Complexity of Postural Sway Affects Affordance Perception of Reachability in Virtual Reality

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Abstract

Visual perception of whether an object is within reach while standing in different postures was investigated. Participants viewed a 3D virtual reality (VR) environment with a stimulus object (red ball) placed at different egocentric distances. Participants reported whether the object was reachable while in a standard pose as well as in two separate active balance poses (yoga tree pose, and toe-to-heel pose). Feedback on accuracy was not provided, and participants were not allowed to attempt to reach. Response time, affordance judgments (reachable, not reachable), and head movements were recorded on each trial. Consistent with recent research on perception of reaching ability (Weast & Proffitt, 2018), the perceived boundary occurred at approximately 120% of arm length, indicating overestimation of perceived reaching ability. Response times increased with distance, and were shortest for the most difficult pose - the yoga tree pose. Head movement amplitude increased with increases in balance demands. Unexpectedly, the coefficient of variation was comparable in the two active balance poses, and was more extreme in the standard control pose for the shortest and longest distances. More complex descriptors of postural sway (i.e. effort-to-compress) were predictive of perception while in the tree pose and the toe-to-heel pose, as compared to control stance. This demonstrates that standard measures of central tendency are not sufficient for describing multiscale interactions of postural dynamics in functional tasks.

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The hallmark of efficacious behavior is the ability to perceive and act on opportunities for action termed affordances (Gibson, 1979). In most everyday settings, multiple affordances are simultaneously available and performing a given behavior requires perceiving (and acting upon) multiple affordances. For example, if a person intends to pick up an object from a table, that person has to perceive the nested behaviors that must be performed such that the goal can be achieved. That is, the person must perceive how the present state of affairs must be modified to bring about the intended state of affairs (Wagman, 2012). For example, the person must (simultaneously) perceive whether (and how) it would be necessary to change body position, arm extension, and grasp width to successfully pick up the object. Typically, leaning and reaching are behaviors that bring effectors into the vicinity of a target object, to allow for subsequent (or simultaneous) grasping. That is, affordances for grasping are (typically) nested within affordances for leaning and reaching.

The multiple affordances available to a given person at any given moment are nested across multiple levels of a means-ends hierarchy (Wagman, Caputo, & Stoffregen, 2016; Vicente & Rasmussen, 1990; see Ye, Cardwell, & Mark, 2009). Higher levels of the hierarchy function as ends, or goals, while lower levels function as means to those ends. At every level of the hierarchy, affordances are simultaneously constrained by lower levels (i.e., by lower order affordances or means of performing a given behavior) but also by higher levels (i.e., higher order affordances or goals for performing a given behavior). In the context of reaching for an object, affordances for reaching are nested within affordances for maintaining (or changing) posture (i.e., how the reaching is to occur) and the goal of reaching (i.e., why the reaching is occurring) (Wagman, Ciadella, & Stoffregen, 2018).

Postural control can facilitate performance in suprapostural tasks such as focusing attention (or behavior) on a target object (Balasubramaniam, Riley, & Turvey, 2000; Stoffregen, Pagulayan, Bardy, & Hettinger, 2000; Stoffregen, Smart, Bardy, & Pagulayan, 1999). Postural control can also maintain stability and support perceptual performance under dynamically changing environmental constraints (Stoffregen, Villiard, & Yu, 2009; Walter, Wagman, Stergiou, Erkmen, & Stoffregen, 2017; Walter, Li, Wagman, & Stoffregen, 2019). Such studies have clearly demonstrated that postural demands influence affordance perception. However, the nature of the relationship ~~between posture and perception of affordances~~ is unclear. Posture exhibits dynamical stability through continuous body sway. Such minute fluctuations of the body's center of mass cause corresponding complex, but subtle head movements. These head movements generate subtle optic flow and gravito-inertial patterns. In principle, the patterning of information in the global ambient energy array generated by postural sway ought to be informative for affordance judgments (Stoffregen, Mantel, & Bardy, 2017; Yu, Bardy, & Stoffregen, 2010). How can this pattern be described? In a virtual reality study, Mantel et al. (2015) demonstrated that perception of affordances for reaching is specific to complex patterns of ambient energy arrays that include optical and gravito-inertial patterns. Importantly, Mantel and colleagues noted that such information is only useful to the extent that perceptual systems are able to detect it. They hypothesized that complex exploratory activity is necessary to detect and pick up the information. Our aims in the present study were to (1) characterize the complexity of such ambient energy patterns using a global measure of movement complexity and (2) demonstrate that perception of affordances for reaching is a function of such complexity. As such, our current investigation is complementary to Mantel et al.'s in that we focused on the circumstances that permit optimal detectability of information, rather than on the information

itself. We hypothesized that optimal detectability is promoted by complex exploratory activity including postural sway and subsequent head movements, and thus focused on measuring the complex variability of head movements in a reaching task.

Postural sway, and in turn the optic flow pattern that is generated by it, are nonstationary signals. This means that classical measures of central tendency (e.g. mean magnitude, standard deviation) describe the movement at a very coarse level. By calculating the (stationary) mean of the fluctuations of the center of mass during upright stance, researchers can miss the rich structure of variability that exists in the movement. To remedy this shortcoming a complexity measure called effort-to-compress (ETC) was calculated for each trial's time series of head movements. ETC is a measure of the heterogeneity of the time series and the ease with which it can be converted into a homogeneous series (Nagaraj & Balasubramanian, 2017a; 2017b). ETC is especially well suited for the description of short time series (less than 500 samples) in a variety of fields, such as neuroscience (e.g., neural spikes, heart rate) and engineering (e.g., structural complexity of materials, Virmani & Nagaraj, 2019). ETC measures the heterogeneity by identifying "streaks" in the time series. These repeated occurrences (streaks or patterns) are then labeled as a unit, effectively shortening the time series. This logic is also used in engineering technology and computer science to compress data files such as music files and digital images. The number of steps involved in compressing the time series into its smallest possible length is a measure of how complex the original series was. In the present experiment we used ETC as a measure of complexity of head movements by analyzing the Euclidean distance series for each trial. More complex head movements yield more complex optical patterns and perhaps more effective sampling of the ambient optic array. This may yield perception of affordances that more closely matches action capabilities.

Does complexity of postural sway inform perception of affordances for other behaviors such as reaching to grasp a target from a standing posture? One way to test this is to manipulate the difficulty of the posture adopted during an ostensibly perceptual task (cf. Mark, Balliet, Craver, Douglas, & Fox, 1990). It is hypothesized that the difficulty of the posture will influence postural sway that will in turn affect perception of whether a target object is within reach. Importantly, it is also hypothesized that effort-to-compress (the movement parameter that describes the complexity of postural sway variability) will modulate perception of affordances.

Perception of Affordances in Virtual Reality. Virtual reality has become a widely used tool in several areas of research, particularly perception (e.g. Durgin, & Li, 2010; Flach & Holden, 1998; Geuss, McCardell, & Stefanucci, 2016; Pointon et al., 2018). Due to the ease of manipulating task demands and stimuli within a virtual environment and the convenience for designing and running experiments that could not be conducted otherwise, researchers utilize it regularly. Specifically, VR has become a useful tool in investigating affordance judgments. For example, Geuss, Stefanucci, Creem-Regehr, and Thompson (2010) examined accuracy of affordance judgements in the real-world versus a virtual world. They modeled the virtual environment after the real-world environment and investigated perception of affordances for fitting through an aperture, following up on a study by Warren & Whang (1987). Judgments of affordances for passage between two poles were compared at matching distances in each setting. It was found that accuracy in participants' responses were no different between the real-world and the VR. Perception of affordances for reaching have also been shown to be comparable in both real-world (Carello, Grosofsky, Reichel, Solomon, & Turvey, 1989) and virtual environments (Bhargarva, Lucaites, Hartman, Solini, Bertrand, Robb, Pagano, & Babu, 2020; Day, Ebrahimi, Hartman, Pagano, Robb, & Babu, 2019). In real-world judgments of reachability, participants

typically overestimate their reaching ability, even when reaching is part of the response (Weast & Proffit, 2018). As in real world settings, participants who are asked to judge whether an object in a virtual world is within reach tend to overestimate their actual reaching abilities (Doyon, 2018). It is not clear what the source of the overestimation is. While virtual reality technology cannot simulate the full richness of the optic flow patterns that are generated by ambient light patterns in the real environment, it serves as a compelling approximation that drives a lot of contemporary perceptual research.

In the present study observers wore a head mounted display that showed a target object (red ball) placed at different egocentric distances in a virtual room. Participants viewed this object while (actually) performing one of three postures: normal pose, heel-to-toe pose, and a tree yoga pose. They reported whether the object would be reachable at that distance from the performed posture. Participants' verbal reports were recorded, along with response latencies. Head movements were recorded by the HMD during each trial. It was predicted that response times would be longer during more difficult[1] postural tasks. We based our prediction on past research on response latencies in tasks that require physical effort (Hajnal, Bunch, Kelty-Stephen, 2014; 2016). Second, given that previous research has shown that performing a balance task inhibits the ability to perceive affordances (Mark et al., 1990; Wagman & Hajnal, 2014) it was predicted that affordance judgments would be less accurate (would less closely reflect reaching ability) as balance demands increase. Third, it was expected that head movements would increase with more difficult balance tasks in order to meet the demands of maintaining stable posture.

Our general predictions considered two main sources of influence on affordance judgments: task demands and organismic factors. The three poses constituted the main task

demand. The placement of the stimuli at different distances was a (relative) spatial variable that was determined by the π-ratio, an intrinsic measure of affordance capability. In this sense the π-ratio was a combination of external spatial task demands and organismic constraints, spanning both task- and organismic variables. Each pose was grouped into blocks of trials, defining a temporal task demand. Given the differential effort requirements of maintaining some postures for an extended period of time, we expected that both the ability to maintain posture and the perception of reaching affordance would change across blocks of trials.

The second class of factors that were predicted to influence perceptual performance were organismic factors that described postural sway during trials: mean head movement (Mean), variability of head movement expressed as the coefficient of variation (CV), and effort-to-compress (ETC), indicating the complexity of postural sway. We assumed that these variables would differentially account for variability in affordance judgments given the nature of each variable. Specifically, we assumed that the Mean would be the least useful predictor, given the nonstationary nature of postural sway, CV would be significantly better, and ETC would be the best predictor. Spatiotemporal task demands (π, Block) were predicted to differentially interact with organismic factors (Mean, CV and ETC) in the context of the three poses. Specifically, we expected that ETC would be the best predictor of affordance judgments and latencies, and that high values of ETC would improve the accuracy of perception.

Method

Participants

Students were recruited through the Sona participant pool at the University of Southern Mississippi. Data was collected from a total of 38 participants. Five participants were excluded due to misinterpretation of experimental instructions (N = 33). This is a sufficient sample size

based on an approximate power analysis performed using the G*Power software package (Version 3.1.9.2; Faul, Erdfelder, Lang, & Buchner, 2007) in order to obtain a medium (η_p^2=0.09) to large (η_p^2=0.25) effect size, and is consistent with what has been obtained in similar research (Doyon, 2018). Participants included 29 women and 4 men, ranging from ages 18 to 26 (*M* = 18.97, *SD* = 1.69). Individuals were required to be 18 years of age or older and have normal or corrected-to-normal vision as well as no existing physical injuries (e.g. broken bones, sprained joints).

Materials and Apparatus

This study employed a virtual reality environment administered by a consumer version Oculus Rift head mounted display (HMD). Participants recorded their responses using two wireless handheld controllers, a button on the right controller was used to indicate a “yes” response and a button on the left controller was used to indicate a “no” response. The Unity game engine software (Version 2017.1.1f1) was used to program and deliver the environment, along with the C# programming language to script events and data recordings. Two table mounted Oculus motion sensors as well as sensors contained in the HMD tracked participant’s movement. The data drawn from the HMD was the data used to record head movement and assess postural instability.

The virtual environment consisted of a room with textured walls and natural lighting. The visual stimulus was a sphere (approximately the size of a tennis ball) that was suspended on a wire at the specific shoulder height of each participant (see Figure 1). This allowed for comfortable judgments of reachability. Reachability was defined as the ability to grasp the object with both the thumb and forefinger without leaning or bending forward at the hip or ankle.

Experimental Design

This study employed a 3 Pose (Normal, Tandem, Tree) × 5 Distance (π-ratios of 0.9, 1.0, 1.1, 1.2, and 1.3) repeated-measures design. The stimulus was placed at different relative distances in front of participants. These distances were determined by dimensionless π-ratios (Carello et al., 1989) ranging from 0.9 to 1.3 (reflecting proportions of a participant's maximum reaching distance). It was originally proposed that the distances be set at a range of 0.8 to 1.2. However, after analyzing pilot data, it was determined that a shift in distances was necessary to achieve greater variability in responses due to overestimation observed in recent research.

The equation for these ratios is as follows:

$$\pi = \frac{d}{a}$$

The equation takes into account both environmental and participant specific measurements. Here, *d* equals the physical distance to the target or visual stimulus, and *a* equals the length of the individual's arm. Thus, a ratio of $\pi = 1.00$ represents the individual's maximum reaching distance. Therefore, ratios of $\pi \leq 1.00$ will be within the participant's reach and ratios of $\pi > 1.00$ will be out of reach. Participants were randomly exposed to all five distances (π-ratios of .9, 1.0, 1.1, 1.2, and 1.3) three times in each pose for a total of 45 trials. The repetitions were grouped into three sequences for each pose to minimize back-to-back trials being presented with the same distances.

Over the course of the study participants were required to perform three separate balance positions to the best of their ability. The first was a normal pose (see left panel of Figure 2) where both feet were comfortably placed on the floor, the second was a toe-to-heel (tandem) pose (see middle panel of Figure 2) where one foot was placed directly in front of the other so that the toes of one met the heel of the other. Lastly, there was a tree pose (commonly used in

yoga practice, see right panel of Figure 4; Yu et al., 2012) where the sole of one foot was brought to rest on the alternate calf.

Procedure

After providing informed consent, physical measurements (e.g. shoulder height, eye height, arm length) were taken for each participant and entered into the VR software. Arm length was measured from the shoulder joint to the tip of the thumb. Verbal instructions were given on how to operate the VR equipment as well as what to expect within the virtual environment. Demonstrations were given on how to perform the appropriate poses. After the participant had been fitted with the HMD and had each of the wireless controllers in hand, they began a series of practice trials. There were 15 total practice trials. At each increment of five trials verbal instructions were given instructing a transition into the next pose. This allowed participants to become acquainted with the virtual environment as well as all three different poses. At all points of verbal instruction throughout the experiment, participants were allowed to rest if needed.

Once the practice trials were complete, participants were assigned a beginning pose. This differed depending on the counterbalancing order into which they were randomly assigned. The first group performed the following order of poses: Normal, Tandem, Tree; the second group: Tandem, Tree, Normal; whereas the third group: Tree, Normal, Tandem. Before beginning the experimental trials, participants were given verbal instructions on which pose to perform first. After each sequence of 15 trials participants were allowed the opportunity to rest as additional verbal instructions were provided indicating which pose they would transition to next. Once they were comfortable in that pose they pushed a button to proceed. Each individual trial concluded after participants reported their perceived ability to reach the ball in the current pose by pushing the relevant button. After finishing all 45 experimental trials, the experiment was complete.

Participants were then asked to answer a brief demographic questionnaire and were given the opportunity to ask any questions. They were then granted credit for participation and excused.

Measurements and Data Analysis

Response times were recorded in milliseconds for each trial. Response time recording began with a button press marking the start of the trial and continued until the participant again pressed a button giving a response. There was a 500ms inter-stimulus interval (ISI) between trials. Head and body movements were not restricted in any way. Participants were asked to not perform any type of reaching or leaning while making judgements. In the event that the participant had to step out of a pose and regain balance during a trial, the researcher recorded this by the press of a button. These recordings were documented in an excel file accompanied by a time stamp.

Head movements were recorded by tracking motion via the Oculus Rift headset's position sensor in a three-dimensional coordinate system. The position sensor sampled the data at 30Hz. The time series of head position coordinates were converted into Euclidean distances by computing the straight-line distance between each adjacent sample's position coordinates. These timeseries were processed in MATLAB using the effort-to-compress algorithm (ETC, Nagaraj et al., 2017a). This analysis assesses the heterogeneity of variability across the timeseries and characterizes the efficiency with which the time series can be turned into a completely homogeneous signal. The resulting parameter ETC is a reliable descriptor of the level of disorder, or randomness, in the signal, rather than raw variability. Accordingly, the signal might be highly variable, but not very complex, or it may be highly complex, but not very variable. Smaller values of ETC indicate lower complexity, while higher values of ETC indicate higher complexity.

Results

Probability Data. Since affordance judgments are measured with a dichotomous variable (yes/no), we used a mixed-effects hierarchical logistic regression (Bates, Maechler, Bolker, & Walker, 2014) as it is a more appropriate analysis than ANOVA for this type of data. The following model was used:

Response ~ Trial + Pose x π x Block x Mean + Pose x π x Block x CV + Pose x π x Block x ETC + (Trial|Participant),

Trial and participant were set as random effects; all other variables were fixed effects. Pose was coded as a categorical variable with three levels: 1= normal (control), 2= tandem, 3= tree pose. The model was built to test how affordance responses were affected by postural demands (Pose) along with spatial aspects of the task (distance ratio π), and temporal aspects of the task (blocks of trials). In addition, the model tested the contributions of various measures of head movement: magnitude (Mean), variability (CV), and complexity (ETC). Table 1 shows the output of the statistical analysis. Due to the constraints of the *lmer* statistical package in R, the main effects of Pose, and interactions involving the Pose variable are always based on the comparison with the control pose.

Table 1. Best fitting mixed-effects logistic regression model of Affordance Judgments. Significant effects (p<0.05) are in bold font.

Predictor	β	*SE*	*p*
Intercept	-4.31	43.29	0.920
Trial	-0.02	0.03	0.465
Block	9.39	19.07	0.623
π	4.37	35.41	0.902

Tandem Pose	16.65	51.63	0.747
Tree Pose	69.5	58.76	0.237
Mean	-32485.65	45300.05	0.473
CV (Coefficient of variation)	26.07	48.36	0.589
ETC	142.21	81.66	0.082
π × Mean	33564.84	36188.07	0.354
π × Block	-7.86	15.75	0.618
π × CV	-19.78	39.51	0.617
π × ETC	-128.18	67.19	0.057
Block × ETC	-44.82	35.68	0.209
Block × CV	-5.29	21.05	0.802
Block × Mean	18285.52	20491.22	0.372
π × Mean × Block	-17151.48	16204.34	0.29
π × CV × Block	3.75	17.33	0.829
π × ETC × Block	40.89	29.63	0.168
Interactions of Tandem Pose with other terms			
Tandem Pose × Mean	30174.96	47833.84	0.528
Tandem Pose × π	-16.5	42.7	0.699
Tandem Pose × Block	-5.37	26.71	0.841
Tandem Pose × CV	-51.68	55.44	0.351
Tandem Pose × ETC	-92.71	99.9	0.354
Tandem Pose × π × Mean	-27698.81	38624.71	0.473
Tandem Pose × π × Block	5.33	22.19	0.810
Tandem Pose × π × CV	39.35	45.71	0.389
Tandem Pose × π × ETC	88.38	83.01	0.2872
Tandem Pose × Block × Mean	-23137.76	21475.48	0.282
Tandem Pose × Block × CV	30.44	29.45	0.302
Tandem Pose × Block × ETC	28.96	48.87	0.554

Tandem Pose × π × Mean × Block	19016.48	17168.93	0.268
Tandem Pose × π × CV × Block	-22.93	24.3	0.346
Tandem Pose × π × ETC × Block	-27.97	40.75	0.493
Interactions of Tree Pose with other terms			
Tree Pose × Mean	19220.4	45683.49	0.674
Tree Pose × π	-64.33	48.78	0.187
Tree Pose × Block	-28.71	27.02	0.288
Tree Pose × CV	-41.01	67.61	0.544
Tree Pose × ETC	-198.85	101.7	0.051
Tree Pose × π × Mean	-22032.8	32314	0.496
Tree Pose × π × Block	-21509	36545.36	0.556
Tree Pose × π × CV	37.66	56.03	0.502
Tree Pose × π × ETC	**187.93**	**84.28**	**0.026**
Tree Pose × Block × Mean	-16243.04	20752.58	0.434
Tree Pose × Block × CV	11.74	30.16	0.697
Tree Pose × Block × ETC	89.37	47.09	0.058
Tree Pose × π × Mean × Block	15093.58	16440.37	0.359
Tree Pose × π × CV × Block	-10.63	25.05	0.671
Tree Pose × π × ETC × Block	**-80.66**	**39.24**	**0.04**

Overall, there was no effect of Mean or Coefficient of Variation (CV) on affordance judgments. There was a significant positive three-way Tree Pose × π × ETC interaction (β =187.93, SE = 84.28, p = 0.026). There was also a significant negative four-way Tree Pose × Block × π × ETC interaction (β =-80.66, SE = 39.24, p = 0.04). There were no interactions for Tandem Pose.

The four-way interaction is presented in Figure 3. A schematic diagram of all significant interactions is presented in Figure 4 to visualize the apportionment of the total explained variance.

A linear mixed-effects model was created to predict Response Time. The model was built using the same combination of predictors as the logistic model (random effects are not shown, but included):

Response Time ~ Pose × π × Block × Mean + Pose × π × Block × CV + Pose × π × Block × ETC

Table 2 shows the output of the statistical analysis.

Table 2. Best fitting mixed-effects linear regression model of Response Time. Significant effects (p<0.05) are in bold font.

Predictor	*β*	*SE*	*p*
Intercept	-0.548	4.375	0.9004
Block	-0.852	2.19	0.6975
π	4.102	3.772	0.277
Tandem Pose	-12.986	6.698	0.0527
Tree Pose	-4.36	6.768	0.5195
Mean	-4782.12	3917.017	0.2223
CV (Coefficient of variation)	-2.743	4.7	0.5595
ETC	8.124	7.561	0.2828
π × Mean	6105.579	3517.489	0.0828
π × Block	0.546	1.922	0.7766
π × CV	1.61	4.045	0.6907
π × ETC	**-13.584**	**6.657**	**0.0415**
Block × ETC	-0.072	3.817	0.9849

Block × CV	1.824	2.291	0.4261
Block × Mean	1840.701	1427.372	0.1974
π × Mean × Block	-2223.7	1290.595	0.0851
π × CV × Block	-1.238	1.993	0.5346
π × ETC × Block	0.256	3.421	0.9404
Interactions of Tandem Pose with other terms			
Tandem Pose × Mean	**13282.71**	**5325.755**	**0.0127**
Tandem Pose × π	11.422	5.926	0.0541
Tandem Pose × Block	6.303	3.235	0.0516
Tandem Pose × CV	**19.12**	**6.712**	**0.0045**
Tandem Pose × ETC	2.462	11.691	0.8333
Tandem Pose × π × Mean	**-12574.4**	**4780.974**	**0.0086**
Tandem Pose × π × Block	-5.461	2.883	0.0584
Tandem Pose × π × CV	**-16.094**	**5.976**	**0.0072**
Tandem Pose × π × ETC	-2.992	10.444	0.7745
Tandem Pose × Block × Mean	**-4060.67**	**2011.021**	**0.0437**
Tandem Pose × Block × CV	**-8.341**	**3.261**	**0.0106**
Tandem Pose × Block × ETC	-4.339	5.656	0.4431
Tandem Pose × π × Mean × Block	**4158.464**	**1814.68**	**0.0221**
Tandem Pose × π × CV × Block	**6.802**	**2.91**	**0.0196**
Tandem Pose × π × ETC × Block	4.126	5.094	0.4181
Interactions of Tree Pose with other terms			
Tree Pose × Mean	**9583.523**	**4134.994**	**0.0206**
Tree Pose × π	3.255	5.996	0.5873
Tree Pose × Block	3.431	3.188	0.2821
Tree Pose × CV	8.638	7.585	0.255
Tree Pose × MFW	-6.261	10.781	0.5615
Tree Pose × π × Mean	**-10695.4**	**3728.789**	**0.0042**

Tree Pose × π × Block	-2.943	2.819	0.2967
Tree Pose × π × CV	-6.363	6.741	0.3454
Tree Pose × π × ETC	6.724	9.672	0.487
Tree Pose × Block × Mean	**-4032.94**	**1566.61**	**0.0101**
Tree Pose × Block × CV	-5.359	3.479	0.1237
Tree Pose × Block × ETC	-0.018	5.185	0.9972
Tree Pose × π × Mean × Block	**4470.826**	**1415.767**	**0.0016**
Tree Pose × π × CV × Block	4.307	3.073	0.1612
Tree Pose × π × ETC × Block	-0.212	4.643	0.9637

There were no significant main effects. π interacted with ETC, (β = -13.58, *SE* = 6.65, *p* = 0.042). Tandem pose interacted with Mean (β = 13282.71, *SE* = 5325.76, *p* = 0.013) and CV (β = 19.12, *SE* = 6.71, *p* = 0.005), indicating that response times increased as the mean magnitude and variability of head movement increased in the Tandem pose compared to the control pose. There were four significant negative three-way interactions for Tandem pose. Tandem Pose × π × Mean (β = -12574.4, *SE* = 4780.97, *p* = 0.009), Tandem Pose × π × CV (β = -16.09, *SE* = 5.98, *p* = 0.007), Tandem Pose × Block × Mean (β = -4060.67, *SE* = 2011.02, *p* = 0.044), and Tandem Pose × Block × CV (β = -8.34, *SE* = 3.26, *p* = 0.011) . There were two significant positive four-way interactions: Tandem Pose × π × Block × Mean (β =4158.46, *SE* = 1814.68, *p* = 0.022) and Tandem pose × π × Block × CV (β =6.80, *SE* = 2.91, *p* = 0.019).

There was a significant positive two-way interaction of Tree Pose and Mean (β = 9583.52, *SE* = 4134.99, *p* = 0.021). There were also two significant negative three-way interactions including Tree Pose. These include the Tree pose × π × Mean interaction (β =-10685.4, *SE* = 3728.80, *p* = 0.004) as well as Tree Pose × Block × Mean (β = -4032.94, *SE* = 1566.61, *p* = 0.01. Lastly, there was a significant positive four-way interaction of Tree Pose × π

× Block × Mean (β = 4470.83, SE = 1415.76, p = 0.002). A schematic diagram of all significant main effects and interactions was presented in Figure 5 to visualize the apportionment of the total explained variance.

Mean, CV and ETC were used as predictor variables in mixed effects models. However, just like with affordance judgments and response time, we expected these variables to be influenced by the postural manipulation as well. In order to check our specific hypotheses, we conducted 3 Pose (Normal, Tandem, Tree) × 5 Distance (π-ratios of 0.9, 1.0, 1.1, 1.2, and 1.3) repeated measures analyses of variance (ANOVAs) on response time, Mean, CV, and ETC.

For response time, there was a statistically significant main effect of both Pose, $F(2,64)$ = 3.23, p = .046, η_p^2=0.09, and Distance, $F(2.44, 78.13)$ = 11.29, p <.01, η_p^2=0.26, (Greenhouse-Geisser correction, due to significant Mauchly's test on sphericity). Overall, participants took less time to respond while maintaining the tree pose than the tandem pose (p=.027, Bonferroni correction was applied to mitigate the potential for Type I error by multiplying the actual obtained p value by 3, the number of comparisons conducted). See Figure 6 for details. Response times increased with distance.

The mean magnitude of head movements (Mean) was calculated to estimate the magnitude of postural sway in each pose. There was a significant main effect for distance, $F(3.17, 101.5)$ = 2.83, p = .04, η_p^2=0.08 (Greenhouse-Geisser correction). In all three poses the largest head movements occurred at the largest distance. There was also a significant main effect of pose, $F(1.36, 43.58)$ = 59.76, p <.001, η_p^2=0.65 (Greenhouse-Geisser correction). The most head movement occurred in the tree pose, followed by the tandem pose, and the normal control pose (see Figure 7 for details). The coefficient of variation (CV) for head movements was analyzed in order to assess variability. Once again, we found a significant main effect for

distance, $F(3.25, 107.33) = 4.83$, $p = .003$, $\eta_p^2=0.13$ (Greenhouse-Geisser correction) as well as a significant interaction of distance and pose, $F(8,256) = 2.19$, $p = .03$, $\eta_p^2=0.06$. The coefficient of variation was most extreme for the shortest and longest distances in the normal pose (see Figure 8).

The ANOVA on ETC returned a significant main effect of distance, $F(2.81, 89.9) = 16.81$, $p = .001$, $\eta_p^2=0.34$, as well as a significant main effect of pose, $F(2, 64) = 3.26$, $p = .045$, $\eta_p^2=0.09$. Participants' head movements were more complex while maintaining the tree pose (M=0.335, SD=0.10) than the standard control pose (M=0.314, SD=0.09; p=.02, Fisher's PLSD post hoc test). The data are plotted in Figure 9.

Discussion

The purpose of this study was to investigate 1) the effects of balance demands on perception of affordances for reaching, and 2) the contribution of body movements on predicting affordance judgments. The results showed that more complex movement patterns are better predictors of affordance judgements than less complex movement patterns. This could mean that complex movements with large effort-to-compress values more effectively generated ambient information patterns that specify whether certain actions are possible (e.g. whether a target object is within reach from a given pose).

As a reminder, this study included five separate hypotheses for the five variables that were used as dependent measures in ANOVA designs, listed in Table 3.

Table 3. Overview of pose effect predictions for reachability, response time, and movement parameters using ANOVA designs.

	Normal (Control)	*Tandem*	*Tree*
Reachability Judgments	Most Accurate	Less Accurate	Least Accurate
Response Time	Least Time	More Time	Most Time
Head Movement (Mean)	Least Movement	More Movement	Most Movement
Head Movement (CV)	Least Variability	More Variability	Most Variability
Head Movement (Complexity)	Least Complex	More Complex	Most Complex

The ANOVA analyses showed that increased postural demands during perceptual tasks result in more overall postural sway and faster judgements of affordances. As such, the second hypothesis about response times was not supported. It is possible that the tree pose was so demanding that participants sped up their responses to minimize energy expenditure or to avoid losing balance. This contradicts the "posture first" principle (Horak, 2006) which predicts longer latencies when the postural task is difficult. However, increases in response time did occur in all three poses as object distance increased.

Movement variability (CV) exhibited a more complex pattern of dependency on postural demands. The significant $\pi \times$ pose interaction showed that the two difficult poses (tandem and tree) produced the same level of variability across distances, and that variability steadily increased over distances only in the control pose. This latter finding is consistent with past research on quiet stance where viewing more distant targets caused more variability in postural sway (Stoffregen et al., 1999; Bonnet, Temprado, & Berton, 2010; Stoffregen et al., 1999; 2000). It is still unclear why more difficult poses used in the present experiment did not follow the same

effect of distance. Future research is needed to disentangle the interaction between distance and postural demands.

The magnitude and variability of head movements were largest while participants maintained the tree pose. This is consistent with our hypotheses. In all three poses it was found that as object distance increased, head movement also increased. This was also found in past research that showed that increased object distance is associated with increased postural sway ().

The complexity of head movements (as measured by ETC) was the highest in the tree pose, which was consistent with our hypothesis. It appears that more demanding postures facilitated more complex movement patterns in the service of detecting information patterns that guide prospective action. Whether complex movement patterns are a byproduct of increased postural instability, or part of intentional exploratory activity to ensure optimal information detection is an open question for future research.

In order to get a more complete description of the data, regression models were constructed to predict responses. The models combined both spatial (π) and temporal (block) aspects of the task in order to assess movement parameters.

Affordance judgments are a function of task demands and complexity of postural sway

Mixed effects hierarchical logistic regression modeling showed that the strongest predictor of affordance judgments was a pattern of significant interactions among ETC and Pose. Mean head position and CV of head position did not interact with Pose. Thus, affordance judgments in the most difficult balance task were predicted by the most complex descriptor of head movements.

The four-way interaction of Tree Pose × π × Block × ETC is important to consider (see Figure 5). Participants who maintained the tree pose and exhibited high ETC, showed gradually increasing sensitivity in differentiating possible from impossible actions, as indicated by the increase in the slope of logistic curve around the 50th percentile across blocks of trials. This pattern was noticeable less consistent when ETC was low. In other words, on trials with high ETC, participants exhibited more certainty that the object was *within reach* at the two closest distances and more certainty that the object was *out of reach* at the two farthest distances compared to trials with low ETC. The fact that this perceptual sensitivity increased over blocks suggests that the most accurate responses while maintaining a difficult pose occurred when participants explored their environment through complex movements (i.e. high ETC). This finding is congruent with recent findings showing that increases in movement complexity yielded greater reliance on multimodal information and resulted in more accurate affordance judgments (Hajnal et al., 2018). Responses were not as accurate (i.e. showing overestimation) and not as sensitive (indicated by shallow slope of psychometric curve) during the tree pose in Blocks 1 and 2 for high ETC (see bottom panel of Figure 5). The fact that affordance judgments changed over blocks means that performance was influenced by temporal factors. As mentioned before, this could be attributed to practice effects for either familiarity with repeated stimulus distance or balance maintenance. This finding is interesting because response times were shorter overall for the tree pose than for the other poses. This could suggest that perception of affordances is more accurate when judgments are made without taking too much time to dwell on the task at hand (see Heft, 1993; Wagman, Bai, & Smith, 2016). One could argue that this is due to participant's underestimation of abilities based on being in an unstable standing position. However, in this circumstance, it is still the case that an overestimation of reachability occurs for

closer distances. In sum, participants who held the tree pose as the final portion of the experiment responded faster than those in the control pose and were more likely to be accurate.

Response Times are affected by increased task demands and more complex movements

In a linear mixed effects model of response time there were influences of Mean and CV on response times in the tandem pose as compared to the control pose. As mean magnitude and variability of movement increased, the differences in response times between the tandem pose and control pose became smaller, as indicated by the positive four-way interactions containing Mean and CV, respectively. Increasing movement magnitude resulted in less deliberation of affordances, i.e. shorter response times (see Figure 7 for details). For the tree pose the pattern of results was such that only Mean magnitude (but not CV) modulated response latencies. In general, this means that increased postural demands go hand in hand with increased postural sway, but not necessarily complexity as they influence the time course of affordance judgments. In short, large movements in the tree pose resulted in comparably longer response times. It is possible that this effect may have been due an artifact of larger movements demanding more time to be performed. Notably absent was the effect of ETC on response time. This is not congruent with the original hypothesis because it was originally predicted that greater postural instability and complexity would result in longer latency of response decisions.

We concluded that postural complexity contributes to what is perceived (affordance judgments), but not to latency of responding. Responses during the tree pose posture were the shortest and were modulated simply by the magnitude of postural sway. Although we did not collect any information on strategy, it is possible that participants did not want to hold the difficult tree pose for extended periods of time due to fatigue (or concern for losing balance), and that the brevity of the trials may have overshadowed or masked an effect of complexity on

latencies. This result does not exclude the possibility that other affordance tasks that require longer encounters with the stimulus may affect latencies through the complexity of postural sway.

Contribution of the complexity of the haptic system to affordance perception

In the ecological approach to perception and action, perception and behavior are reciprocal and mutually constraining. Exploratory behaviors aid the perceiver in detecting the invariants within a structured energy array that specify affordances. Postural sway serves this exploratory function and is thus a key contributor to perception of affordances (e.g., Mark et al., 1990; Stoffregen, Yang, & Bardy, 2005). Importantly, exploratory postural sway involves movements of the eyes, head, torso, and whole body (Eddy & Kelty-Stephen, 2015; Palatinus, Dixon, & Kelty-Stephen, 2013; Palatinus, Kelty-Stephen, Kinsella-Shaw, Carello, & Turvey, 2014; Yu, Bardy, & Stoffregen, 2010). Such movements create flow patterns both within and across energy arrays, the detection of which supports perception of affordances.

Movements of any kind (even those of the eyes) implicate the haptic perceptual system (Cabe, 2019). Recently, the haptic system has been described as a multifractal biotensegrity system (Turvey & Fonseca, 2014) — a system that efficiently and immediately redistributes applied forces across the tension and compression elements of the system at all levels of organization from the individual cell to the body as whole. The multifractal nature of the movement system may be one reason why complexity is a better measure of the variability of postural sway than more traditional (stationary) measures of central tendency. We have shown that, at least to some extent, the complexity of postural sway predicted affordance judgements. Due to the shortness of trials we were unable to use multifractal measures, but effort-to-compress

provided insight into the role of complexity in tying perception and action together in an exemplary affordance task.

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Endnotes

[1]As a manipulation check, we conducted a separate pilot experiment in which participants (n=26) were asked to hold a pose (normal, tandem, or tree pose) in VR for 90 seconds and rate the difficulty of the pose on a scale of 1 (easy) to 7 (hard). We also measured head movement magnitude and variability. The tree pose was reliably rated as more difficult (M=6.39, SD=0.94) than the other poses, $F(2,50)=351.4$, $p<.001$. Similarly, the tree pose resulted in larger head movements (M=0.2mm, SD=0.1mm; $p<.001$), more variability as measured by the coefficient of variation (M=0.98, SD=0.22; $p<.007$), and in more complex movement patterns as measured by multifractal spectrum width (M=0.74, SD=0.25; $p<.044$, Kantelhardt et al., 2002). CV and MFW are dimensionless numbers.

Figures

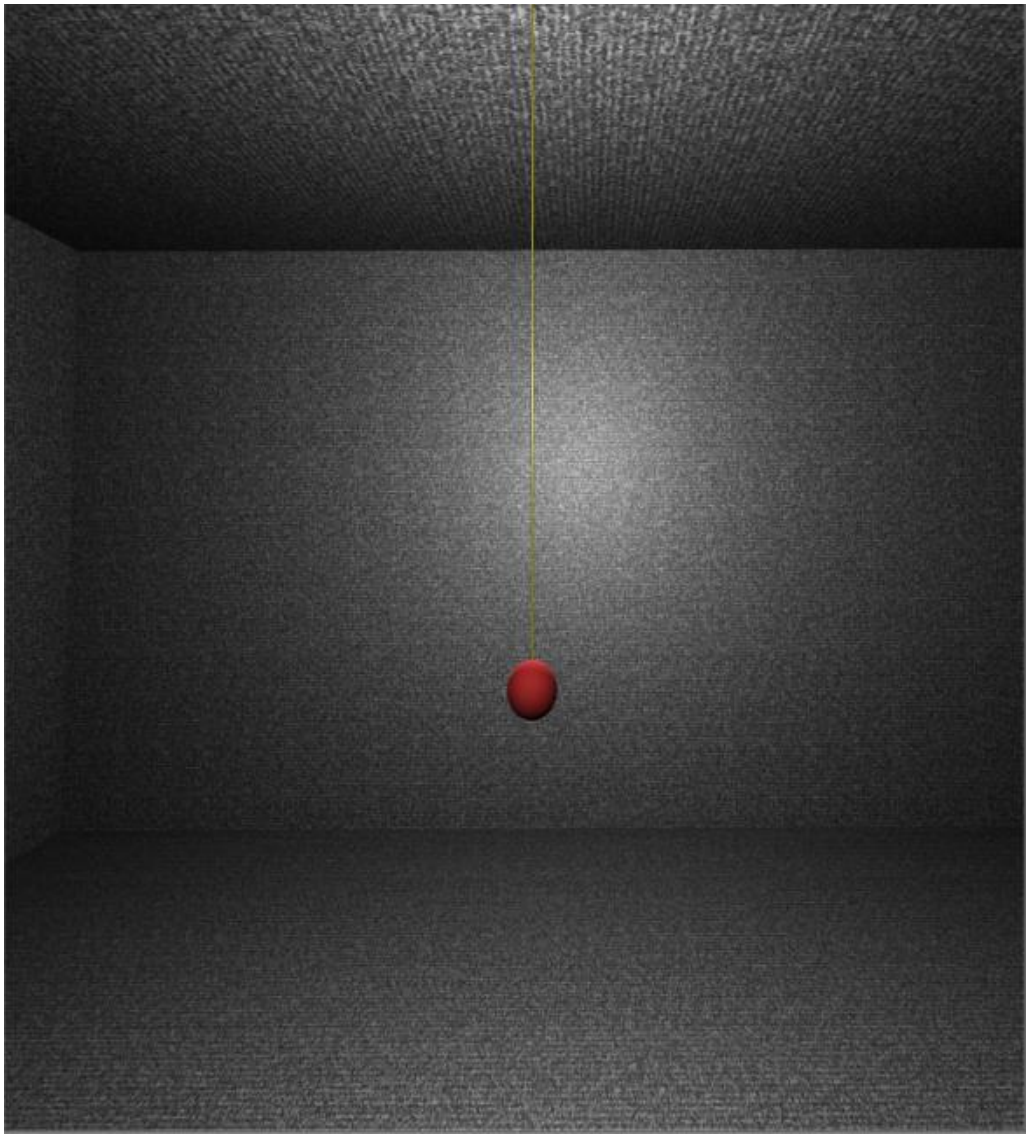

Figure 1. Virtual reality environment: ball hanging from ceiling at shoulder height

Figure 2. Control pose (left panel), tandem pose (middle panel), and tree pose (right panel).

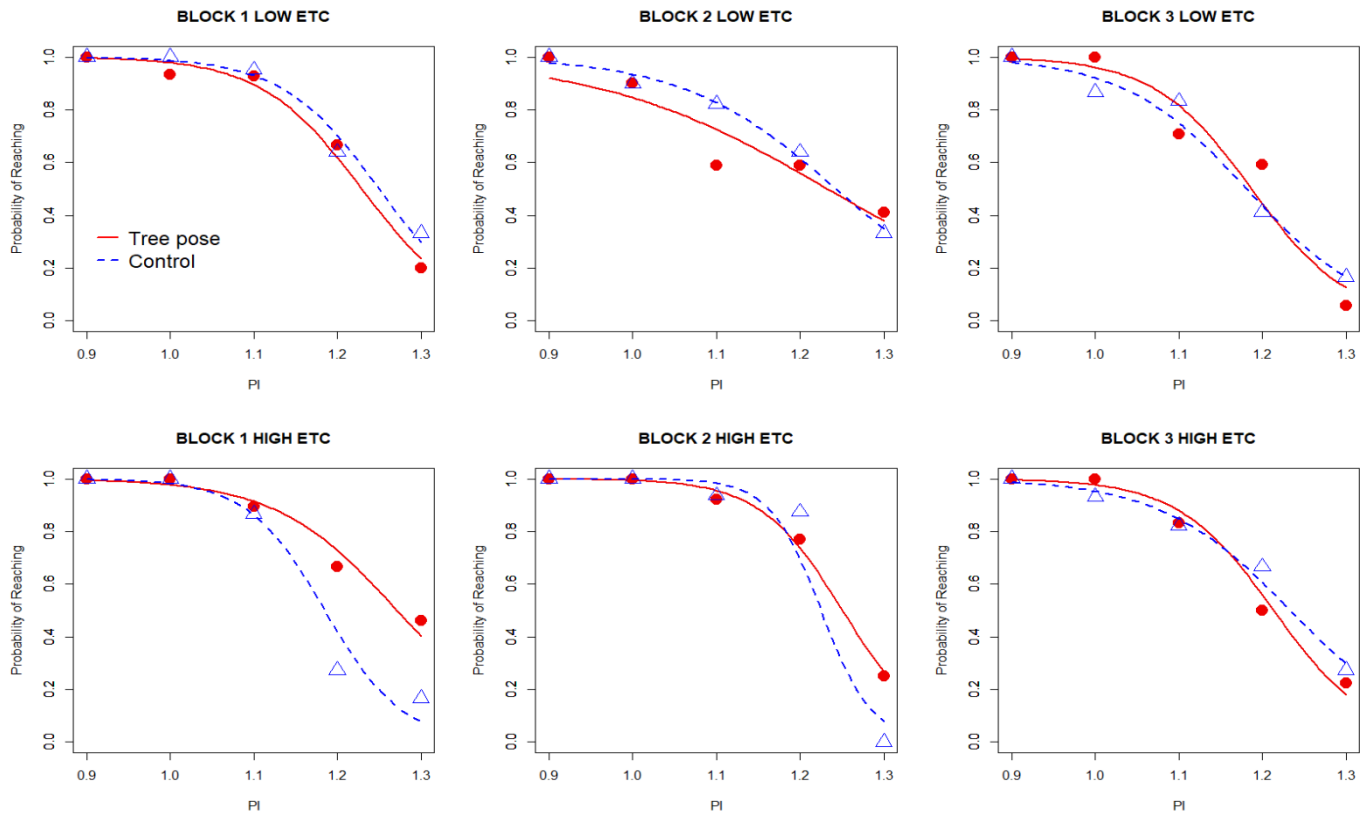

Figure 3. The four-way Tree Pose × Block × π × ETC interaction on affordance judgments in the hierarchical logistic regression. The plots show the comparison between Tree pose (continuous lines) and Control pose (dashed lines) over blocks and across low and high values of ETC. The points represent average probability of reaching (based on yes/no affordance judgments) at each value of π. ETC is a continuous variable, but for the purposes of better visualization ETC was dichotomized by a median split (LOW and HIGH ETC) in the plots.

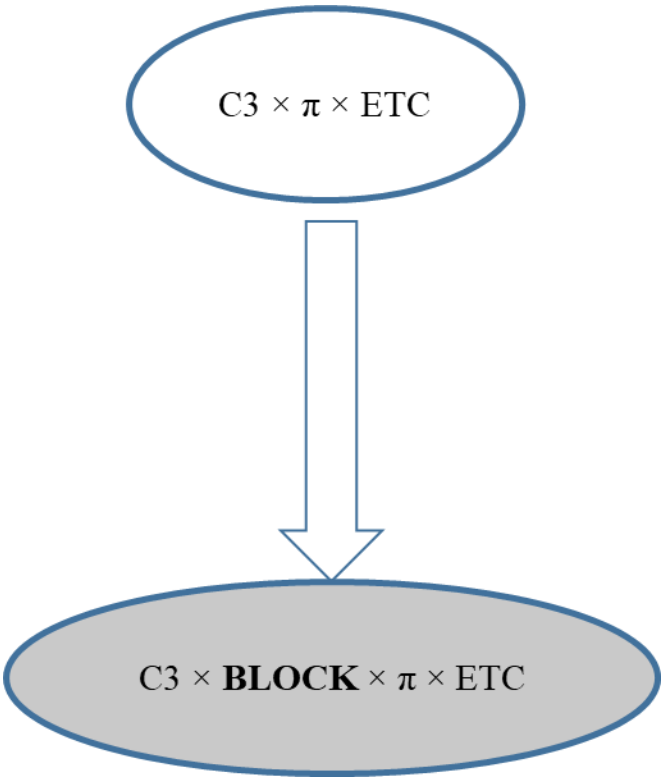

Figure 4. Schematic diagram presenting significant effects of the logistic regression on affordance judgments. The shaded oval represents a negative effect, the unfilled oval is a positive effect. C3: represents the comparison between Tree pose and Control pose. The arrow indicates how the variance explained is apportioned from lower- to higher-order interactions. Each new row represents the addition of a new dimension by the significant interactions. The boldface font indicates which new term was added at each, more complex level of interactions.

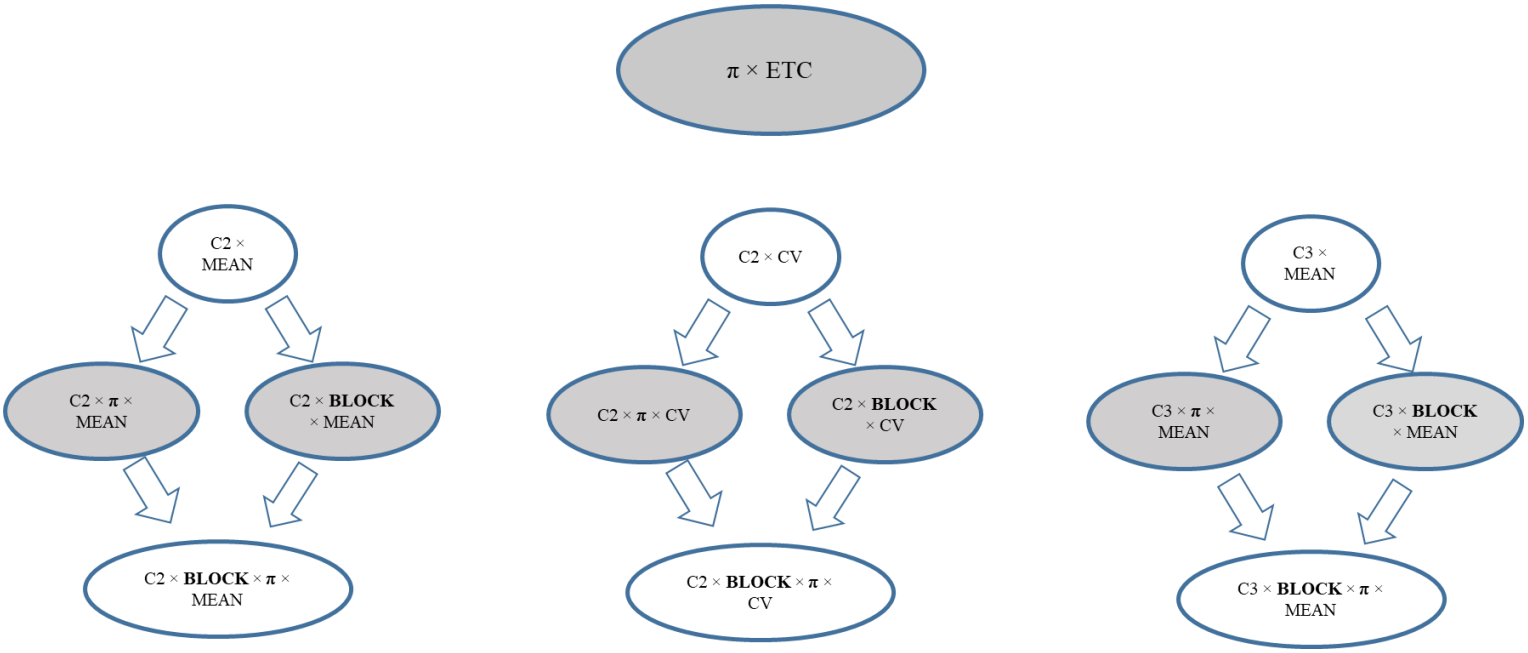

Figure 5. Schematic diagram presenting significant effects of the mixed effects model on response time. The shaded ovals are negative effects, the unfilled ovals are positive effects. C2: represents the comparison between Tandem pose and Control pose. C3: represents the comparison between Tree pose and Control pose. The arrows indicate how the variance explained is apportioned from lower- to higher-order interactions. Each new row represents the addition of a new dimension by the significant interactions. The boldface font indicates which new term was added at each, more complex level of interactions.

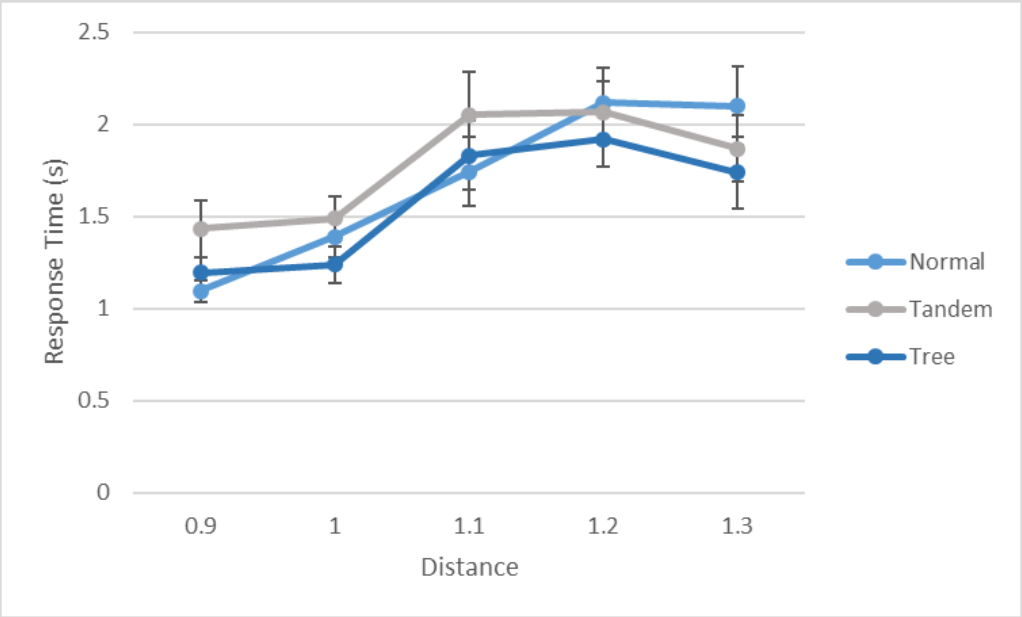

Figure 6. Mean of Response Time across π (Distance) for each pose. Distance was expressed as ratio of arm length to actual distance of target object. Response times increase with distance and are smallest for the most difficult tree pose. Error bars represent the standard error of the mean.

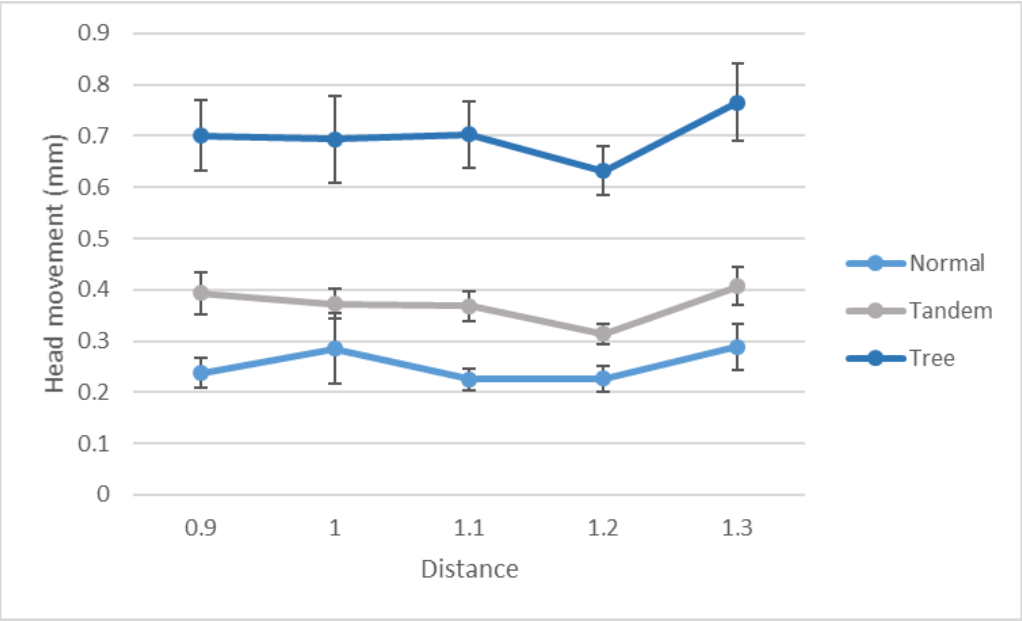

Figure 7. Mean of head movements across π (Distance) for each pose. Head movement increased with pose difficulty. Error bars represent the standard error of the mean.

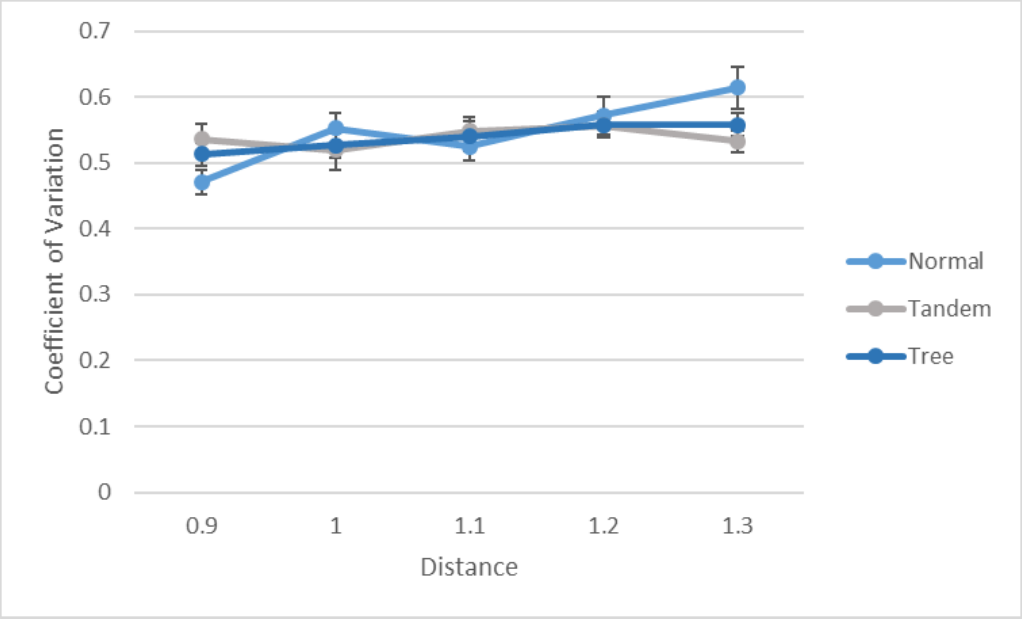

Figure 8. Coefficient of variation (CV) of head movements across π (Distance) for each pose. The coefficient of variation was most extreme for the shortest and longest distances in the normal stance. Error bars represent the standard error of the mean.

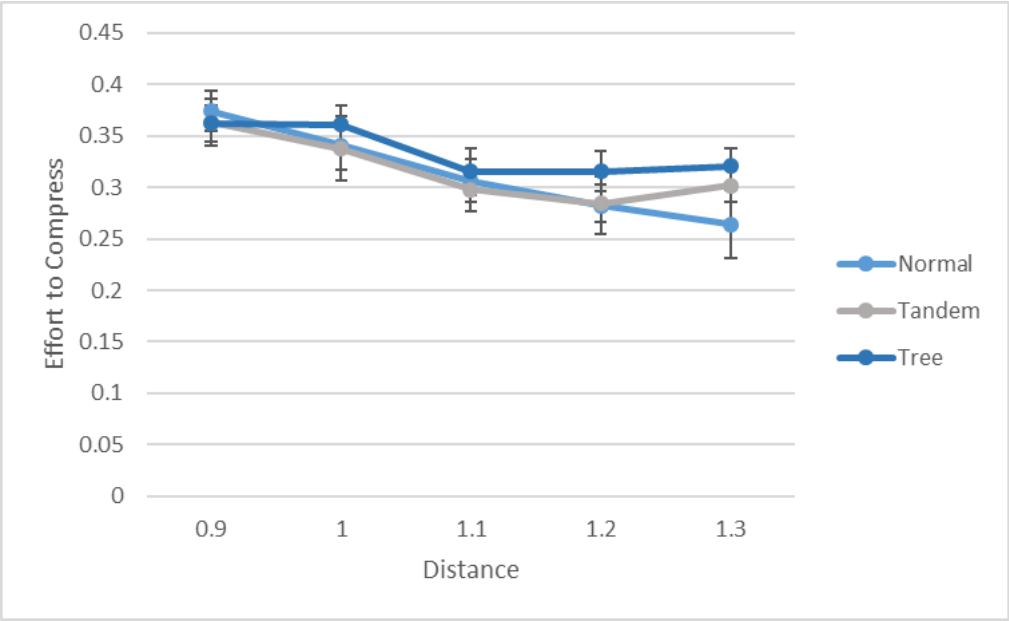

Figure 9. Effort to Compress (ETC) of head movements across π (Distance) for each pose. ETC was the largest in the tree pose, and significantly different from the standard control pose. Error bars represent the standard error of the mean.