Visual effort moderates a self-correcting nonlinear postural control policy

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33 Abstract

34 A growing consensus across otherwise disparate perspectives on perception and 35 action is that visually guided postural control emerges from within task constraints. Task constraints generate physiological fluctuations across various parts of the body. These 36 fluctuations foster exploration of the available sensory information. For instance, standard 37 38 deviation (SD) and temporal correlations of bodily sway can indicate how richly postural control samples available mechanical and visual information. Too much or too little SD entails 39 40 destabilization of posture. Temporal correlations show a similar relationship, but they have 41 also been shown to support carrying sampled information to other aspects of the postural system. The present study shows that increasing visual constraints on posture reveals an 42 adaptive relationship between SD and temporal correlations of postural fluctuations. In short, 43 changing the viewing distance of a fixation target shows that temporal correlations self-correct 44 themselves across time and diminish SD across time as well. Notably, these relationships 45 were strong for all viewing distances except the most comfortable viewing and reaching 46 47 distance. This self-correcting relationship allows the visual layout itself to press the postural system into a poise for engaging with objects and events in the surrounding. 48

49 **Keywords:** biotensegrity, center of mass, center of pressure, fractality, Hurst's exponent, 50 postural sway

51 **1. Introduction**

52 **1.1. Stability of suprapostural visual activities at longer scales rests on fluctuating** 53 **behavior at shorter scales**

54 Standing quietly and maintaining focus on a target in front of us is the preamble to very many coordinated behaviors-we might lean forward and reach or track the target's progress and 55 bat it away. However, this starting position is not merely the preamble to action but is already 56 a rich wellspring of the action itself, exhibiting a continuous stream of intermittent fluctuations. 57 We can see these fluctuations in our bodily center of mass (CoM) and center of pressure 58 (CoP), where ground reaction forces meet our lower extremities. So long as they do not pitch 59 the CoP beyond the base of support, these fluctuations are crucial to maintaining a quiet 60 61 stance [1,2]. This variability offers the body a subtle and flexible command of the mechanical surface underfoot [3,4], exemplifying long-respected proposals that noise can stabilize 62 63 nonlinear-dynamical systems [5,6].

64 Lacing our postural system into our visual field are eyes, moving to lock focus on a distal point in the world. Admittedly, maintaining focus involves "fixations" of the eyes no less 65 than upright posture can seem "still," but this fixation is not stasis: fixations are regularly 66 67 recognized as a class of movement [7] consisting of a vibrant, fluctuating foundation of smaller movements called "microsaccades" [8]. These microsaccades serve to stabilize 68 images that would otherwise fade on a static retina [9], thus playing a similar role to the visual 69 system that fluctuations play for the postural system. Indeed the exploratory role of fluctuating 70 movements extends to the extremities of the body besides and intermediating between 71 72 upright posture and vision [10], suggesting a strong role for postural sway in supporting visual 73 perception [11–13]. Thus, even when standing quietly upright while fixating at a visual target, 74 the body is coursing with fluctuations ferrying information across the body.

75 The present work aims to explore how visual effort might affect how fluctuations flow within the bodywide postural system. Postural fluctuations produce translations and rotations 76 77 of visible surfaces specific to the spatial relationships of the objects in the visual field. These movement-induced translations and rotations compose an optic flow that provides visual 78 79 support for the subsequent movement. Thus, subtle postural sway offers the sighted organism a rich source of information about the layout of objects in the visual field. The visual layout 80 itself then presses the postural system into a poise for engaging with objects and events in 81 the surrounding. Visual targets appearing closer to or farther from the looking postural system 82 83 impose retina-specific constraints of oculomotor convergence [14,15] and chromatic aberration [16]. Consequently, changes in a target's size relative to other aspects of the visual 84 field entails changes in optic flow (figure 1). These multi-scale factors affect postural stability, 85 86 reflecting changes in postural configurations and hence in the flow of information needed to organize these postures. 87

88 **1.2.** Perceptual constraints on postural stability could reshape intrapostural 89 interactivity

In the present study, we aim to explore how changing the viewing distance might change how the postural system exchanges fluctuations within and between CoM and CoP. We examined the relationship between bulk variability in CoP fluctuations (i.e., standard deviation, *SD*) and temporal structure (i.e., fractal scaling, *H*) in CoM and CoP fluctuations. The implication of *SD* is the prevailing tradition, but that of fractality rests on two until-recently parallel bodies of evidence, one specifically requiring variations in fractal geometry for modeling the bodywide organization of the movement system and the second suggesting that

97 capacity of bodily fluctuations to ferry information inheres at least partially in its fractal structure. Movement depends on the bodywide network of connective tissues and nervous 98 tissues, forming flexible relationships that balance tensions with compressions at multiple 99 100 scales of analysis [17-23]. This organization entails a specifically multifractal geometry that 101 embodies multiple scale-invariant patterns of behavior (e.g., microsaccades within the saccades that intersperse larger saccades by the eye and turns by the head) across time and 102 103 across space. CoP fractality has repeatedly borne a consistent relationship to perceptual judgments of visual and haptic stimuli [24-29], and research into perceptual tasks (e.g., 104 manually wielding an object to judge heaviness or length) while standing shows that a 105 106 bodywide flow of fractal fluctuations precedes and shapes the verbal articulation of perceptual 107 judgments [30,31]. Hence, a fractal flow within posture seems to support information flow and 108 might provide a glimpse of the control policy emerging from bodily situation in task 109 constraints.

110 **1.3.** Visual effort for fixating across different viewing distances could reveal different 111 relationships amongst CoM fractality, CoP fractality, and CoP *SD*

112 **1.3.1. The task**

113 The present work is a reanalysis of a previous study that manipulated viewing distance while measuring CoM and CoP [32]. Healthy adults stood maintained a guiet stance under six 114 different conditions: a control condition with eyes closed and five conditions with eyes open 115 and fixating on a red laser point projected on surfaces at 20, 50, 135, 220, and 305 cm 116 117 distance. We reanalyzed these data by carving individual trials under each viewing condition 118 into non-overlapping sub-trial segments, estimating fractal scaling and SD within each 119 segment, and using vector autoregression (VAR) modeling to test the interactions among 120 these descriptors across segments within each trial.

121 **1.3.2. The hypotheses**

122 Hypothesis 1: Weaker intrapostural interactivity while standing quietly with eyes closed.

First, respecting the evidence that maintaining fixation recruits oculomotor effort that can perturb posture [33,34], we predicted that the addition of a fixation task to quiet standing would generally accentuate intrapostural interactivity, suggesting that standing quietly with eyes closed would show weaker evidence of intrapostural interactivity.

127 *Hypothesis 2: Resemblance between the 50-cm viewing condition and the eyes-closed* 128 *condition.*

The 50-cm viewing distance is within the comfortable viewing distance, ideal for the human eyes' focus of red light [16], as well as ideal for requiring the least straining oculomotor convergence [14,15]. Hence, our last and most specific prediction was that the 50-cm viewing condition would yield intrapostural interactivity most closely resembling that in the eyes-closed condition. That is, because 50-cm requires the least visual strain, the effects among CoM fractality, CoP fractality, and CoP *SD* would show the least differences from the eye-closed condition.

136 Hypothesis 3: Self-correction of fractality across 10-s segments.

Postural sway is more correlated at short timescales on the order of 10 s and more anticorrelated over longer timescales [35]. For instance, posture roams freely about a fixed average CoP position but self-corrects at the margins of the base of support to maintain a quiet stance [35–37]. In this sense, we predicted that fractality itself would show similar self-

141 corrections over time, with prior increases in fractality followed by subsequent alternating 142 decreases and increases in fractality. This self-correcting feature would be a crucial part of 143 any control in which temporal correlations stabilize sway.

144 Hypothesis 4: Inverse relationship between fractality and SD across 10-s segments.

Because fractality entails long-range temporally organized responsivity to mechanical perturbations [38,39], we expected an inverse relationship between either or both of CoP and CoM fractality and CoP *SD*. That is, increases in CoP and CoM fractality would predict later decreases in CoP *SD* (Hypothesis 4a), as well as increases in CoP-*SD* would predict later decreases in CoP and CoM fractality (Hypothesis 4b). This feature could reflect a second key component of task-dependent emergent postural control.

151

152 **2. Materials and methods**

153 **2.1. Participants**

Seven adult men and nine adult women ($M\pm 1SD$ age = 23.8 \pm 3.9 years) without any skeletal or neuromuscular disorder voluntarily participated after providing verbal and written consent approved by the Institutional Review Board (IRB) at the University of Georgia (Athens, GA).

158 **2.2. Experimental task and procedure**

Each participant stood barefoot with one foot on each of two force plates (AMTI Inc., Watertown, MA), 25 cm apart (figure 1*a*). From behind the participant, a laser pen projected a static point-light on the center of a 5×5" white tripod-mounted screen in front of a white visualfield-filling background. The two force plates measured 3D moments and ground reaction forces. The full-body motion of each participant was measured using VICON Plug-in Gait fullbody 39 marker set and an 8-camera VICON motion tracking system (VICON Inc., Los Angeles, CA). The kinetic and kinematic data were synchronized and sampled at 100 Hz.

Each participant was instructed to maintain a quiet stance for 120 s under six different viewing conditions: eyes closed and while fixating visually on the point-light point positioned at 25, 50, 135, 220, and 305 cm distance in front. Each participant completed 18 trials (6 conditions × 3 trials) in a single 90-min session with randomized trial order and with breaks on request and between every six trials.

171 2.3. Data processing

All data processing was performed in MATLAB 2019b (Matlab Inc., Natick, MA). The 172 173 position of the bodily center of mass (CoM) was estimated by submitting segment lengths of 174 the head, trunk, pelvis, and left and right hand, forearm, upper arm, thigh, shank and foot to the equations provided by Zatsiorsky and Seluyanov [40], which yielded a 3D center of 175 pressure (CoP) series describing CoM position along the participant's anterior-posterior (AP), 176 medial-lateral (ML), and superior-inferior axes. 3D moments and ground reaction forces 177 178 measured on each trial yielded a 2D center of pressure (CoP) series describing CoP position along the participant's AP and ML axes. Over 120 s duration, each trial vielded a 3D CoM 179 series and a 2D CoP series each of 120 s or 12000 samples, divided into 12 segments of 10 180 s or 1000 samples each. Each segment yielded two 999-sample one-dimensional series: a 181 182 CoM spatial Euclidean displacement (SED) series describing the amplitude of CoM displacement (figures 2a to 2f) and a CoP planar Euclidean displacement (PED) series 183 describing the amplitude of CoP displacement (figures 2a to 2f). 184

185 **2.4. Detrended fluctuation analysis (DFA)**

186 DFA estimates Hurst's exponent, H, describing the growth of root mean square 187 (RMS) fluctuations with time for first-order displacements known as fractional Gaussian 188 noises (fGn) [41,42]. First, it integrates time series x(t) with N samples to produce 189 y(t):

190
$$y(t) = \sum_{i=1}^{N} x(t) - \overline{x(t)}$$

191 Next, DFA computes RMS residuals from the linear trend $y_n(t)$ over nonoverlapping *n*-192 length bins of y(t) to build a fluctuation function f(N):

193
$$f(N) = \sqrt{(1/N) \sum_{i=1}^{N} (x(t) - \overline{x(t)})^2}$$

194 for n < N/4. On standard scales, f(N) is a power law:

195
$$f(N) \sim n^H$$
,

196 where *H* is the scaling exponent. *H* is estimated as the slope of f(N) in log-log 197 plots:

$$\log f(N) = H \log(n) \quad .$$

DFA estimated H_{fGn} for the original version (i.e., unshuffled) and a shuffled version (i.e., a version with the temporal information destroyed) of each CoM SED series (CoM- H_{fGn}) and CoP PED series (CoP- H_{fGn}) over the following bin sizes: 4, 8, 12,... 128; figures 2g and 2h).

202 **2.5. Vector autoregression (VAR) analysis**

VAR captures linear interdependencies amongst concurrent series and here modeled intrapostural effects of CoM- H_{fGn} , CoP- H_{fGn} , and CoP-SD in one segment on CoM- H_{fGn} , CoP- H_{fGn} , and CoP-SD in subsequent segments (figure 3). VAR describes each variable based on its own lagged value and that of each other variable. Lag is ideally increased until the residuals appear independently and are distributed identically [43].

208 VAR allows forecasting unique effects of endogenous variables on later values of each 209 other through impulse-response functions (IRFs). IRFs evaluate the relationship between 210 and $a(t+\tau)$, or between q(t) and $f(t+\tau)$, where τ is a whole number f(t)corresponding to a segment within a trial. Provided VAR residuals are independent and 211 212 identically distributed (i.i.d.), orthongonalizing these residuals allows simulating an "impulse" to the system by adding 1SEM to any single variable, and using VAR coefficients to describe 213 propagation of later "responses" across all endogenous variables. The IRF describes how an 214 215 impulse in one series changes later predicted values in a different time series [44,45]. All VAR models converged with lag 1, with residuals passing all tests for i.i.d. status. We performed 216 VAR analysis using the vars package in RStudio [46]. 217

218 **2.6. Statistical analysis of pairwise IRFs**

A regression model [47] treated IRFs between each pair of postural descriptors as the dependent measure and tested the effect of predictors including the full-factorial set Trial × Segment × Impulse × Response using the *nIme* package for RStudio [48]. Impulse and Response served as class variables encoding the different descriptors (CoP- H_{fGn} and CoM- H_{fGn} , and CoP-*SD*) serving as impulse and as response variables, respectively. Orthogonal linear, quadratic, and cubic polynomials of Segment modeled how impulse-response relationships changed over 999-sample segments within a trial. We used the cubic polynomial to capture the general nonlinear decay of IRFs across later segments. The interactions of H_{fGn} or *SD* with Segment indicated changes in these effects with different third-order polynomial responses over subsequent trials. The Impulse × Response terms highlighted significant differences of specific impulse-response pairs from the global patterns.

230

231 **3. Results**

232 **3.1 CoM and CoP showed fractal fluctuations**

233 H_{fGn} for all original series fell in the fractal range (0.5 < H_{fGn} < 1; figures 2g and 2h) and significantly exceeded for all corresponding shuffled series (ps < 0.0001; table S1), indicating 234 235 fractal fluctuation in both CoM and CoP. Crossovers between shorter- (bin sizes: 4, 8, 12,... 64) and longer-scale (bin sizes: 4, 8, 12,... 128) behavior exhibited no reliable differences, as 236 H_{fGn} estimates from only shorter-scale behavior correlated strongly with H_{fGn} estimates from 237 238 the entire DFA fluctuation function (CoM: Spearman's ρ s = 0.96, 0.91, 0.94, 0.94, 0.93, and 0.94 for the eyes-closed and the 25-, 50-, 135-, 220-, and 305-cm eyes-open conditions, 239 respectively, *ps* < 0.0001); CoP: *ps* = 0.96, 0.89, 0.93, 0.92, 0.91, and 0.94, *ps* < 0.0001). 240

3.2. Maintaining a quiet stance with eyes closed weakened intrapostural interactivity with trials (Hypothesis 1)

243 When maintaining a quiet stance with eyes closed, prior increases in CoM- H_{IGn} showed no significant later CoP-SD responses and only subtle later CoP- H_{IGn} and CoM- H_{IGn} 244 responses (figures 4a and 4b). Regression modeling of IRFs (table S2) showed that 245 increases in CoM- H_{IGn} preceded a short-term subsequent decrease and slow, nonlinear 246 247 rebound (Segment(Quad): $b = -6.19 \times 10^{-1}$, p = 0.017; and Segment(Cubic): $b = 5.36 \times 10^{-1}$, p = 0.017; and Segment(Cubic): b = 0.017; and S 0.040) in all variables except CoP-SD (Segment(Quad) × Response(CoP-SD): $b = 6.21 \times 10^{-1}$, 248 p = 0.092). This decrease-and-nonlinear-rebound was canceled out with Trial for later CoM-249 H_{fGn} responses (Trial × Segment(Quad): $b = 4.29 \times 10^{-1}$, p < 0.001; Trial × Segment(Cubic): b =250 -3.27×10^{-1} , p = 0.007) but showed no such change for later CoP- H_{fGn} responses (Trial × 251 Segment(Quad) × Response(CoP- H_{fGn}): $b = -4.04 \times 10^{-1}$, p = 0.018; and Trial × 252 253 Segment(Cubic) × Response(CoP- H_{fGn}): $b = 3.45 \times 10^{-1}$, p = 0.042) and CoP-SD responses (Trial × Segment(Quad) × Response(CoP-SD): $b = -4.27 \times 10^{-1}$, p = 0.012; and Trial × 254 Segment(Cubic) × Response(CoP-SD): $b = 3.28 \times 10^{-1}$, p = 0.054). 255

256 Closing eyes weakened the responsivity of all measures to prior increases in each other and in CoM- H_{fGn} , amounting to no later effects of SD and vanishing effects of CoP- H_{fGn} 257 with Trial (figure 4c and 4d). Specifically, regression terms canceled out and reversed effects 258 of prior increases of CoP-SD (Segment(Quad) × Impulse(CoP-SD): $b = 7.95 \times 10^{-1}$, p = 0.031) 259 and CoP- H_{fGn} (Segment(Quad) × Impulse(CoP- H_{fGn}): $b = 1.35 \times 10^{\circ}$, p < 0.001). The eyes-260 closed condition did show positive effects of prior increases in CoP- H_{fGn} on later effects 261 262 decaying slowly with Segment (Segment(Linear) × Impulse(CoP- H_{fGn}): $b = -7.05 \times 10^{-1}$, p =0.056; and Segment(Quad) × Impulse(CoP- H_{fGn}): $b = 1.35 \times 10^{\circ}$, p < 0.0001), but this effect 263 264 disappeared with Trial (Trial × Segment(Linear) × Impulse(CoP- H_{fGn}): b = 4.86×10⁻¹, p = 0.004; Trial × Segment(Quad) × Impulse(CoP- H_{fGn}): b = -1.04×10⁰, p < 0.0001). 265

Critically, the eyes-closed condition diminished intrapostural interactions between CoP- H_{fGn} and CoP-*SD*, leaving CoP-*SD* to predict much of the later behavior elsewhere. All significant interactions involving Impulse(CoP- H_{fGn}) and Response(CoP-*SD*) significantly canceled out the corresponding lower-order interactions of Impulse(CoP- H_{fGn}), effectively

muting the effects of a prior CoP- H_{fGn} impulse on later CoP-SD responses [e.g., 270 Segment(Quad) × Impulse(CoP- H_{fGn}) × Response(CoP-SD): $b = -1.36 \times 10^{\circ}$, p = 0.009; Trial × 271 Segment(Linear) × Impulse(CoP- H_{fGn}) × Response(CoP-SD): $b = -4.81 \times 10^{-1}$, p = 0.046; Trial 272 × Segment(Quad) × Impulse(CoP- H_{fGn}) × Response(CoP-SD): $b = 1.04 \times 10^{\circ}$, p < 0.0001]. 273 Effects promoting greater CoP- H_{fGn} at first generally vanished with Trial (Trial × 274 Segment(Linear) × Impulse(CoP- H_{fGn}) × Response(CoP- H_{fGn}): $b = -5.54 \times 10^{-1}$, p = 0.021; Trial 275 × Segment(Quad) × Impulse(CoP- H_{fGn}) × Response(CoP- H_{fGn}): $b = -1.55 \times 10^{\circ}$, p = 0.003). 276 Across trials, prior increases in CoP-SD exerted a weaker decrease-and-nonlinear-rebound 277 form on later CoM- H_{fGn} responses (Trial × Segment(Quad) × Impulse(CoP-SD): $b = -5.50 \times 10^{-1}$ 278 279 ¹, p = 0.001; and Trial × Segment(Cubic) × Impulse(CoP-SD): $b = 3.02 \times 10^{\circ}$, p = 0.077) but retained this later effect on CoM- H_{fGn} (Trial × Segment(Quad) × Impulse(CoP-SD) × 280 Response(CoP- CoM- H_{fGn}): b = 5.37×10⁻¹, p = 0.023) and on itself (Trial × Segment(Quad) × 281 Impulse(CoP-SD) × Response(CoP-SD): $b = 5.48 \times 10^{-1}$, p = 0.023). 282

Though not pictured here, this latter effect held robustly across all viewing conditions: prior increases in CoP-*SD* predicted later increases in CoP-*SD*, with the size of this later increase dwindling quadratically at a decreasing rate with Segment (table S2).

286 **3.3.** Intrapostural interactivity in the 50-cm viewing condition resembled that in the 287 eyes-closed condition than that in other viewing conditions (Hypothesis 3)

Visually fixating at 50 cm elicited the least amount of intrapostural interactivity, closely 288 resembling the eyes-closed condition. This point is evident first in terms of the number of 289 290 significant effects. For instance, the regression model yielded 72 coefficients for each 291 condition (tables S2–S6). Compared to effects for all other eyes-open conditions, the 50-cm 292 condition showed significant but opposite effects of Segment(Linear), Trial × Segment(Linear), 293 and Trial × Segment(Linear) × Response(CoP-SD) from the 135-cm condition (table S3), and 294 a significant but opposite effect of Trial × Segment(Linear) × Response(CoP- H_{fGn}) from all other eyes-open conditions (table S4). Of the remaining nine significant effects, Impulse(CoP-295 296 H_{fGn}), Segment(Linear) × Impulse(CoP-SD) and Trial × Impulse(CoP- H_{fGn}) did not show significance in any other eyes-open condition, and one other followed the same sign but was 297 little more than half as large as the same significant effect for all other eyes-open conditions 298 299 (table S4).

300 In short, these distinctions entailed that, with Trial, the 50-cm condition showed greater but shorter-term reductions in SD following increases in $CoP-H_{fGn}$, for instance, more negative 301 302 change in CoP-SD with Trial (Trial × Impulse(CoP- H_{fGn}) × Response(CoP-SD): $b = -4.98 \times 10^{-10}$ ³, p = 0.023; table S6) and stronger subsequent positive linear growth in CoP-SD (Trial × 303 Segment(Linear) × Impulse(CoP- H_{fGn}): $b = 4.87 \times 10^{-1}$, p = 0.043; table S4) than in other eyes-304 305 open conditions. The other eyes-open conditions typically showed a decrease in CoP-SD following an increase in CoP- H_{fGn} , but the subsequent rebound of CoP- H_{fGn} to zero change 306 was slower and more nonlinear with Trial (Trial × Segment(Quad) × Impulse(CoP- H_{fGn}) × 307 Response(CoP-SD): $bs = -1.19 \times 10^{\circ}$, -9.22×10^{-1} , $-1.17 \times 10^{\circ}$, and $-1.12 \times 10^{\circ}$ for the 20-, 135-, 308 220-, and 305- cm conditions, respectively, $p_{\rm S} < 0.01$; table S4). Critically, the 50-cm condition 309 was the only condition that did not show this change in the nonlinearity of later responses in 310 CoP-SD. 311

312 **3.4.** CoM- H_{fGn} and CoP- H_{fGn} self-corrected from segment to segment within a trial but 313 showed sparse effects on each other (Hypothesis 3)

In the eyes-open conditions, increases in CoM- H_{fGn} and CoP- H_{fGn} (CoM- H_{fGn} and CoP-315 H_{fGn} , respectively) predicted later increases and decreases in alternation over subsequent

segments (tables S2 and S5; figures 4*a* and 4*d*), suggesting that the eyes-open conditions prompted a sort of self-correcting maintenance of fractality within CoM and CoP. Thus, the act of visually fixating prompted fractality to fall in and out of zero change or to cycle around zero change with negative and positive changes following each other. The model did not yield significant IRF relationships between CoM- H_{fGn} and CoP- H_{fGn} (table S2; figures 4*b*, *c*): only the 220-cm viewing condition was accompanied by a CoM- H_{fGn} impulse that predicted later CoP- H_{fGn} responses (figure 4*d*).

323 **3.5.** Increases in CoP-*H*_{fGn} and CoP-*SD* predicted subsequent decreases in each other 324 with trials (Hypothesis 4)

325 In the eves-open conditions, prior impulses in $CoP-H_{fgn}$ and CoP-SD both predicted 326 later decreases in CoP-SD and CoP- H_{fGn} , respectively (figure 5; table S5). These IRF relationships remained robust with Trial, more so for the effects of a prior CoP-SD impulse on 327 328 later CoP- H_{fGn} responses (figure 5a) than for the effects of a prior CoP- H_{fGn} impulse on later 329 CoP-SD responses (figure 5b). The 305-cm viewing condition failed to show a significant relationship between a prior CoP-SD impulse and later CoP- H_{fGn} responses on only one trial. 330 The 25-, 135-, and 220-cm conditions each exhibited one, one, and two trials, respectively, 331 332 that failed to show a relationship between a prior CoP- H_{fGn} impulse and later CoP-SD 333 responses.

334

335 **4. Discussion**

336 We tested four specific hypothesis concerning how visual effort might moderate 337 intrapostural interactivity. First, we predicted that standing quietly with eyes closed would 338 exhibit weaker intrapostural interactivity (Hypothesis 1). Second, we predicted that CoM- H_{fGn} 339 and CoP- H_{fGn} would self-correct over time (Hypothesis 2). Third, we predicted an inverse 340 relationship between SD and fractality over time, that is, that increases in CoM-H_{fGn} and CoP- H_{fGn} would prompt later decreases in CoP-SD (Hypothesis 3a) and that increases in CoP-SD 341 would prompt later decreases in CoM- H_{fGn} and CoP- H_{fGn} (Hypothesis 3b). Fourth, we 342 343 predicted that these intrapostural interactions in the 50-cm viewing condition would most 344 closely resemble intrapostural interactions in the eyes-closed condition (Hypothesis 4). Results supported all four hypotheses with the only exception being the failure of CoM- H_{fGn} to 345 346 participate in the relationships predicted in Hypothesis 3.

The regression modeling of IRFs revealed that in the eyes-closed condition, most effects of CoM- H_{fGn} , CoP- H_{fGn} , and CoP-SD on themselves and on each other were brief and canceled out with Segment and Trial (Hypothesis 1). Figures 4 and 5 show that IRF modeling did yield some significant later responses, but the non-significant coefficients yielded by the model reflect the fact that these significant responses were sparse and unstable.

 $CoM-H_{fGn}$ and $CoP-H_{fGn}$ did indeed self-correct (Hypothesis 2), with zig-zag IRF plots 352 353 indicating alternation between temporal correlations (i.e., persistence) and anticorrelations (i.e., antipersistence) or at least between varying degrees of temporally correlated 354 355 persistence. These switches occurred as quickly as from one 10-s segment to the next, but 356 this lag-1-segment relationship was not uniform across time or conditions (figures 4a and 4c). 357 This finding resonates with the canonical idea that sway shows short-term persistence followed by long-term antipersistence [35,36]. The variation from greater or lesser temporal 358 359 correlations from segment to segment is fleeting. These zig-zag IRF plots may reflect, first, 360 greater persistence of sway within the base of support's canter and, second, braking or 361 reversing by the postural control system as it approaches the margins of the base of support

Interpretation would benefit from "rambling-trembling"
 frameworks that recognize a slow-moving reference point anchoring CoP within the base of
 support [49,50]. These findings thus warrant further investigations into how visual information
 moderates the rambling-trembling aspects of posture (e.g., [50,51]).

366 The 50-cm viewing condition yielded intrapostural interactivity that most closely 367 resembled that in the eves-closed condition (Hypothesis 3). The effects between CoP-SD and CoP- H_{fGn} in the 50-cm condition gradually decayed across trials (figure 5). These effects did 368 369 not show up in every trial for all other viewing conditions, but the regression coefficient found 370 significant nonzero effects between fractality and SD for all other viewing conditions and only predicted the canceling out of these effects for 50-cm condition. Hence, the viewing distances 371 372 known to strain oculomotor convergence [14,15] prompted less of the intrapostural relationships that supported posture at other viewing distances. Additionally, the predicted 373 374 effects of SD on later fractality were robust for all trials across all condition, and those of fractality on later SD were less robust for the 135- and 220-cm conditions. This latter 375 376 difference indicates that, to some extent, targets at medium distances beyond the comfortable viewing distance might also stabilize posture [52]. 377

Prior increases in CoP-*SD* and CoP- H_{fGn} predicted later decreases in CoP-*SD* and CoP- H_{fGn} , respectively (Hypothesis 4). As noted in Results for Hypothesis 1, prior increases in CoP-*SD* predicted later increases in itself with Segment, thus showing none of the selfcorrective aspects shown by CoP- H_{fGn} . Hence, increase in CoP-*SD* predicted both later increases in CoP-*SD* and later decreases in CoP- H_{fGn} , and increases in CoP- H_{fGn} predicted later decreases in both CoP-*SD* and CoP- H_{fGn} .

384 **4.2.** Glimpses of a possible control policy for visually guided quiet stance

The present results offer insights into a possible control policy for postural stability that 385 balances CoP- H_{fGn} with an excess of CoP-SD. If left to SD alone, posture would lean towards 386 higher variability without clear bound: any increase in SD would predict later increases, and 387 those later increases would predict even later increases, and so on. The predicted later 388 decreases in fractality would then only serve to promote greater SD. It is only the corrective 389 390 aspect of fractality that might allow posture to rein in the apparently self-promoting and 391 unbounded SD. For instance, any decreases in fractality following increases in SD might 392 trigger subsequent increases in fractality that would induce a negative check on SD. This 393 causal interpretation aims only to offer a possible control policy that these results could 394 reflect. Such causal interpretation warrants manipulations of SD and fractality of CoP 395 fluctuations (if only indirectly) through a balance board or vibrotactile stimulation.

396 The present results from VAR analysis examining relationships between earlier impulses and later responses raise new questions for future work. For instance, past work 397 involving explicit feedback to participants completing a motor task found that performance 398 399 feedback weakened temporal correlations in movement variability in the task [53–55]. In the task of counting seconds by tapping a finger [53], the feedback provided with each tap 400 401 allowed participants to offset deviations in a way that prevented errors from propagating from 402 one tap to the next. At first glance, this finding seems at odds with the present finding that better performance—standing more quietly with less SD—would follow from and contribute to 403 stronger and not weaker temporal correlations. However, it is possible that, in postural tasks, 404 greater sway is endogenous, implicit feedback that signals the postural control system that 405 corrections are appropriately implemented. In this way, if some proportion of SD reflects sway 406 407 that triggers postural corrections (e.g., [56]), then the present findings would align with past 408 findings of feedback decorrelating movement variability.

409 This proposed control policy may resolve long-standing questions about how fluctuations support movement stability-explicitly speaking to the "loss of complexity" 410 hypothesis that fractal sway might be the signature of stability, suggestive of young, healthy, 411 412 and typically developing physiology. This hypothesis has proven provocative but controversial. Indeed, exploratory clinical research found that temporal correlations might wander within but 413 also beyond the fractal range. But the clinical implications were mixed, with some results 414 indicating stronger temporal correlations in sway for younger, healthier and more typically 415 developing participants [38,57] and other results indicating the opposite [57–59]. Meanwhile, 416 experimental work applying "white-noise"-that is, temporally uncorrelated-mechanical 417 vibration to the feet found that this, by definition, non-fractal and so non-complex signal 418 419 stabilized sway [60,61]. In finding that greater temporal correlations were associated with later 420 decreases in SD of sway, the present results align well with only half of the exploratory 421 evidence and poorly with the finding that uncorrelated stimulation reduced sway.

422 Making matters seem even more paradoxical, results have curiously diverged within 423 the same research paradigms in this vein. A reanalysis of Priplata et al.'s [61] data yielded two details [62]. Firstly, white-noise stimulation reduced temporal correlations in sway. So, in the 424 425 case of unhealthy level of complexity, decorrelating overly correlated fluctuations may be an 426 effective clinical strategy. However, secondly and less straightforwardly, the reanalysis 427 showed that white-noise stimulation elicited stronger reduction of sway for participants exhibiting stronger temporal correlations. In a sense, white-noise stimulation seems to wipe 428 429 out its efficacy by counteracting the very conditions of endogenous postural fluctuations that 430 give it a stabilizing effect. This self-nullifying aspect of the stimulation seemed guite puzzling.

431 The present work solves some of this puzzle. All past work sought to find predictive effects of fluctuation patterns by associating concurrent variables: temporal correlations and 432 433 sway variability for the same postural measurement series. The major contributions of 434 examining prior effects and later responses are twofold: first, fractal temporal correlations self-435 correct, and second, stronger temporal correlations reduce CoP-SD. Together, these two points provide a framework in which the present findings align neatly with research on white-436 437 noise stimulation stabilizing posture [60,61] and to explain how fractal temporal correlations 438 could be sometimes stabilizing and sometimes destabilizing.

439 Self-correction of fractal temporal correlations has been the key feature missing from the portrayal of postural stability until now. If fractal temporal correlations did not self-correct, 440 then SD would increase or decrease unchecked, subverting postural stability [3,4]. Lack of 441 442 self-correction in temporal correlations would mean that temporal correlations and SD might 443 push each other to opposite extremes. Posture lacking sufficient variability would be unstable and overly temporally correlated; posture having too much variability would be unstable and 444 445 have too little temporal correlations. Understanding self-correction in temporal correlations might then be one of the key directions for future work. Differences is temporal correlations 446 are well-known [35,36] and often replicated [37]. The novelty lies in recognizing that weaker 447 temporal correlations in longer timescales may hold only on average, consisting of shorter-448 timescale ebbing and flowing of temporal correlations. Across 10-s segments within a single 449 trial, the VAR found a sequence of fleeting (e.g., 10-s) bouts of postural sway predicting later 450 451 alternations between more or less temporal correlations.

The exact basis of this alternation of temporal correlations warrants further investigation. The question of whether these spatial constraints govern temporal correlations' self-correction would benefit from rigorous test in the "rambling-trembling" framework. This framework recognizes that the fixed reference point anchoring CoP within the base of support drifts slowly. Thus, it is important to model the rise and fall of temporal correlations as a function of the distance between the fixed reference point and the edges of the base of support. The space that "rambling" leaves open for stable, "trembling" may govern how quickly temporal correlations alternate. Such modeling could add to the ongoing elaborations of the rambling-trembling framework to include visual constraints [50,51].

461 We do mean this proposal to only serve as a glimpse of what needs further validation. 462 Naturally, the correlational analysis results are prone to mischaracterizing the measured 463 variables as actual causal variables. SD and fractal scaling are measurements commonly 464 thought to be essential state variables in postural control. They may reflect contributions from a limited subset of actual control parameters. Certainly, SD and fractal exponents are not 465 inherently physiological features but emergent properties of the postural task. However, actual 466 467 control parameters may be no less emergent from task constraints-one of the rare 468 agreements between current cognitivist theorizing about visual attention [63] and longstanding views in ecological psychology [64]. So, although the emergent control may not have 469 470 the same labels for its control parameters, similar observed relationships could explain a host of previous results, as discussed above. 471

472 Visually fixating brings a prestressed quiet stance into one with informational coupling 473 with the visual stimulus. Past work has repeatedly implicated fractal fluctuations in the head 474 and upper torso for using visual information to organize action [28,29,65-68]. Visual inspection of IRF plots indicated rare instances of effects from or responses from CoM 475 fractality on or to SD (1 trial in the 50-, 135-, and 305-cm conditions), but the regression 476 modeling indicated no stable relationship. So, the absence of significant IRF relationships for 477 478 $CoM-H_{fGn}$ on CoP-SD is puzzling. However, past evidence suggests that fluctuations in the 479 upper body moderate the use of visual information beyond and possibly in collaboration with 480 the retina's microsaccades. CoP and movements of the upper extremities exhibit a close 481 mutual predictive relationship in fractal and multifractal fluctuations even without involving a 482 significant role of torso fluctuations [30,31]. Indeed, should tensegrity-themed metaphors for 483 the movement system be apt [18], then we can expect relatively less local relationships, and 484 CoM may be one of the multiple intermediary links in the anatomical change that need not 485 always participate in controlling posture. Fuller-body set of measurements may allow clearer portrayal of causal relationships knitting retinal fluctuations with CoP fluctuations. 486

487 Supplementary materials

488 **Dataset 1.** DFA exponents used for VAR analysis.

489 **Table S1.** *Mean*±*s.e.m.* values of H_{fGn} yielded by DFA for the original (unshuffled) and a 490 shuffled version of each CoM SED and CoP PED time series, and coefficients of paired 491 samples *t*-tests comparing the two.

492 **Table S2.** Regression coefficients for all effects for the eyes-closed condition.

493 **Table S3.** Regression coefficients by the eyes-open conditions for the effects and interactions 494 of Segment, Trial, Response(CoP- H_{fGn}), and Response(CoP-SD) without specific pairwise 495 interactions.

496 **Table S4.** Regression coefficients by the eyes-open conditions for interactions of Segment, 497 Trial, Impulse(CoP- H_{fGn}), and Impulse(CoP-*SD*) without specific pairwise interactions.

498 **Table S5.** Regression coefficients by the eyes-open conditions for interactions of Segment 499 and Trial with specific pairwise self-interactions (i.e., of prior impulses of CoP- H_{fGn} on itself, 500 and of prior impulses of CoP-*SD* on itself).

Table S6. Regression coefficients by the eyes-open conditions for interactions of Segment and Trial with specific pairwise other-interactions (i.e., of prior impulses of CoP- H_{fGn} on later values of CoP-SD, and of prior impulses of CoP-SD on later values of CoP- H_{fGn}).

504 **References**

- Zatsiorsky VM, Duarte M. 1999 Instant equilibrium point and its migration in standing
 tasks: Rambling and trembling components of the stabilogram. *Motor Control* 3, 28–38.
 (doi:10.1123/mcj.3.1.28)
- 508 2. Winter DA. 1995 Human balance and posture control during standing and walking. *Gait* 509 *Posture* **3**, 193–214. (doi:10.1016/0966-6362(96)82849-9)
- 510 3. Chen L-C, Metcalfe JS, Chang T-Y, Jeka JJ, Clark JE. 2008 The development of infant 511 upright posture: Sway less or sway differently? *Exp. Brain Res.* **186**, 293–303. 512 (doi:10.1007/s00221-007-1236-1)
- 513 4. Rajachandrakumar R, Mann J, Schinkel-Ivy A, Mansfield A. 2018 Exploring the 514 relationship between stability and variability of the centre of mass and centre of 515 pressure. *Gait Posture* **63**, 254–259. (doi:10.1016/j.gaitpost.2018.05.008)
- 516 5. Shinbrot T, Muzzio FJ. 2001 Noise to order. *Nature* **410**, 251–258. 517 (doi:10.1038/35065689)
- 518 6. Turing AM. 1990 The chemical basis of morphogenesis. *Bull. Math. Biol.* 52, 153–197.
 519 (doi:10.1007/BF02459572)
- 520 7. Montesano G, Crabb DP, Jones PR, Fogagnolo P, Digiuni M, Rossetti LM. 2018
 521 Evidence for alterations in fixational eye movements in glaucoma. *BMC Ophthalmol.* 18,
 522 191. (doi:10.1186/s12886-018-0870-7)
- 523 8. Meyberg S, Sinn P, Engbert R, Sommer W. 2017 Revising the link between 524 microsaccades and the spatial cueing of voluntary attention. *Vision Res.* **133**, 47–60. 525 (doi:10.1016/j.visres.2017.01.001)
- Martinez-Conde S, Otero-Millan J, Macknik SL. 2013 The impact of microsaccades on vision: Towards a unified theory of saccadic function. *Nat. Rev. Neurosci.* 14, 83–96. (doi:10.1038/nrn3405)
- 52910.Murnaghan CD, Carpenter MG, Chua R, Inglis JT. 2016 Keeping still doesn't "make530sense": Examining a role for movement variability by stabilizing the arm during a531postural control task. *J. Neurophysiol.* **117**, 846–852. (doi:10.1152/jn.01150.2015)
- 532 11. Stoffregen TA, Pagulayan RJ, Bardy BG, Hettinger LJ. 2000 Modulating postural control
 533 to facilitate visual performance. *Hum. Mov. Sci.* **19**, 203–220. (doi:10.1016/S0167534 9457(00)00009-9)
- 535
 12.
 Stoffregen TA. 2010 Affordances as properties of the animal-environment system. *Ecol.*

 536
 Psychol. **15**, 115–134. (doi:10.1207/S15326969ECO1502_2)

- 537 13. Stoffregen TA, Smart LJ, Bardy BG, Pagulayan RJ. 1999 Postural stabilization of
 538 looking. *J. Exp. Psychol. Hum. Percept. Perform.* 25, 1641–1658. (doi:10.1037/0096 539 1523.25.6.1641)
- Jaschinski W. 2002 The proximity-fixation-disparity curve and the preferred viewing
 distance at a visual display as an indicator of near vision fatigue. *Optom. Vis. Sci.* **79**,
 158–168.
- 54315.Jaschinski-Kruza W. 1991 Eyestrain in VDU users: Viewing distance and the resting544position of ocular muscles.Hum.Factors33, 69–83.545(doi:10.1177/001872089103300106)
- 546 16. Párraga CA, Troscianko T, Tolhurst DJ. 2002 Spatiochromatic properties of natural
 547 images and human vision. *Curr. Biol.* **12**, 483–487. (doi:10.1016/S0960-9822(02)00718548 2)
- 549 17. Schleip R, Mechsner F, Zorn A, Klingler W. 2014 The bodywide fascial network as a 550 sensory organ for haptic perception. J. Mot. Behav. 46. 191–193. 551 (doi:10.1080/00222895.2014.880306)
- 552
 18.
 Turvey MT, Fonseca ST. 2014 The medium of haptic perception: A tensegrity

 553
 hypothesis. J. Mot. Behav. 46, 143–187. (doi:10.1080/00222895.2013.798252)
- 19. Cabe PA. 2018 All perception engages the tensegrity-based haptic medium. *Ecol. Psychol.* **31**, 1–13. (doi:10.1080/10407413.2018.1526037)
- Ingber DE. 2006 Cellular mechanotransduction: Putting all the pieces together again.
 FASEB J. 20, 811–827. (doi:10.1096/fj.05-5424rev)
- Nelson CM, Jean RP, Tan JL, Liu WF, Sniadecki NJ, Spector AA, Chen CS. 2005
 Emergent patterns of growth controlled by multicellular form and mechanics. *Proc. Natl. Acad. Sci. U. S. A.* **102**, 11594–11599. (doi:10.1073/pnas.0502575102)
- 56122.IngberDE.2010Fromcellularmechanotransductiontobiologicallyinspired562engineering. Ann. Biomed. Eng. 38, 1148–1161. (doi:10.1007/s10439-010-9946-0)
- 56323.Ingber DE. 2008 Tensegrity-based mechanosensing from macro to micro. Prog.564Biophys. Mol. Biol. 97, 163–179. (doi:10.1016/j.pbiomolbio.2008.02.005)
- Hajnal A, Clark JD, Doyon JK, Kelty-Stephen DG. 2018 Fractality of body movements 565 24. 566 predicts perception of affordances: Evidence from stand-on-ability judgments about 567 slopes. J. Exp. Psychol. Hum. Percept. Perform. 44. 836-841. (doi:10.1037/xhp0000510) 568
- 569 25. Doyon JK, Hajnal A, Surber T, Clark JD, Kelty-Stephen DG. 2019 Multifractality of 570 posture modulates multisensory perception of stand-on-ability. *PLoS One* **14**, 571 e0212220. (doi:10.1371/journal.pone.0212220)

- Palatinus Z, Dixon JA, Kelty-Stephen DG. 2013 Fractal fluctuations in quiet standing
 predict the use of mechanical information for haptic perception. *Ann. Biomed. Eng.* 41,
 1625–1634. (doi:10.1007/s10439-012-0706-1)
- Palatinus Z, Kelty-Stephen DG, Kinsella-Shaw J, Carello C, Turvey MT. 2014 Haptic
 perceptual intent in quiet standing affects multifractal scaling of postural fluctuations. *J. Exp. Psychol. Hum. Percept. Perform.* 40, 1808–1818. (doi:10.1037/a0037247)
- 578 28. Mangalam M, Chen R, McHugh TR, Singh T, Kelty-Stephen DG. 2020 Bodywide 579 fluctuations support manual exploration: Fractal fluctuations in posture predict 580 perception of heaviness and length via effortful touch by the hand. *Hum. Mov. Sci.* **69**, 581 102543. (doi:10.1016/j.humov.2019.102543)
- 582 29. Mangalam M, Kelty-Stephen DG. 2020 Multiplicative-cascade dynamics supports
 583 whole-body coordination for perception via effortful touch. *Hum. Mov. Sci.* **70**, 102595.
 584 (doi:10.1016/j.humov.2020.102595)
- Mangalam M, Carver NS, Kelty-Stephen DG. 2020 Global broadcasting of local fractal
 fluctuations in a bodywide distributed system supports perception via effortful touch. *Chaos, Solitons & Fractals* 135, 109740. (doi:10.1016/j.chaos.2020.109740)
- Mangalam M, Carver NS, Kelty-Stephen DG. 2020 Multifractal signatures of perceptual
 processing on anatomical sleeves of the human body. *bioRxiv*, 091702.
 (doi:10.1101/2020.05.12.091702)
- Lee I-C, Pacheco MM, Newell KM. 2019 The precision demands of viewing distance
 modulate postural coordination and control. *Hum. Mov. Sci.* 66, 425–439.
 (doi:https://doi.org/10.1016/j.humov.2019.05.019)
- 594 33. Fiorelli CM, Polastri PF, Rodrigues ST, Baptista AM, Penedo T, Pereira VAI, Simieli L,
 595 Barbieri FA. 2017 Gaze position interferes in body sway in young adults. *Neurosci. Lett.*596 660, 130–134. (doi:10.1016/j.neulet.2017.09.008)
- 597 34. Lê T-T, Kapoula Z. 2008 Role of ocular convergence in the Romberg quotient. *Gait* 598 *Posture* **27**, 493–500. (doi:10.1016/j.gaitpost.2007.06.003)
- 599 35. Collins JJ, De Luca CJ. 1993 Open-loop and closed-loop control of posture: A random-600 walk analysis of center-of-pressure trajectories. *Exp. Brain Res.* **95**, 308–318. 601 (doi:10.1007/BF00229788)
- 602 36. Collins JJ, De Luca CJ. 1995 Upright, correlated random walks: A statistical603 biomechanics approach to the human postural control system. *Chaos An Interdiscip. J.*604 *Nonlinear Sci.* 5, 57–63. (doi:10.1063/1.166086)
- Gilfriche P, Deschodt-Arsac V, Blons E, Arsac LM. 2018 Frequency-specific fractal
 analysis of postural control accounts for control strategies. *Front. Physiol.* 9, 293.
 (doi:10.3389/fphys.2018.00293)

- Buarte M, Sternad D. 2008 Complexity of human postural control in young and older
 adults during prolonged standing. *Exp. Brain Res.* **191**, 265–276. (doi:10.1007/s00221008-1521-7)
- 611 39. Duarte M, Zatsiorsky VM. 2001 Long-range correlations in human standing. *Phys. Lett.* 612 A 283, 124–128. (doi:10.1016/S0375-9601(01)00188-8)
- 40. Zatsiorsky V, Seluyanov V. 1985 Estimation of the mass and inertia characteristics of
 the human body by means of the best predictive regression equations. *Biomechanics*IX-B, 233–239.
- 41. Peng C-K, Buldyrev S V, Havlin S, Simons M, Stanley HE, Goldberger AL. 1994 Mosaic
 organization of DNA nucleotides. *Phys. Rev. E* 49, 1685–1689.
 (doi:10.1103/PhysRevE.49.1685)
- 42. Peng C-K, Havlin S, Stanley HE, Goldberger AL. 1995 Quantification of scaling
 exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos An Interdiscip. J. Nonlinear Sci.* 5, 82–87. (doi:10.1063/1.166141)
- 622 **43**. Sims CA. 1980 Macroeconomics and reality. *Econometrica* **48**, 1–48. 623 (doi:10.2307/1912017)
- 44. Lutkepohl H. 2007 *New Introduction to Multiple Time Series Analysis*. New York, NY:
 Springer.
- 62645.Hatemi-J A. 2004 Multivariate tests for autocorrelation in the stable and unstable VAR627models. *Econ. Model.* 21, 661–683. (doi:10.1016/j.econmod.2003.09.005)
- 628 46. Pfaff B, Stigler M, Pfaff MB. 2018 Package 'vars'. R Packag. version 1.5-3
- 47. Singer JD, Willett JB. 2003 Applied Longitudinal Analysis: Modeling Change and Event
 630 Occurrence. New York, NY: Oxford University Press.
- 48. Pinheiro J, Bates D, DebRoy S, Sarkar D, Team RC. 2018 nlme: Linear and nonlinear
 mixed effects models. *R Packag. version 3.1-137*
- 49. Zatsiorsky VM, Duarte M. 2000 Rambling and trembling in quiet standing. *Motor*634 *Control* 4, 185–200. (doi:10.1123/mcj.4.2.185)
- 63550.Ferronato PAM, Barela JA. 2011 Age-related changes in postural control: Rambling and636trembling trajectories. *Motor Control* **15**, 481–493. (doi:10.1123/mcj.15.4.481)
- Yamagata M, Popow M, Latash ML. 2019 Beyond rambling and trembling: Effects of 637 51. 638 feedback on slow postural drift. visual Exp. Brain Res. 237, 865-871. (doi:10.1007/s00221-019-05470-w) 639
- Kapoula Z, Lê T-T. 2006 Effects of distance and gaze position on postural stability in
 young and old subjects. *Exp. Brain Res.* **173**, 438–445. (doi:10.1007/s00221-006-03821)

- 643 53. Kuznetsov N, Wallot S. 2011 Effects of accuracy feedback on fractal characteristics of 644 time estimation. *Front. Integr. Neurosci.* **5**, 62. (doi:10.3389/fnint.2011.00062)
- Kelty-Stephen DG, Dixon JA. 2014 Interwoven fluctuations during intermodal
 perception: Fractality in head sway supports the use of visual feedback in haptic
 perceptual judgments by manual wielding. *J. Exp. Psychol. Hum. Percept. Perform.* 40,
 2289–2309. (doi:10.1037/a0038159)
- 55. Stephen DG, Hajnal A. 2011 Transfer of calibration between hand and foot: Functional
 equivalence and fractal fluctuations. *Attention, Perception, Psychophys.* **73**, 1302–
 1328. (doi:10.3758/s13414-011-0142-6)
- 652 56. Hagio K, Obata H, Nakazawa K. 2018 Effects of breathing movement on the reduction
 653 of postural sway during postural-cognitive dual tasking. *PLoS One* **13**, e0197385.
 654 (doi:10.1371/journal.pone.0197385)
- 65557.Thurner S, Mittermaier C, Ehrenberger K. 2002 Change of complexity patterns in656human posture during aging. Audiol. Neurotol. 7, 240–248. (doi:10.1159/000063740)
- 65758.Lipsitz LA. 2002 Dynamics of stability: The physiologic basis of functional health and658frailty. Journals Gerontol. Ser. A 57, B115–B125. (doi:10.1093/gerona/57.3.B115)
- Ko J-H, Newell KM. 2016 Aging and the complexity of center of pressure in static and
 dynamic postural tasks. *Neurosci. Lett.* 610, 104–109.
 (doi:10.1016/j.neulet.2015.10.069)
- 662 60. Priplata A, Niemi J, Salen M, Harry J, Lipsitz LA, Collins JJ. 2002 Noise-enhanced
 663 human balance control. *Phys. Rev. Lett.* 89, 238101.
 664 (doi:10.1103/PhysRevLett.89.238101)
- 665 61. Priplata AA, Niemi JB, Harry JD, Lipsitz LA, Collins JJ. 2003 Vibrating insoles and 666 balance control in elderly people. *Lancet* **362**, 1123–1124. (doi:10.1016/S0140-667 6736(03)14470-4)
- 668 62. Kelty-Stephen DG, Dixon JA. 2013 Temporal correlations in postural sway moderate
 669 effects of stochastic resonance on postural stability. *Hum. Mov. Sci.* 32, 91–105.
 670 (doi:10.1016/j.humov.2012.08.006)
- 63. Vecera SP, Cosman JD, Vatterott DB, Roper ZJJ. 2014 The control of visual attention:
 Toward a unified account. In *The Psychology of Learning and Motivation* (ed BH Ross),
 pp. 303–347. Burlington, MA: Academic Press.
- 674 64. Bardy BG, Marin L, Stoffregen TA, Bootsma RJ. 1999 Postural coordination modes
 675 considered as emergent phenomena. *J. Exp. Psychol. Hum. Percept. Perform.* 25,
 676 1284–1301. (doi:10.1037/0096-1523.25.5.1284)

- 677 65. Teng DW, Eddy CL, Kelty-Stephen DG. 2016 Non-visually-guided distance perception 678 depends on matching torso fluctuations between training and test. *Attention,* 679 *Perception, Psychophys.* **78**, 2320–2328. (doi:10.3758/s13414-016-1213-5)
- 680 66. Eddy CL, Kelty-Stephen DG. 2015 Nesting of focal within peripheral vision promotes
 681 interactions across nested time scales in head sway: Multifractal evidence from
 682 accelerometry during manual and walking-based fitts tasks. *Ecol. Psychol.* 27, 43–67.
 683 (doi:10.1080/10407413.2015.991663)
- 684 67. Bell C, Carver N, Zbaracki J, Kelty-Stephen D. 2019 Nonlinear amplification of 685 variability through interaction across scales supports greater accuracy in manual 686 aiming: Evidence from a multifractal analysis with comparisons to linear surrogates in 687 the Fitts task. *Front. Physiol.* **10**, 998. (doi:10.3389/fphys.2019.00998)
- 688 68. Carver NS, Bojovic D, Kelty-Stephen DG. 2017 Multifractal foundations of visually-689 guided aiming and adaptation to prismatic perturbation. *Hum. Mov. Sci.* **55**, 61–72. 690 (doi:10.1016/j.humov.2017.07.005)

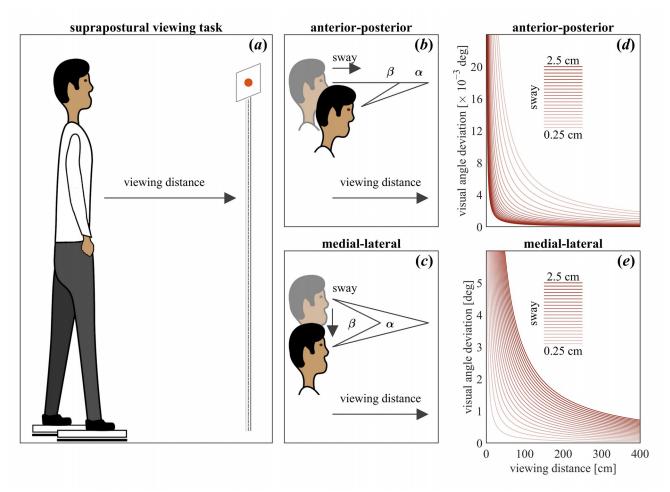


Figure 1. Schematic of the task and effects of eye-to-target distance on postural sway. (*a*) The suprapostural viewing task of standing quietly with the eyes fixated at a distant visual element. (*b*, *c*) Visual angle gain for short vs. long eye-to-target distances along the anteriorposterior (AP) and medial-lateral (ML) axes. (*d*, *e*) Visual angle gain as a function of eye-to-target distance for different sway magnitudes. Closer targets increase *AP* sway, whereas farther targets increase *ML* sway.

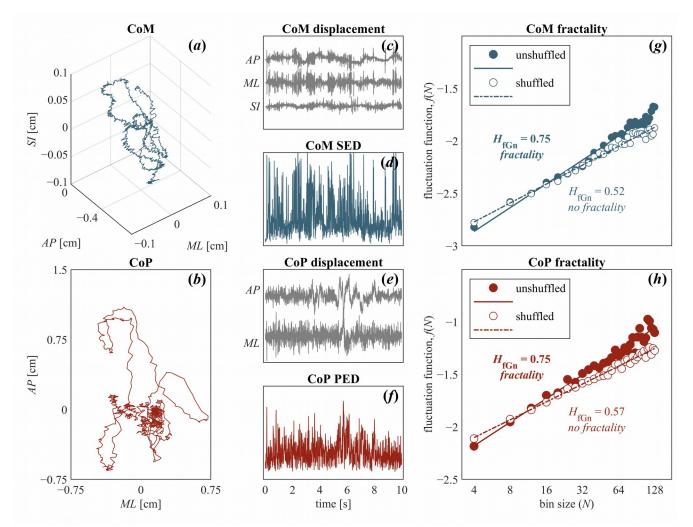


Figure 2. An overview of the detrended fluctuation analysis (DFA). (*a*, *b*) CoM and CoP in a representative 10 s segment. (*c* to *f*) CoM displacement along the medial-lateral (ML), anterior-posterior (AP), and superior-inferior (SI) axes; CoM SED series; CoP displacement along the ML, AP, and SI axes; CoP PED series. (*g*, *h*) Log-log plots of fluctuation function, f(*N*), vs. bin size (*N*), reflecting the fractal scaling exponent, H_{fGn} , yielded by DFA. Solid circles and solid trend lines represent *f*(*N*) for the original (unshuffled) series; open circles and dashed trend lines represent *f*(*N*) for a shuffled version of the original series.

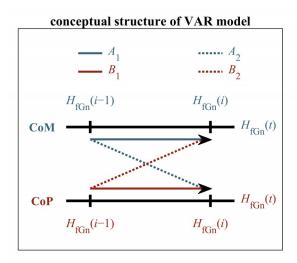


Figure 3. An overview of the vector autoregressive (VAR) analysis. VAR analysis was used to model the diffusion of fractal fluctuations across the body, as a time series of segment-by-

segment values of CoM- H_{fGn} , CoP- H_{fGn} , and CoP-SD. Black arrows indicate the effects of H_{fGn}

in the previous segment on H_{fGn} in the current segment.

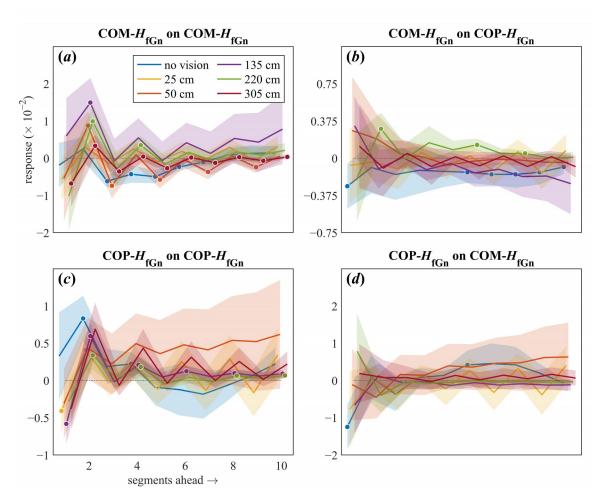


Figure 4. IRFs predicting the responses over ten segments ahead to an impulse in the current segment for each viewing condition. (*a*) CoM- H_{fGn} on CoM- H_{fGn} . (*b*) CoM- H_{fGn} on CoP- H_{fGn} . (*c*) CoP- H_{fGn} on CoP- H_{fGn} . (*d*) CoP- H_{fGn} on CoM- H_{fGn} . Shaded areas indicate *mean*±1s.e.m. of trial averages across all participants (n = 15). Solid circles indicate statistically significant (p < 0.01) responses to an impulse in the *i*th segment. The curves eventually approach zero, indicating that impulse-responses weakened over subsequent segments and eventually diminished completely.

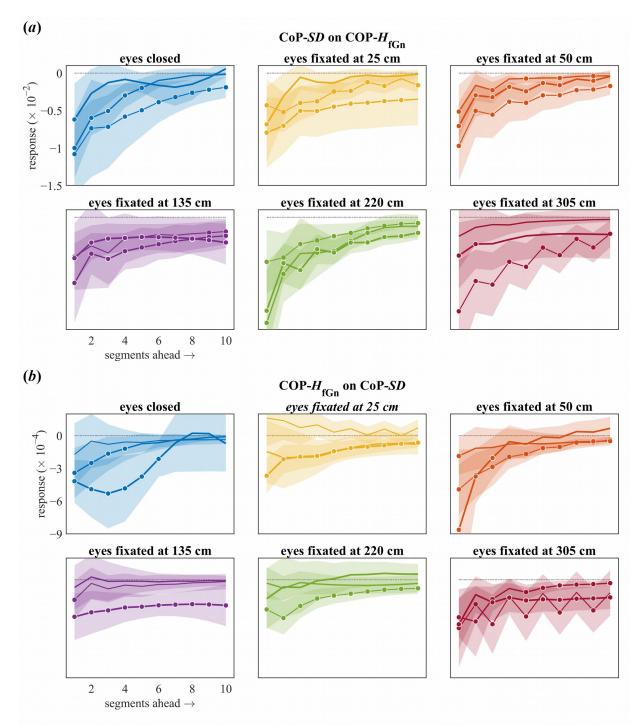


Figure 5. IRFs predicting the responses over ten segments ahead to an impulse in the current segment for each trial for each viewing condition. (*a*) CoP-*SD* on CoP- H_{fGn} . (*b*) CoP- H_{fGn} on CoP-*SD*. Line widths encode trial order (thin: trial-1; medium: trial-2; thick: trial-3). Shaded areas indicate *mean*±1*s.e.m.* of trial averages across all participants (*n* = 15). Solid circles indicate statistically significant (*p* < 0.01) responses to an impulse in the *i*th segment. The curves eventually approach zero, indicating that impulse-responses weakened over subsequent segments and eventually diminished completely.