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Correlations of pelvis state to foot placement do not imply within-step active control

Navendu S. Patil [a,b,*], Jonathan B. Dingwell [a], Joseph P. Cusumano [b]

[a] Department of Kinesiology, Pennsylvania State University, University Park, PA 16802, USA
[b] Department of Engineering Science & Mechanics, Pennsylvania State University, University Park, PA 16802, USA

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ABSTRACT

Experimental studies of human walking have shown that within an individual step, variations in the center of mass (CoM) state can predict corresponding variations in the next foot placement. This has been interpreted by some to indicate the existence of active control in which the nervous system uses the CoM state at or near mid-stance to regulate subsequent foot placement. However, the passive dynamics of the moving body and/or moving limbs also contribute (perhaps strongly) to foot placement, and thus to its variation. The extent to which correlations of CoM state to foot placement reflect the effects of within-step active control, those of passive dynamics, or some combination of both, remains an important and still open question. Here, we used an open-loop-stable 2D walking model to show that this predictive ability cannot by itself be taken as evidence of within-step active control. In our simulations, we too find high correlations between the CoM state and subsequent foot placement, but these correlations are entirely due to passive dynamics as our system has no active control, either within a step or between steps. This demonstrates that any inferences made from such correlations about within-step active control require additional supporting evidence beyond the correlations themselves. Thus, these within-step predictive correlations leave unresolved the relative importance of within-step active control as compared to passive dynamics, meaning that such methods should be used to characterize control in human walking only with caution.

1. Introduction

Humans stay upright during walking in part by choosing appropriate stepping locations on the ground (Townsend, 1985; Redfern and Schumann, 1994). Exactly how this is accomplished from one walking step to the next is the topic of much current research, a central aim of which is to understand the nature and importance of active neuromotor control during gait. Complicating matters, however, is the fact that the word "control" can take on a variety of meanings in different contexts. It might refer to the active control of foot placements within one step, the adjustments made between steps, postural control needed to coordinate whole-body movements while walking, balance control needed to enhance stability and avoid falling, or the regulation needed to achieve walking goals (such as maintaining a desired walking speed or heading), among other possibilities. Moreover, the fundamental biomechanics of the human body endows it with intrinsic dynamical properties, including "self-stabilizing" mechanisms (Wagner and Blickhan, 2003; Eriten and Dankowicz, 2008; Iida et al., 2008), which are independent of specific stepping regulation processes and which, therefore, should properly be considered part of the "plant" being acted upon by any "controller". This poses an additional challenge to understanding the role of neuromuscular control during walking, because one must attempt to untangle the effects of active control from those of passive dynamics. Thus, to effectively use experimental gait analysis methods, researchers need to have a clear understanding of the degree to which such methods can provide insights into the role of active control in generating observed locomotor behavior.

When humans walk on a treadmill, their pelvis, or center of mass (CoM), state is a good proxy for the next foot placement (Wang and Srinivasan, 2014b; Rankin et al., 2014; Bruijn and van Dieën, 2018). Within a given step, small variations in the CoM are consistently mapped to variations in the subsequent foot placement. The resulting linear correlations have been interpreted as indicating active control (Perry and Srinivasan, 2017; Arvin et al., 2018; Stimpson et al., 2018, 2019). Physiological evidence related to muscle activations (Hof and Duysens, 2013; Rankin et al.,

* Corresponding author at: Department of Kinesiology, Pennsylvania State University, 276 Recreation Building, University Park, PA 16802, USA.
E-mail address: nsp129@psu.edu (N.S. Patil).

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2014; Kubinski et al., 2015) and/or proprioception (Arvin et al., 2018; Roden-Reynolds et al., 2015) provides some support for such interpretations. However, correlations of CoM state to subsequent foot placement could also arise from passive dynamics (Wang and Srinivasan, 2014b; Bruijn and van Dieën, 2018), given that movements of the feet are mechanically coupled to those of the rest of the body. This alternative hypothesis has, however, not been directly tested in human subject experiments. Thus, to use such correlation analyses to make inferences about within-step control during walking, it is critically important to understand the extent to which they might arise from strictly passive dynamics that is *not* related to active control.

This question is exceptionally difficult to address with experiments alone. Human bodies have limb segments with mass and inertia, so they intrinsically exhibit passive dynamics. Humans also have brains and nervous systems that both actuate and regulate the movements of those limb segments. One cannot completely decouple the brain from its body, nor (even if this were possible) would it make sense to do so as the body and its nervous system are intrinsically integrated such that the overall "control" of any movement is likely shared between the nervous system and the biomechanical structures and components being moved (Chiel et al., 2009). Thus, in experiments, the extent to which correlations of deviations in CoM state to deviations in foot placement can be attributed to within-step feedback control, feedforward control, passive dynamics, or some combination of all three will be inherently ambiguous. Appropriate computational models, wherein the passive dynamics and control elements can be clearly identified, separated, and accounted for, are an important tool that can help untangle these different effects.

Here, we used an open-loop-stable (i.e., stable without any type of error-correcting control) 2D walking model to show that one cannot take predictions of foot placement from a preceding pelvis state, by themselves, as evidence of within-step active control. Our simulations also reveal high correlations between the pelvis state and subsequent foot placement in the sagittal plane. However, this is entirely due to passive dynamics as our system, by design, has no active control within or between steps. Our simulations therefore suggest that much of the aforementioned predictability in humans *could* perhaps be attributed to the passive or "ballistic" nature of trajectories between consecutive heel strikes (McGeer, 1990). Thus, the extent to which correlations of CoM state to foot placement reflect the effects of within-step active control, those of passive dynamics, or some combination of both, remains an important and still open question. As a result, such correlation statistics should be used to characterize within-step active control in human walking only with caution, and require supporting evidence beyond the correlations themselves.

2. Methods

2.1. Stochastic simulations of an uncontrolled walker

We used a 2D compass walker (Kuo, 2001) actuated by toe-off impulse, P, applied just before heel strike (Fig. 1). Each walking step has an *unactuated* continuous stance phase (Fig. 1b) between consecutive heel strikes (Fig. 1a, c).

This 2D sagittal plane model achieves stable gaits without stabilizing feedback, so its dynamics are entirely passive. However, as exemplified by the dynamics of a 3D walker (Kuo, 1999), there is inherent *lateral* instability in walking. Thus, studies of human balance draw a distinction between the anteroposterior and mediolateral directions. However, our focus here is not on stability, but on the active control interpretation of within-step correlations, which are significant in both mediolateral and anteroposterior directions (Wang and Srinivasan, 2014b). Thus, the question of the validity of this interpretation is of equal relevance to both anteroposterior and mediolateral motions. Therefore, precisely because it requires *no* control, the powered sagittal plane walker provides us with the most appropriate model with which to unambiguously examine this issue.

The step-to-step dynamics of our model is described by a 2D impact Poincaré map (Fig. 1). For simulations, we selected three stable gaits with nondimensionalized step speeds $v^* \in \{0.120, 0.145, 0.170\}$, corresponding to fixed impulses $P^* \in \{0.057, 0.085, 0.120\}$. For reference, these speeds correspond to roughly 40% of the nondimensionalized human speeds from the experimental data of Wang and Srinivasan (2014a,b). We now discuss estimating linear maps for the prediction of foot placement from the walker's noisy trajectories, using two noise regimes and three predictor state vectors.

2.1.1. "Motor" or process noise only: σ_p

For each gait, we simulated 600 consecutive steps with Gaussian "motor" (process) noise of amplitude $\sigma_p = 0.3\%$ added to the fixed-point-impulse P^*, so that the impulse for step k was $P_k = P^*(1 + \sigma_p \eta_k)$ (Fig. 1c), where η_k was a Standard Normal random variable drawn independently of everything else, making every impulse sequence serially uncorrelated. Moreover, P_k was not state-dependent, and was not chosen to achieve any specific response, i.e., it was merely an *input*. Thus, there was *no active control* imposed in our model.

We replicated the analyses of Wang and Srinivasan (2014b), modified for sagittal plane analysis. Each trajectory of the stance phase was divided into 100 intervals ($\Delta t = T_{\text{step}}/100$, for step period T_{step}). While Wang and Srinivasan (2014b) used "distance of pelvis from mid-stance [y_p in our notation] normalized by trial's mean stride length" as their phase variable, here we used $\tau := t/T_{\text{step}} \in [0, 1]$. From each time series (length $N = 60600$), we estimated a linear map, at each phase τ, between deviations of the pelvis state $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ from its mean to corresponding deviations of the next foot placement, y_{foot} (Fig. 1), using the ordinary least squares,

$$\Delta y_{\text{foot}} \approx J_1 \Delta y_p + J_2 \Delta \dot{y}_p + J_3 \Delta z_p + J_4 \Delta \dot{z}_p, \tag{1}$$

and calculated the R^2 statistic for each such linear fit. We constructed 25 realizations of the data using distinct seeds to MATLAB's pseudo-random generator, and reported means and standard deviations for the final R^2 statistic as functions of τ.

2.1.2. Adding measurement noise: σ_o

To study the effect of experimental measurement errors, we added random fluctuations to every time series from the simulations of Section 2.1.1. We perturbed all variables, $w_i \in \{y_p, \dot{y}_p, z_p, \dot{z}_p, y_{\text{foot}}\}$ at every phase τ to obtain "measurements" $\widetilde{w}_i = w_i[1 + \sigma_o \zeta_i(\tau)]$, where $\zeta_i(\tau)$ is an independent Standard Normal random variable and σ_o the measurement noise amplitude. We then repeated the estimation in Eq. (1), for each of 3 measurement noise amplitudes, $\sigma_o \in \{0.1, 0.2, 0.3\}\%$.

2.1.3. Additional state predictors for the foot placement

In the above, we used a 4-variable pelvis state, $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ to predict foot placement. In experiments, this state is estimated from pelvis and stance-foot markers. For comparison, we repeated our regressions with two additional predictors, both associated with the walker's two angular degrees of freedom: the pelvis state, $\left(\theta, \dot{\theta}\right)$, which uniquely determines $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ (Fig. 1); and the

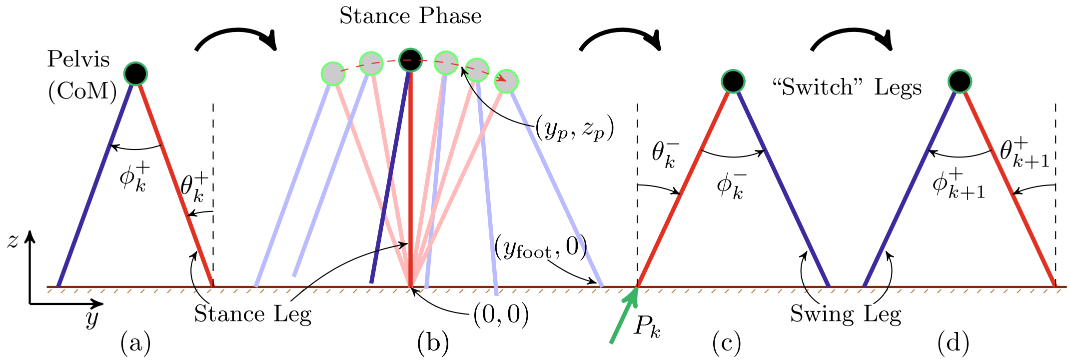

Fig. 1. Snapshots of a 2D powered compass walker (Kuo, 2001): (a) just after k^{th}, (c) just before $(k+1)^{\text{st}}$, (d) just after $(k+1)^{\text{st}}$ heel strike, and also (b) at the mid-stance position. The walker has straight, massless, stance (*red*) and swing (*blue*) legs, and a mass at the pelvis or CoM (circle). The toe-off impulse, P, applied just before the heel strike, allows walking steps on an even ground in the forward direction (*positive y axis*). During the stance phase, pelvis (CoM) location (in Cartesian coordinates) is given by $(y_p, z_p) := (-\sin\theta, \cos\theta)$, or simply by θ (in angular coordinates). Correspondingly, the pelvis state (i.e., its position and velocity) during the stance phase becomes $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ with $\dot{y}_p = -\dot{\theta}\cos\theta, \dot{z}_p = -\dot{\theta}\sin\theta$, and $\left(\theta, \dot{\theta}\right)$, respectively. The heel strike, at the end of the stance phase, occurs when $\phi^- = 2\theta^-$ and the corresponding swing-foot location is at $y_{\text{foot}} := -2\sin(\theta^-)$. The walker's full state during the stance phase is $\left(\theta, \dot{\theta}, \phi, \dot{\phi}\right)$ and that just after the heel strike is $(\theta^+, \dot{\theta}^+)$. The step-to-step dynamics of this walker is described by an impact Poincaré map defined over the 2D state space $\left(\theta^+, \dot{\theta}^+\right) : \theta^+_{k+1} = F_1\left(\theta^+_k, \dot{\theta}^+_k\right); \dot{\theta}^+_{k+1} = F_2\left(\theta^+_k, \dot{\theta}^+_k; P_k\right)$. Single-step periodic gaits of the walker are fixed points $(\theta^*, \dot{\theta}^*)$ of this map corresponding to a given fixed value of the input impulse, $P^* : \theta^* = F_1\left(\theta^*, \dot{\theta}^*\right); \dot{\theta}^* = F_2\left(\theta^*, \dot{\theta}^*; P^*\right)$. This walker admits stable gaits with "motor" input, $P_k = P^*$, for $0 \leqslant P^* \lessapprox 0.1357$, without the need for active control. We selected three such stable gaits with nondimensionalized step speeds, $\upsilon^* \in \{0.120, 0.145, 0.170\}$, corresponding to $P^* \in \{0.057, 0.085, 0.120\}$, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

walker's full mechanical state $\left(\theta, \dot{\theta}, \phi, \dot{\phi}\right)$, which completely specifies its dynamics during the stance phase.

2.2. Sagittal plane analysis of treadmill walking data

We re-analyzed the data of Wang and Srinivasan (2014a,b), obtained for 10 healthy young adults walking on a treadmill for about 5 min at each of 3 different speeds, collected at 100 Hz from the left and right heels and the pelvis (a proxy for the CoM). We performed a sagittal, *yz*-plane analysis of those data (forward walking is in positive *y*-direction of the lab reference frame) for direct comparison with our 2D walker. We up-sampled each experimental time series to 1000 Hz using piecewise cubic spline interpolation to increase the accuracy of step calculations (Dingwell and Cusumano, 2019). We identified heel strikes when the sign of $\dot{y}$ of the swing heel-marker changed from positive to negative (Zeni et al., 2008). We approximated $\dot{y}$ and $\dot{z}$ using first-order forward differences, followed by moving-average smoothing (window-size 51). We used the same phase variable for the stance phase, τ, as in Section 2.1.1. For each walking trial, we regressed y_{foot} at $\tau = 1$ on $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ at each τ over left and right leg stance phases separately (Eq. 1; Fig. 1; variables in the treadmill-belt frame). We calculated corresponding R^2 statistics, and estimated means and standard deviations, at each τ, over twenty R^2 values (10 trials; 1 fit each for left and right legs).

3. Results

Our sagittal plane analysis of human walking data demonstrated that correlations between CoM state and foot placement are significant (Fig. 2), consistent with previous results from 3D analysis (Wang and Srinivasan, 2014b). For each speed, mean R^2 values (Fig. 2) show an increasing trend in predictability as the stance phase progresses. Inter-subject variability contributes significantly to the high R^2 standard deviations (Fig. 2).

In Fig. 3, for our uncontrolled walker with only process ("motor") noise ($\sigma_p = 0.3\%, \sigma_o = 0$), linear predictability of y_{foot} from the pelvis state $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ is high across the stance phase for all 3 speeds ($R^2 > 0.8$), thus confirming the CoM state's ability to predict the next foot placement. With measurement noise ($\sigma_o > 0$), the R^2 curves (Fig. 3) show increasing predictability as the stance phase progresses, qualitatively similar to humans (Fig. 2). Measurement noise reduces predictability (lowers R^2), with this effect being more pronounced earlier in the stance phase and not seen at all with $\sigma_o = 0$ (Fig. 3). Thus, the R^2 curves' overall increasing trend is a consequence of the interaction of measurement noise with the walker's intrinsic passive dynamics.

Phase-dependent *collinearity* (i.e., strong linear dependence; Belsley et al., 1980) among the predictors contributes to the "valley" in the R^2 curves seen after mid-stance with the pelvis-state predictor (Fig. 3). Adding measurement noise reduces this collinearity by adding diagonal variance to the covariates, thus "regularizing" the R^2 curves, though at the cost of overall predictability. Standard deviations of the R^2 curves (Fig. 3, *shaded bands*) also increase with σ_o. Interestingly, for all of the $\sigma_o > 0$ cases, the R^2 values increase with the speed of the walker.

Comparing Fig. 3 and Fig. 2, correlations between CoM state and foot placement for the uncontrolled walker are qualitatively similar to those seen for sagittal plane analysis of human walking data. While the shapes of R^2 curves differ somewhat for humans and the 2D model, we made no attempt to "fit" simulation parameters to the human data. Nevertheless, the model reproduces significant predictability/correlations with an overall increasing trend, similar to human results.

R^2 curves obtained with the alternative pelvis-state predictor $\left(\theta, \dot{\theta}\right)$ and the walker's full state appear in Fig. 4. With no measurement noise, the walker's full state predicts y_{foot} almost perfectly ($R^2 \approx 1$ for all τ), indicating that linearization of the walker's passive dynamics is a good approximation for small σ_p. However, the relatively high effectiveness of the walker's full state in predicting y_{foot}, as compared to the pelvis states, diminishes with increasing σ_o. Finally, the 4-variable pelvis state predicts y_{foot} better than the kinematically minimal angular, 2-variable pelvis state (Fig. 4). However, R^2 curves for both pelvis-state predictors have similar shapes, and the curves for all predictors become increasingly similar with increasing measurement noise.

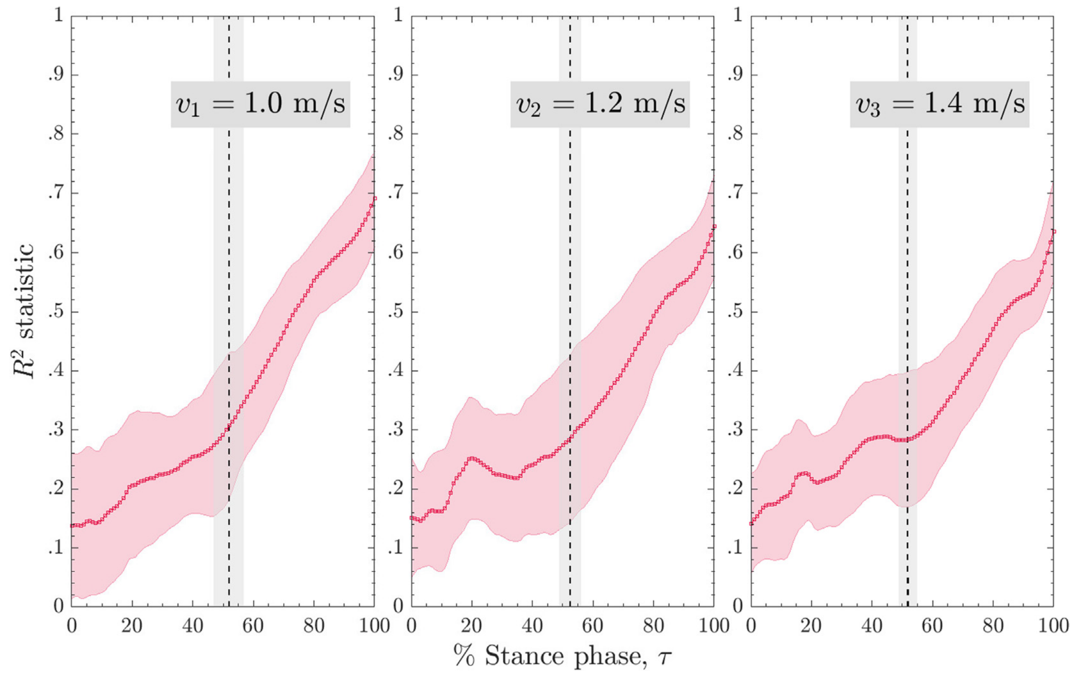

Fig. 2. *Sagittal plane analysis of 3-marker data of humans walking on a treadmill* (Wang and Srinivasan, 2014b): R^2 statistic of the linear prediction (Eq. 1) of deviations in y_{foot} from its mean based on corresponding deviations in pelvis state $(y_p, \dot{y}_p, z_p, \dot{z}_p)$, as stance phase ($\tau$) progresses from the ipsilateral, stance-foot heel strike ($\tau = 0$) to the next contralateral, swing-foot heel strike ($\tau = 1$). For a given speed, mean R^2 values (over fits from all trials) at each τ are shown using *curve joining red squares*. Corresponding ± 1 standard deviation (SD; 0.06–0.14 depending on τ) are shown using *shaded bands*. Compare to Fig. 3 for the 2D walker model. Ten subjects walked at 3 speeds ($\upsilon_1, \upsilon_2, \upsilon_3$; one 5-min trial/speed). For each trial, fits for the left and the right stance leg were done separately, at every $\Delta\tau = 1\%$ phase interval (or, $\Delta t = T_{\text{step}}/100$, for step time T_{step}). Mid-stance was identified when y_p (Fig. 1) changed its sign from negative to positive (posterior to anterior; Wang and Srinivasan, 2014b). The averaged mid-stance location (*broken vertical line*), estimated from step data pooled from all trials at a given speed, occurs at $\approx 52\%$ of the stance phase; and corresponding *vertical bands* show ± 1 SD (3–5%) around each averaged mid-stance location. For each speed, the R^2 values show overall increasing trend in predictability as the stance phase progresses. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

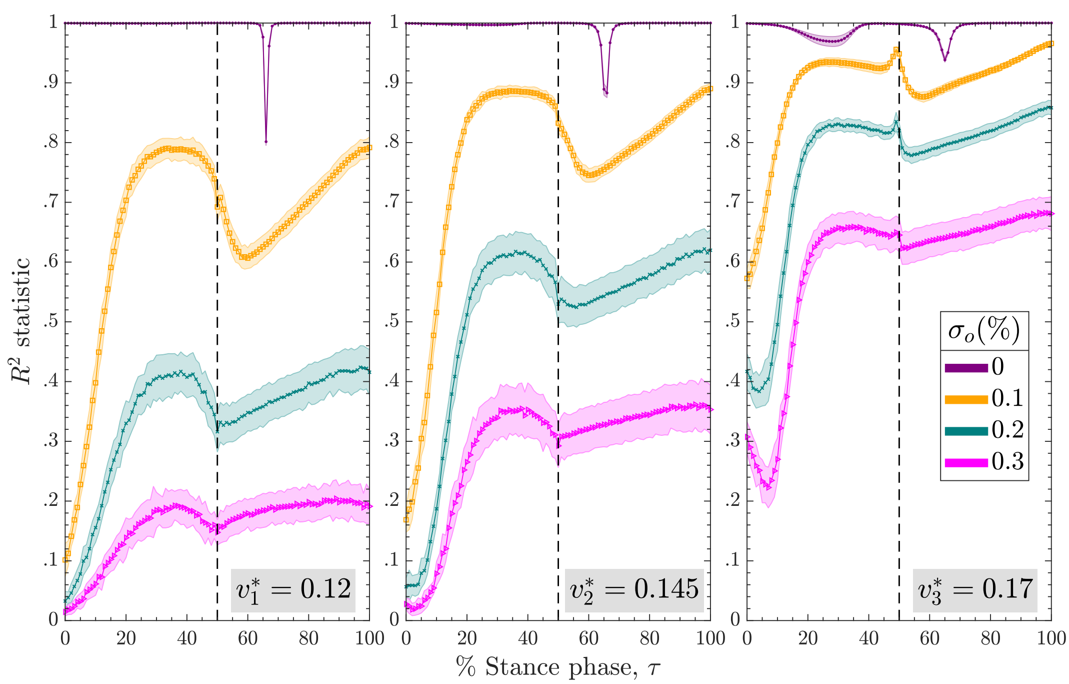

Fig. 3. *2D open-loop-stable walker*: R^2 statistic of linear prediction of deviations in y_{foot} from its mean based on corresponding deviations in pelvis state $(y_p, \dot{y}_p, z_p, \dot{z}_p)$, as the stance phase ($\tau$) progresses from stance-foot heel strike ($\tau = 0$) through mid-stance ($\tau = 0.5$; *broken line*) to next swing-foot heel strike ($\tau = 1$). For a given speed and measurement noise level (σ_o) mean R^2 values (over 25 samples) at each τ are shown using *curve joining markers*; corresponding ± 1 standard deviation (SD; 0–0.05 depending on τ and σ_o) is shown using *shaded bands* around the mean. Compare to Fig. 2 for humans walking on a treadmill. For each of the three stable periodic gaits (nondimensionalized open-loop speeds: $\upsilon_1^*, \upsilon_2^*, \upsilon_3^*$) there are 4 curves (*different colors*), from top to bottom, corresponding to increasing measurement noise $\sigma_o \in \{0, 0.1, 0.2, 0.3\}\%$, as shown in the legend. The "motor" noise in P was fixed at $\sigma_p = 0.3\%$ throughout. See methods (Section 2.1) for more details. For $\sigma_o = 0$, pelvis state remains highly correlated ($R^2 > 0.8$) with y_{foot} throughout the stance phase. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

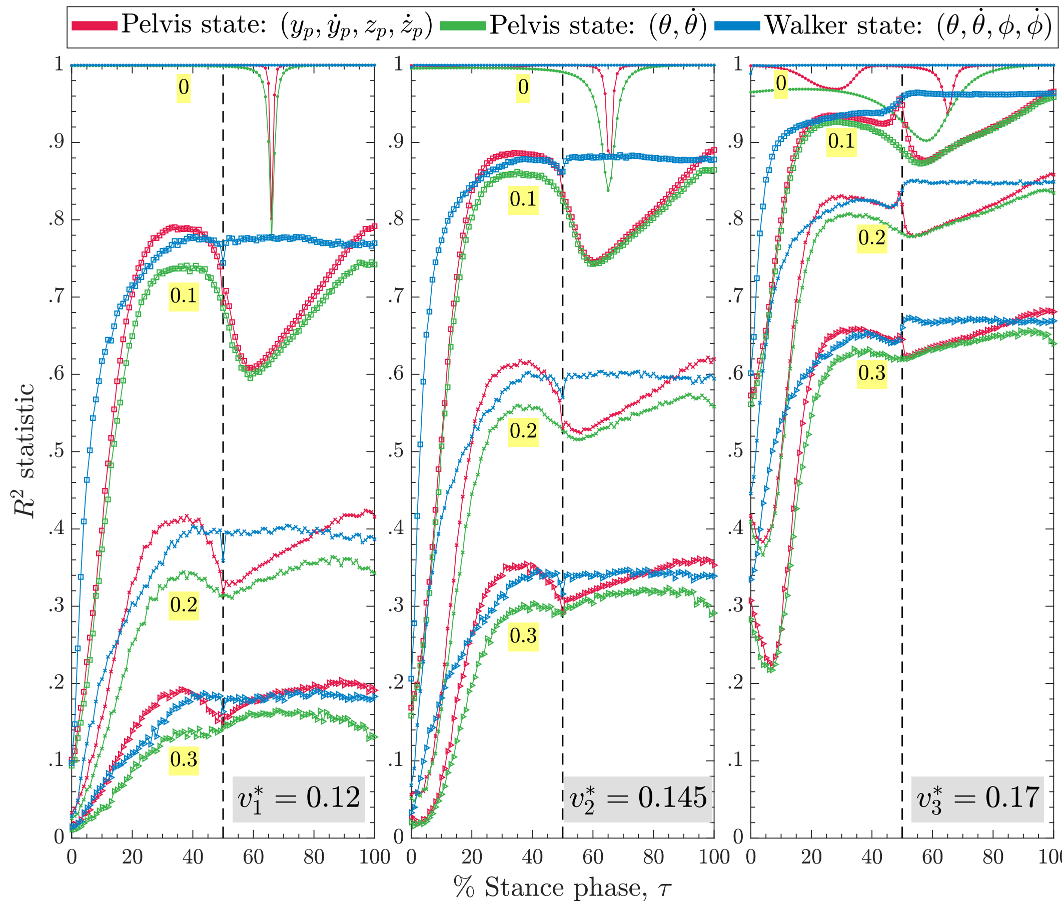

Fig. 4. *2D open-loop-stable walker*: comparison of R^2 statistic of linear prediction of deviations in y_{foot} from its mean, based on corresponding deviations in pelvis and walker states (*3 distinct colors*). All statistics shown as stance phase (τ) progresses from stance-foot heel strike ($\tau = 0$), through mid-stance ($\tau = 0.5$, *broken line*) to next swing-foot heel strike ($\tau = 1$). For each of the three stable periodic gaits (nondimensionalized open-loop speeds: v_1^*, v_2^*, v_3^*) there are 4 sets of curves, from top to bottom, labeled according to increasing measurement noise $\sigma_o \in \{0, 0.1, 0.2, 0.3\}$%. Within each such set (i.e., for a given σ_o), colors distinguish three covariates (2 pelvis states and walker's full state) of the linear regression (legend at the top). The "motor" noise in P was fixed at $\sigma_p = 0.3$% throughout. See methods (Section 2.1) for more details. The R^2 curves corresponding to the pelvis state $(y_p, \dot{y}_p, z_p, \dot{z}_p)$ in *red* are identical to those in Fig. 3, where they are shown using *4 different colors* for each speed. For clarity, here we do not show standard deviation bands around the mean R^2 curves. With no measurement noise ($\sigma_o = 0$), using the walker's full state yields almost perfect prediction of the foot placement: $R^2 \approx 1$ for all τ ($\sigma_o = 0$; *blue curve at the top of each panel*). Both pelvis states also remain highly correlated ($R^2 > 0.75$) with y_{foot} throughout the stance phase. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

Within-step correlations between variations in CoM state and variations in subsequent foot placement clearly occur (Fig. 2; Wang and Srinivasan, 2014b; Rankin et al., 2014; Bruijn and van Dieën, 2018). The idea that within-step active control is likely to at least affect such correlations is not in dispute. The challenge arises when one attempts to make an inference about the *inverse* relationship: namely, that such correlations, when observed experimentally, imply within-step active control. This "inverse hypothesis" is intuitively appealing and is partly (if indirectly) supported by biomechanical (Perry and Srinivasan, 2017; Arvin et al., 2018; Stimpson et al., 2018) and neurophysiological (Hof and Duysens, 2013; Rankin et al., 2014; Kubinski et al., 2015; Roden-Reynolds et al., 2015; Arvin et al., 2018) experimental data. Appealing though it may be, however, this inverse hypothesis requires the assumption that neuromuscular control actions are the *only* thing that can produce the observed correlations. Here, however, we have shown that passive dynamics are certainly a viable alternative cause (Wang and Srinivasan, 2014b; Bruijn and van Dieën, 2018).

Our simulations of a 2D open-loop-stable walker demonstrate that passive dynamics alone can yield significant correlations between within-step CoM state and foot placement (Figs. 3 and 4), similar to those observed in humans (Fig. 2; Wang and Srinivasan, 2014b). Furthermore, the simulations suggest not only that the overall shape of observed R^2 curves does not require within-step active control, but may, in addition, be strongly affected by even small amounts of noise in the experimental measurements (and the statistical estimation methods employed).

The central feature of the walking model used here is that it includes no mechanisms to detect CoM deviations, nor to adjust foot placements to "correct" such "errors". Indeed, no stepping "error" of any type is defined in our model. That is, the model possesses *no control* of any type, and so its dynamics are purely passive. Thus, we can unambiguously attribute the corresponding R^2 results obtained from this model (Figs. 3, 4) *only* to the passive dynamics of the walker.

Any number of other models could be used to demonstrate similar findings. For example, one could equivalently simulate the "simplest" walker that walks down an incline (Garcia et al., 1998), with small perturbations introduced by random surface irregularities (Su and Dingwell, 2007). To further demonstrate the robustness of our results, we examined the effect of changing the system's propulsive mechanism from toe-off impulses to continuous gravitational loading. To this end, we ran simulations with this original gravity-powered walker (see Appendix A). We obtained results consistent with those for the powered walker (Figs. 3, 4): the R^2 curves (Fig. S1 of Appendix A) generated by the gravity-powered walker show high correlations, especially late in the step cycle, and have similar shapes to those found for the powered walker. Other passive models could be used, including those with knees (McGeer, 1990), or an upper body (Wisse et al., 2004). Passive 3D walkers are also possible (Collins et al., 2001; Adolfsson et al., 2001). These entirely passive systems can be expected to lead to the same general conclusions found here. One can also expect similar results for simulations of a 3D walker with impulsive lateral stabilizing control (Kuo, 1999), with small random perturbations introduced by varying the stabilizing impulses applied at each step transition (Roos and Dingwell, 2010; Roos and Dingwell, 2011). While such walkers are not completely passive, they are only actuated during step transitions, and hence include no *within-step* active control, as this is not required to stabilize their mediolateral motion (Kuo, 1999).

Exactly as in our model, none of these other walkers have mechanisms to either detect CoM deviations or adjust foot placements *during* a step. However, we would still find substantial within-step correlations between CoM deviations and subsequent deviations in foot placement. While the exact details of the resulting within-step R^2 curves would likely vary, due to differences in the underlying differential equations, the primary general trends (similar to Figs. 3, 4) would almost certainly remain. This is because, for *any* of these models, variations in the initial conditions at the beginning of a step are naturally mapped *by the passive swing dynamics alone* onto corresponding deviations of the next foot placement. Indeed, this is arguably the most fundamental property of any dynamical system, whether controlled or not: that future states depend on (and therefore are correlated with) earlier states. Thus, our primary conclusion would remain unchanged: correlations between CoM states and stepping adjustments within one step cannot distinguish between correlations arising from passive dynamics or active control, or, indeed, between different types of control.

However, it must be emphasized that neither our findings, nor the above discussion, should be taken to mean that within-step active control does not take place in humans. Nor do our findings rule out the possibility that the human nervous system uses CoM state to control subsequent foot placement (Wang and Srinivasan, 2014b; Rankin et al., 2014). Instead, our results mean that such within-step control, its nature (e.g., as either being feedforward or feedback), and its importance relative to passive dynamics, cannot be inferred from experimentally determined within-step correlations alone. Therefore, any such interpretations should be made with caution, and require additional independent evidence. We believe that experiments *could* be devised to more reliably use the within-step correlation analyses to examine active control. However, it will require careful experimental design to untangle active and passive effects and, as currently applied, the correlation analyses by themselves are incapable of this.

Early modeling studies showed that appropriate foot placement can be used to redirect the motion of the CoM on the subsequent step to stabilize walking (Townsend, 1985; Redfern and Schumann, 1994). Subsequent experimental studies of human walking have confirmed that a major role of step-to-step transitions is to redirect the CoM motion, again on the subsequent step (Kuo et al., 2005; Adamczyk and Kuo, 2009; Shorter et al., 2017). Such findings raise additional questions about which is controlling which: is CoM state used to achieve a particular foot placement, or is foot placement used to achieve some particular CoM motion? In all likelihood, both such forms of "control" occur. Indeed, there is also ample evidence, both theoretically and computationally (Dingwell et al., 2010; Zaytsev et al., 2018; Dingwell and Cusumano, 2019) and also experimentally (Chapman and Hollands, 2007; Matthis et al., 2017, 2018) that humans actively regulate their movements across multiple consecutive steps. Thus, a complete understanding of walking control will require synthesizing these currently unconnected concepts into a consistent and complimentary description of both how stepping movements are executed within each step and of how those movements are then regulated across multiple steps.

Declaration of Competing Interest

None declared.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jbiomech.2019.109375.

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