

# Intentional Constraints on the Dynamics of Human Performance and Behavioral Variability in Motor Control

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## Abstract

Manipulation of environmental constraints has been shown to influence the relative amounts of voluntary and involuntary control employed by a person to complete a task, as well as the resulting structure of performance variability. Generally, the voluntary control required when no constraints are present leads to self-similar changes in performance, some constraint provides involuntary control that leads to random fluctuations in performance, and constraint which provides feedback about performance accuracy can result in anti-persistent variability. The current study investigated whether providing two groups of individuals with different intentions for the same task would produce changes in voluntary and involuntary control similar to that observed following the manipulation of task constraints. Results indicated that a difference in intention does result in divergent uses of voluntary and involuntary control and distinctly different structures in performance variability.

**Key words:** intention; fractal structure; voluntary and involuntary control; motor control

Over the past decade, a substantial amount of research has focused on determining what information can be gained about human cognitive and motor processes by assuming that they are inextricably linked through what is often referred to as the ‘interaction-dominant dynamics’ of human behavior (Holden, Van Orden, & Turvey, 2009; Ingber, 2003; Turvey, & Moreno, 2006; Van Orden, & Holden, 2002; Van Orden, Holden, & Turvey, 2003; Van Orden, Holden, & Turvey, 2005). As noted by Van Orden (2010), absolute independence of these processes would allow for random variability in performance within each process, while dominance by one process over all others would cause highly regular fluctuations across processes. Standard, linear statistical methods for assessing performance are based on an assumption of random variability, or noise, in performance and, necessarily, the belief that whatever process is being evaluated can be thought of as independent from all other contemporaneous processes. However, methods for assessing potential structure within variability over time reveal that while fluctuation in performance is

sometimes strictly random, more often variability is characterized by patterns occurring at a variety of different timescales (Ferrer-i-Cancho & Elvevag, 2010; Kiefer, Riley, Shockley, Villard, & Van Orden, 2009; Eke, Herman, Kocsis, & Kozak, 2002; Eke, Herman, Bassingthwaighe, Raymond, Percival, Cannon, Balla, Ikrenyi, 2000; Gilden, 2001; Holden et al., 2009; Kuznetsov & Wallot, 2011; Phillipe, 2000; Rhodes & Turvey, 2007; Wallot & Van Orden, 2011a, b; Warren, Carciun, & Anderson--Butcher, 2005). This type of variability is neither strictly random, nor strictly regular, but is rather somewhere in between the two, and therefore suggestive of both competitive and cooperative interactions between the different cognitive and motor aspects of the behavior under observation (Van Orden, 2010).

The patterned variability in performance described above is defined by a fractal structure, in that *self-similarity* in fluctuations is apparent at multiple timescales (Mandelbrot, 1982; Brown & Liebovitch, 2010; West & Deering, 1995). This type of variability is typically referred to as ‘pink’ noise, in contrast to the ‘white’ noise of random fluctuation (Van Orden, 2010). In order to determine what kind of variability is occurring for a given task, it is important to repeatedly measure some aspect of that task as performance unfolds over time. The resulting series can then be broken down into several composite, sinusoidal series each with a different amplitude and frequency. A Power-Spectral Density (PSD) analysis can then be used to give an assessment of variability (Delignieres, Ramdani, Lemoine, Torre, Fortes, & Ninot, 2006; Holden, 2005; Marmelat & Delignieres, 2011). The slope of a regression line fit to a plot of the logarithm of the power (amplitude squared) of changes with the logarithm of their corresponding frequencies provides a unique scaling relation between the size and frequency of changes in the performance time series. This scaling relation ( $S$ ) is related to a characteristic scaling exponent ( $\alpha$ ), where  $\alpha = -S$  (Holden, 2005). It is this scaling exponent which is used to give a qualitative assessment of the type of variability being observed. Since there will be no systematic relationship between the size and

frequency of change with random variability, or 'white noise',  $\alpha \approx 0$ . In contrast, the scaling relation for pink noise reflects an inversely proportional relationship between the power and frequency of variation such that the scaling exponent associated with fractal variability is  $\alpha \approx 1$ . It is also possible to obtain negative values for the scaling exponent. This indicates a directly proportional relationship between the size and frequency of changes in performance, and occurs as a result of anti-persistent variation (Delignieres & Torre, 2009; Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Schmidt, Beek, Treffner, & Turvey, 1991).

Strong support for interaction-dominant dynamics is provided by the fact that the kind of variability observed in a given task appears to be sensitive to a variety of task characteristics (Chen, Ding, & Kelso, 2001; Delignières, Torre, & Lemoine, 2009; Hausdorff, Purdon, Peng, Ladin, Wei, & Goldberger, 1996; Holden, Choi, Amazeen, & Van Orden, 2011; Jordan, Challis, & Newell, 2007a; Jordan, Challis, & Newell, 2007b). Specifically, the level of task constraint imposed by an experimental setup appears to be directly predictive of variability structure, with greater constraint resulting in white noise ( $\alpha \approx 0$ ), and less constraint leading to pink noise ( $\alpha \approx 1$ ) (Chen et al., 2001; Delignières et al., 2009; Hausdorff et al., 1996). This phenomenon has led to the suggestion that environmental constraint in the context of a specific task demand provides some external control, while the absence of constraint given the same task requires additional voluntary control on the part of the actor (Van Orden, 2010).

One way to summarize the effects of voluntary and involuntary control on variability is to examine different conditions within rhythmic motor tasks. Previous studies have demonstrated that by providing some sort of rhythmic stimulus (e.g. metronome) while participants are required to maintain a consistent movement pattern, spontaneous entrainment between participant and stimulus will constrain behavior and thus reduce the need for voluntary control of movements, ultimately resulting in the random variations in performance characterized by white noise ( $\alpha \approx 0$ ) (Chen et al., 2001). However, it appears that when participants are explicitly instructed to coordinate with a rhythmic stimulus, an altogether different pattern of variability emerges (Delignières et al., 2009; Hausdorff et al., 1996). One might imagine that the requirement to synchronize would introduce the need for additional voluntary control but, more importantly, it also appears to provide the participant with feedback about the accuracy of their movements with respect to the goal of the task (Van Orden, 2010). Accuracy feedback has been considered a unique form of involuntary control, and the constraint emerging from corrective processes results in performance characterized by anti-persistent, dependent fluctuations ( $\alpha \approx -1$ ) (Delignieres & Torre, 2009). An equivalent task to the two previous, but requiring voluntary control, can be constructed through the use of a continuation paradigm. Here the participant has the

opportunity to match their movement to an experimental stimulus for several seconds at the beginning of a trial, and then must maintain that movement pattern for the duration of the trial without any involuntary control provided gained through task constraint. Several studies have demonstrated that the use of a continuation paradigm in this manner leads to the self-similar variability of pink noise ( $\alpha \approx 1$ ) (Chen et al., 2001; Gildea, Thornton, & Mallon, 1995; Lemoine, Torre, & Delignieres, 2006; Torre, & Delignières, 2008).

While previous findings have demonstrated an association between voluntary or involuntary control and performance variability, the potential influence of intending to control a specific task dimension has yet to be examined. The current study was designed to determine the effect of being asked to control one of two task dimensions on performance variability. In order to achieve this, a simple arm-swinging task was employed during which participants were instructed to control either the frequency or amplitude of their movements, while being provided with flashing dots to help control their performance. This ultimately created the single underlying task of maintaining a comfortable, consistent movement, allowing for an isolated evaluation of the effects of intention on constraint and performance.

## Method

### Participants

Seventeen University of Cincinnati undergraduate students participated in this experiment, eight in the amplitude intention condition and nine in the frequency intention condition. Participants ranged in age from 18 to 28 years.

### Procedure and Design

At the beginning of the experiment, participants were instructed to stand at a distance 3.5 feet in front of a flat screen television, facing toward the screen. The experimental task consisted of holding one's upper right arm flush with the side of the body and swinging the forearm in an arc about the elbow, while keeping the forearm parallel to the floor. The right hand was to be held in a fist with the first two fingers extended to point toward the screen and with the knuckles facing toward the right, away from the participant's body. Initially, two red dots (5.5 cm in diameter) appeared on the screen, centered vertically and separated by a distance of 57 cm (see Varlet, Coey, Schmidt, & Richardson, 2011 for information on determining the ideal stimulus amplitude for visuomotor entrainment).

Eight participants were asked to control the amplitude of their movements by traveling the same distance with every arm swing. The other nine participants were asked to control the frequency of their movements by maintaining a constant speed while swinging. All participants participated in two trials, each six minutes in length. The first trial involved a continuation paradigm, with the red dots appearing for the first 10-12 seconds (timed manually), followed by a blank

screen for the duration. This trial was collected as a baseline. The red dots were set to flash in an alternating pattern at a frequency of 1 Hz, (with a dot appearing on one or the other side of the screen every 500 ms) throughout the time they were visible. Participants were instructed to use the dots to help control their designated task dimension, and to do their best to maintain the same movement for the duration of the trial once the dots had disappeared. In the second trial, the flashing dots were displayed for the full six minutes and participants were instructed to use them over the entire trial to help achieve consistency in their designated task dimension. This was the test trial.

By using a comfortable movement frequency for the flashing dots, we expected participants in the frequency intention condition to use the dots to gain feedback about the consistency of their speed in order to engage in corrective processes. For those participants in the amplitude intention condition we expected the stimulus to provide the opportunity for spontaneous entrainment, but not enough feedback about the size of their movements to allow for corrective processes.

The display was generated by an application written using C/C++ and displayed using OpenGL. Data was collected using a magnetic tracking system (Polhemus Fastrak, Polhemus Corporation, Colchester, VT), with the sensor attached to the outside of the extended first two fingers of the right hand. The OpenGL program was also used to record the movement data collected by the tracking system, with a sampling rate of 60 Hz.

## Data Analysis

All participant movement time-series were low-pass filtered using a 10 Hz Butterworth filter and the first and last 5 s of each trial were discarded to remove transients.

For the PSD analysis, the peak to valley intervals and valley to peak intervals were extracted from the movement time-series for each trial. The PSD analysis was then used to assess fractal characteristics of the resultant interval time-series. As the preliminary step to this process each time-series was submitted to a Fourier transform, during which it was broken down into several composite sinusoidal series with varying amplitudes and frequencies. The slope of a regression line fitted to the spectral plot of the logarithm of the power vs. the logarithm of the frequency for each sinusoidal series yielded a unique value  $S$ , for which the characteristic scaling exponent of the series,  $\alpha$ , is equal to  $-S$  (Holden, 2005).

In order to assess possible entrainment of participants' movement to the frequency of the flashing stimulus we found, for each trial, the distribution of relative phase angles occurring between the participant and stimulus time-series. This distribution was based on the proportion of discrete relative phase (DRP) angles between the two time-series which fell into each of nine bins ( $0^{\circ}$ - $20^{\circ}$ ,  $20^{\circ}$ - $40^{\circ}$ ,  $40^{\circ}$ - $60^{\circ}$ ,  $60^{\circ}$ - $80^{\circ}$ ,  $80^{\circ}$ - $100^{\circ}$ ,  $100^{\circ}$ - $120^{\circ}$ ,  $120^{\circ}$ - $140^{\circ}$ ,  $140^{\circ}$ - $160^{\circ}$ , and  $160^{\circ}$ - $180^{\circ}$ ). DRP values were calculated at each oscillatory

peak of the movement time-series. Perfect, inphase coordination between participant and stimulus would result in a relative phase of  $0^{\circ}$ , while antiphase coordination, in which participants exactly matching the frequency of stimulus movement but pointed at the side of the screen opposite the dot each time, would lead to a relative phase of  $180^{\circ}$ .

The stability of any unintentional coordination was established by calculating the circular variance of the relative phase angles found between the participant and stimulus time-series for each trial. This measure provides an index of synchronization on a scale from 0 to 1, with 0 reflecting a situation in which there is no coordination between participant and stimulus movements, and 1 indicating absolute synchronization between the two (Batschelet, 1981; Oullier, de Guzman, Jantzen, Lagarde, & Kelso, 2008).

## Results

A 2 (intention) x 2 (trial) mixed model ANOVA on circular variance values revealed a significant main effect for trial,  $F(1, 15) = 39.93$ ,  $p = .001$ ,  $\eta_p^2 = .73$ , and a significant interaction between intention and trial,  $F(1, 15) = 6.21$ ,  $p = .03$ ,  $\eta_p^2 = .29$ . This interaction appears to be driven by the fact that the effects of intention are different for the baseline and test conditions (see Figure 1). While there did not appear to be a significant change in coordination stability for those with the intention to control amplitude, the difference for those in the frequency intention condition between baseline and test was significant,  $t(8) = -10.13$ ,  $p = .001$ .

A 2 (intention) x 2 (trial) x 9 (relative phase bin) mixed model ANOVA on the DRP between participant and stimulus movements revealed a main effect for relative phase bin,  $F(8, 15) = 81.86$ ,  $p = .001$ ,  $\eta_p^2 = .85$ , significant two-way interactions between intention and relative phase bin,  $F(8, 15) = 4.62$ ,  $p = .001$ ,  $\eta_p^2 = .24$ , and trial and relative phase bin,  $F(8, 15) = 105.76$ ,  $p = .001$ ,  $\eta_p^2 = .88$ , and a significant three-way interaction between intention, trial and relative phase bin,  $F(8, 15) = 2.06$ ,  $p = .045$ ,  $\eta_p^2 = .12$ . Follow-up analyses revealed a significant interaction between intention and relative phase bin for the test trials,  $F(8, 120) = 4.64$ ,  $p = .001$ ,  $\eta_p^2 = .24$ , but not for the baseline trials (see Figure 2). A comparison of the proportion of time spent in the DRP bin associated with inphase coordination ( $0^{\circ}$ - $20^{\circ}$ ) during the test trial between the two intention conditions revealed that significantly more in-phase entrainment occurred for those participants instructed to control movement frequency,  $F(1, 15) = 6.96$ ,  $p = .02$ ,  $\eta_p^2 = .32$ . There was no significant difference in the proportion of time spent in the DRP bin associated with antiphase coordination ( $160^{\circ}$ - $180^{\circ}$ ) between the two intention conditions.

The results of a 2 (intention) x 2 (trial) mixed model ANOVA on scaling relations ( $S$ ) from the PSD analysis were similar to those of the ANOVA on circular variance.

There was a significant main effect for trial,  $F(1, 15) = 46.83$ ,  $p = .001$ ,  $\eta_p^2 = .76$ , and a significant interaction between intention and trial,  $F(1, 15) = 5.12$ ,  $p = .04$ ,  $\eta_p^2 = .25$ . As seen in Figure 3, this interaction appears to be driven by the difference in the effects of intention between the baseline and test conditions, with a much larger increase in  $\alpha$  occurring in the frequency intention than the amplitude intention. The  $\alpha$  values for both intention conditions during the baseline trials were closest to the region associated with pink noise ( $S \approx -1$ ,  $\alpha \approx 1$ ). The  $\alpha$  values for those intending to control amplitude during the test condition were characteristic of white noise ( $S \approx 0$ ,  $\alpha \approx 0$ ), while those for participants asked to control movement frequency were closer to the region associated with anti-persistent, dependent behavior ( $S \approx 1$ ,  $\alpha \approx -1$ ).

Given evidence that the effects of intention condition were most apparent during the test trials for both coordination strength and scaling relation, we chose to conduct a regression to determine whether circular variance could account for variation in scaling relation above and beyond that accounted for by intentional condition. A forward regression indicated that intention explained a significant proportion of variation in scaling relation,  $R^2 = .42$ ,  $F(1, 15) = 10.86$ ,  $p = .005$ , and was significantly predictive of scaling relation,  $b = .65$ ,  $t(15) = 3.30$ ,  $p = .005$ , for the test trials. However, the predictive contribution of circular variance was not significant, as it only accounted for an additional 2.8% of the variance in scaling relation above and beyond that accounted for by intention.

### Discussion

The task in the current study was constructed to demonstrate the effects of assigning participants different intentions for a simple motor task, as examined in performance variability and the employment of voluntary and involuntary control.

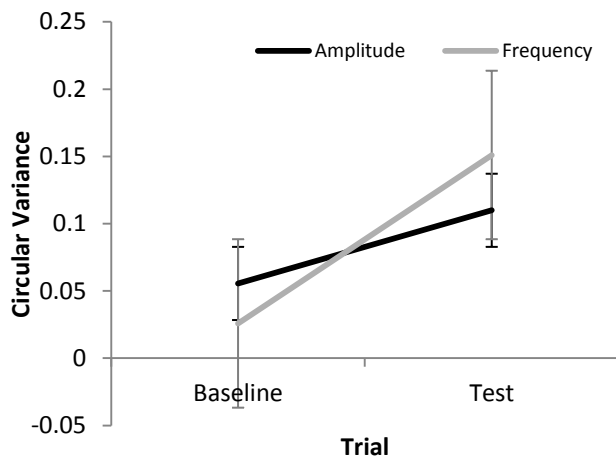


Figure 1. Mean circular variance for each of the intention conditions (Amplitude, Frequency), and under both trial conditions. Error bars show standard error.

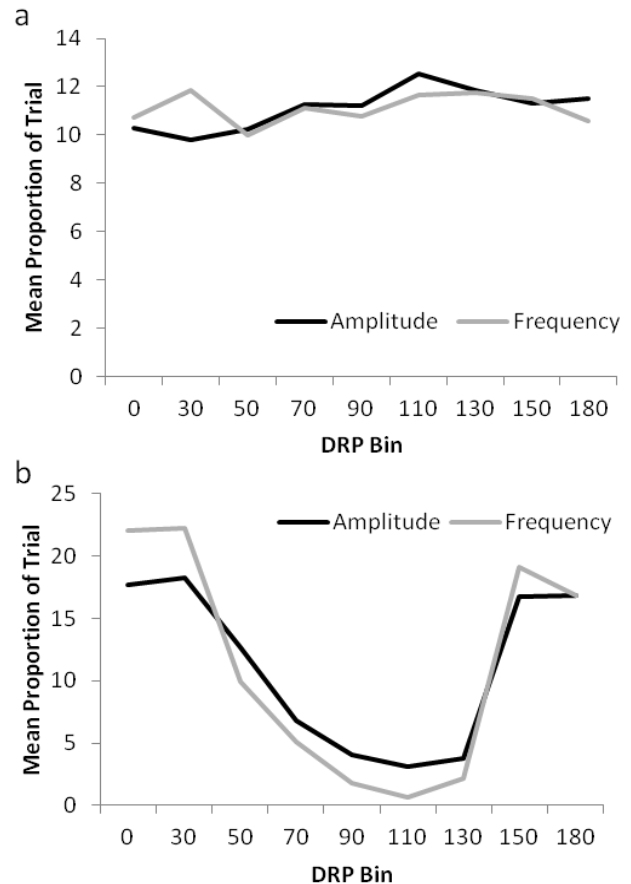


Figure 2. a) Mean proportion of trial spent in each DRP bin during baseline trials for each intention condition (Amplitude, Frequency). b) Mean proportion of trial spent in each DRP bin during test trials for each intention condition (Amplitude, Frequency). Note: DRP bins are labeled by the midpoint of the range of relative phase values they contain, except for the  $0^\circ$ - $20^\circ$  bin and the  $160^\circ$ - $180^\circ$ , which are referred to be the lowest and highest possible DRP values, respectively.

The two different intention conditions introduced are essentially equivalent with respect to a participant's resulting movement; maintaining a consistent speed will result in relatively consistent spacing between movements, and vice versa. As such, one might predict that providing participants with the instruction to control speed versus distance would have no effect on the amount of voluntary or involuntary control required to complete the task, and therefore no effect on the structure of performance variability. This does appear to be the case for the baseline trials. Consistent with previous use of continuation paradigms, measures of performance variability structure for

both intentions during the baseline trials fell within the region associated with self-similar, pink noise thought to indicate the use of voluntary control (Chen et al., 2001;

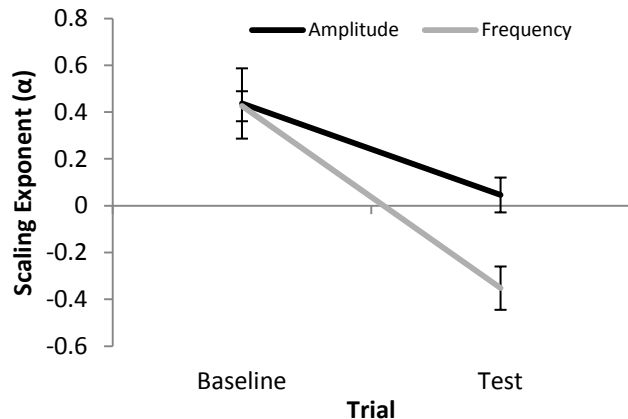


Figure 3. Mean scaling exponents for movement frequency in each of the intention conditions (Amplitude, Frequency), and under both trial condition, as assessed through PSD analysis. Error bars show standard error.

Gilden et al., 1995; Lemoine et. al, 2006; Torre, & Delignières, 2008).

The equivalency in performance variability structure between the intention conditions was not, however, maintained during the test trials. In this case, past research universally predicts that the presence of a rhythmic stimulus will provide a source of involuntary control for the movement task (Chen et al., 2001; Delignieres & Torre, 2009). As previously described, the difference in participant instructions with respect to the use of a rhythmic stimulus can result in two distinct kinds of structure in performance variability. While the mere presence of a rhythmic stimulus results in entrainment and random variability (Chen et al., 2001), the instruction to synchronize with the stimulus and the resulting opportunity to gain accuracy feedback about one's performance leads to anti-persistent changes (Delignieres & Torre, 2009). In the current study, the instructions about use of the stimulus were the same for all participants; they were simply told to use the stimulus to help control their movement, following an explanation about what their intention for the task should be. The difference in intention alone appears to have affected the influence, and constraint, of the rhythmic stimulus on the structure of performance variability.

For those participants who were asked to control the amplitude of their movements, changes in performance during the test trial were found to be random, corresponding to white noise. This suggests that for someone intending to control the amplitude of their movements, the rhythmic stimulus provided involuntary control, but did not allow for sufficient accuracy feedback for corrective anti-persistent movement modulation. In contrast, for the participants

intending to control the frequency of their movements, measurements of variability structure were in the range associated with anti-persistent behavior. It therefore appears that the stimulus did allow for enough accuracy feedback about the timing of movements to support corrective processes by the participant. It is worth noting that the difference in intention conditions during the test trials was associated with differences in coordination, as well as the structure of performance variability. While there was significantly more inphase coordination between participant and stimulus movements for those intending to control frequency, any variation in performance associated with changes in coordination stability appears to be accounted for by intention.

In conclusion, our study has shown that the manipulation of intention alone appears to affect the use of voluntary and involuntary control for an environmentally constrained motor task, as reflected by differences in performance variability. These results also demonstrate that intending to control one specific task dimension over another can substantially alter the influence of any present environmental constraints. Therefore, in addition to identifying the role of intention in performance variability as an area worth further exploration, this study also sounds a cautionary note for research that aims to better understand the recruitment of voluntary and involuntary control and performance variability.

### Acknowledgments

We would like to thank MaryLauren Malone and Veronica Romero for helpful comments during the design of this study. We would also like to thank Guy Van Orden for his invaluable contributions to the field of complexity science.

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