the study is the lack of multiple postural control trials to test the reliability of all metrics. Previous work that examined CoP dynamics in the AP and ML dimensions found that high reliability—assessed with intraclass correlations (ICCs) and standard error of the mean (SEM)—is observed in a clinical population that included ACL deficient patients [33]. Thus, a test–retest method should be used in future research to determine the robustness of the $\Delta\phi$ variable for the characterization of postural control strategies.

In conclusion, the novelty and utility of $\Delta\phi$ is that it allows for a description of directional changes in the CoP that may reflect postural adaptability. The CoP trajectory is a vector quantity and previous metrics have been developed to quantify the magnitude characteristics. This new variable, $\Delta\phi$, adds to the literature by providing a metric that quantifies the direction characteristics of the CoP trajectory. Since balance is maintained by coordinating movement in the AP and ML dimensions simultaneously, $\Delta\phi$ provides a parsimonious description of the direction of postural sway. Magnitude and direction are scalar quantities and a challenge for future research is to develop a vector quantity of CoP dynamics that captures both magnitude *and* direction within a single variable to gain more insight into how posture is controlled.

Conflict of interest
None.

Ethical approval
All procedures were approved by the Institutional Review Board at the Providence VA Medical Center.

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