CONSTRAINTS, COMPLEXITY, AND ADAPTABILITY IN ISOMETRIC FORCE TRACKING

by

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ABSTRACT

There is a long-held assumption that the degree of complexity (fractal dynamics) exhibited in neuro-motor output provides information about the system's health and adaptive capacity. To date, however, direct evidence of this relationship is limited, in part because there are opposing views on how system complexity should be observed and interpreted. One view argues that adaptability can be inferred according to the observed dynamics of a system functioning under minimal constraint (ie. self-selected unperturbed walking), in which pink noise fluctuations reflect the adaptive optimum. The opposing view contends that adaptive capacity is better represented by the observed changes in system dynamics corresponding to variations in task constraint. This contrast in perspective has often led to description of either minimally constrained, or strictly constrained behavioral dynamics, with little understanding of their combination and connection.

This dissertation incorporated the assessment of system dynamics under both minimal and task-relevant constraint according to an isometric force tracking paradigm. In Experiment 1, we observed subjects force in a no vision preferred-force, constant, sine, and pink noise tracking task. This study found that both minimally constrained force complexity, and task-relevant dynamical flexibility both predicted general force tracking ability. Moreover, minimally constrained dynamics did not correspond with pink noise. In Experiment 2, we collected minimally constrained force dynamics, and then had subjects practice either a pink noise or brown noise force target for 5 days. This was done to determine whether different task constraints elicited unique changes to minimally constrained force dynamics over practice. Results from Experiment 2 revealed similar alterations to individual's minimally constrained dynamics, in which both groups showed more complex force output. Still, this change did not correspond with pink noise behavior. Moreover, neither condition demonstrated superiority in adaptive performance of a transfer task.

Together, these findings support the necessity of unified framework in examining complexity according to both intrinsic and task-relevant constraint. To do so may improve insight into unique dynamical structures exhibited in specific movement paradigms. Moreover, additional research is necessary to understand the specific relations between practice and dynamical properties in order to facilitate specific improvement in adaptive control.

INDEX WORDS: Motor Control, adaptability, isometric force tracking, dynamical systems theory, complexity science

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TABLE OF CONTENTS

Page

ACKNOWLEDGEMENTS iv

LIST OF TABLES vii

LIST OF FIGURES viii

CHAPTER

1 Introduction 1

2 Literature Review 8

  Classical Approach to Variability 8

  Loss of Complexity and Optimal Variability 10

  Loss of Adaptability 15

  Complexity Matching 18

  References 21

3 EXPERIMENTAL FOCUS 29

  Purpose Statement 30

  Experiment 1 30

  Experiment 2 31

  References 33

4 Intrinsic dynamics and the adaptability of visuo-motor coupling in isometric force tracking 34

  Abstract 35

Introduction..36

Methods...41

Results...47

Discussion 50

References 59

5 The role of complexity matching on intrinsic, and task specific isometric force dynamics: a practice study 74

Abstract 75

Introduction..77

Methods...85

Results...89

Discussion 94

Conclusion..99

References 100

6 General Discussion 112

References 120

LIST OF TABLES

Page

Table 3.1: Regression equations describing isometric tracking accuracy (|CE|), and shifts in DFA (α) as a function of self-selected force DFA (α)......................................67

Table 3.2: Multiple regression equation describing overall isometric tracking accuracy (|CE|) as a function of self-selected force DFA, and average shift in task relevant force DFA ($R^2 = 0.54$)..68

LIST OF FIGURES

Page

Figure 4.1: Example of force-time series in the constant, pink noise, and sine wave tracking conditions. All trials are the 15th trial from the same subject across conditions..69

Figure 4.2: Violin plots demonstrating changes in young healthy subject's mean absolute CE (A), mean SD of force output (B), mean DFA scaling exponent (α) (C), and subject's between trial SD of their DFA scaling exponent (α) (D) as a function of force tracking conditions (SS= Self Selected Force, CN= Constant Target, PK= Pink Target, SN= Sine Wave Target). Each condition distribution is presented, in which color spectrum corresponds to frequency cluster. The higher a frequency of occurrence, the lighter the color under the curve. The red lines correspond with each conditions Inter-quartile Range (IQR)...70

Figure 4.3: Individual's mean tracking accuracy (|CE|) as a function of mean DFA scaling exponent across all tracking conditions. The solid line represents a 2nd order polynomial least squares fit. The dashed line represents a 2nd order polynomial least squares fit when a bi-square reweighting algorithm is implemented. The corresponding regression equations for all fitted functions can be found in the first and second sections of table 1...71

Figure 4.4: Shift in mean DFA scaling exponent according to tracking task as a function of self selected DFA. The regression equations for all fitted lines can be found in the third section of table 1..72

Figure 4.5: General tracking accuracy (average |CE|) as a function of intrinsic force dynamics (self-selected DFA) and dynamical flexibility (average difference between sine/constant & sine/pink target DFA). The contour surface corresponds to the multiple regression equation in Table 2...73

Figure 5.1: Example of the force-time series of one subject tracking the pink noise (a) and brown noise (b) force target. Both figures represent the 10th trial on day 1 of practice (a) and transfer (b)..107

Figure 5.2: Correlation of subjects average self-selected force output (N) at baseline (x-axis) and after the 5th day of tracking practice (y-axis). Each dot represents one subject, and the corresponding red line represents the least squares fitted line...108

Figure 5.3: Figure 5.3a illustrates the qualitative change in average group DFA (α) as a function of practice. 3b illustrates the overall differences in average group α which reached statistical significance. 3c illustrates group standard deviation (SD), and absolute constant error (|CE|) as a function of trial block and day of practice. For better clarity, days 1, 3, and 5 were selected for plotting. Note that the x-axis has two numbers separated by a colon. The first number represents day, and the second number represent the corresponding trial block. Triangles represent the pink noise practice group, while squares represent the brown noise practice group. Solid lines correspond with SD, while the dotted lines show |CE|..109

Figure 5.4: Figure 5.4a illustrates both group and individual shifts in self-selected DFA (α) at baseline, and after 5 days of tracking practice. The remaining figures illustrate characteristic differences in DFA (α) (5.4b), |CE| (5.4c), and SD (5.4d) between the last 15 trials of practice on day 5, and all 15 transfer trials. Pink lines correspond with the group that practiced with the pink noise target, and brown correspond with the brown noise practice group. Thick solid lines represent group averages, while the thin dotted lines show individual averages......................... 110

Figure 5.5: Wavelet cross-coherence on practice day 1 (5.5a), practice day 5 (5.5b), and transfer (5.5c). Coherence range is between 0-1. Higher coherence values correspond with stronger coupling between force and target at the specified frequency (Hz) band. Pink lines represent the pink noise practice group, and brown represents the brown noise practice group. Thick solid lines are the group mean, while thin dotted lines are individual averages in coherence at each frequency band...111

CHAPTER 1

Introduction

Functional and adaptive movement necessitates coherent organization of the human system, which in and of itself is comprised of an immense entanglement of components and processes operating through a continuum of spatio-temporal scales (ie. cellular, neuromuscular, visual, haptic, vestibular, etc.). Moreover, individuals continually face novel challenges requiring evolution of system organization according to the confluence of contextual constraints imposed by their environments, intrinsic composition, and the task at hand (Newell, 1986; Beer., 2014). It is well established that humans possess an abundance of coordinative configurations relevant to contextually directed behavior (Bernstein, 1967). This fundamental premise, conceptualized as Bernstein's degrees of freedom (DoF) problem, is the foundation in which contemporary studies are expanding rationale for: a) how the complex array of available DoF's assemble across the microscopic-macroscopic levels of observation (Kay, 1988; Chialvo, 2010); b) what drives the operational assembly (and functional re-assembly) of system dynamics (Kugler, Kelso, & Turvey, 1980, 1982); c) what general principles capture and characterize changes in system dynamics with adaptation, mal-adaptation, and degradation, alike (Newell et al., 2003; Slieman-Malkoun, Temprado, & Hong, 2014).

Identifying a reliable index for behavioral stability and flexibility is no straight-forward task. The contrasting nature of stability and flexibility directly reflects the inherent complexity of the human system, as their intricate balance is fundamental to coordinated behavior. Qualitatively, their relationship is an expression of human adaptability, as an abundance of macroscopically stable coordinative regimes available to the system across relative circumstance (and corresponding constraints) reflects positively on the state of individual fitness. As an extension, circumstantial constraint is a dynamic process, and thus self-preservation requires the ability for systems to abruptly transition to a more appropriate coordinative regime whenever necessary. Quantitatively, one could theoretically provide a comprehensive view of an individual's dynamical landscape utilizing measures from the Coordination Dynamics framework (Haken, Kelso, & Bunz, 1985; Kelso, Shölz, & Schöner, 1986). However, an overarching understanding of attractor dynamics in even the most well controlled behavioral paradigm poses an immense task. In spite of these issues, numerous measures quantifying statistical complexity of behavioral output, that is the time and frequency dependent structure, are considered a viable alternative to index system stability/flexibility at any point in time. These measures are believed to provide an alternative view on system dynamics in that they provide a window into the organization and contribution of the many degrees of freedom functioning across the nested array of relevant scales.

Fundamentally, measures of performance outcome and task dispersion within/ across motor conditions provide tremendous insight into how well individuals optimize their behavior according to task demands. These measures alone, however, are insufficient for identification of underlying organization of the system's DoF's that correspond with the respective task manipulation. While an abundance of motor control literature has provided a more comprehensive report of both metrics, there is still a lack of clarity as to how individual performance and their underlying dynamics directly relate.

This relation becomes ever more convoluted when paradigms requiring indirect inference of system stability and flexibility (for ethical reasons or otherwise) are investigated (Lipsitz & Goldberger, 1992; Hausdorff, 2007). In any case, such obstacles often lead to emphasis on one aspect of motor behavior (performance/dispersion outcome OR system dynamics) to index adaptability. That, or both aspects are treated as operationally autonomous functions, in which case their proposed relation to adaptation depends on the experimental focus.

A significant body of literature investigating underlying system dynamics in clinical assessment has primarily focused on changes in dynamical complexity with the progression of age or degenerative disease (Lipsitz & Goldberger, 1992; Hausdorff et al. 1996; Vaillancourt & Newell, 2002). In brief, the dynamical complexity in system output is determined by the degree of serial correlation between successive time series values through analysis of the autocorrelation function. An autocorrelation function that shows no dependence of the current state on previous time points is representative of white noise, thus presenting no structural interactions between system components. Conversely, a function that demonstrates strong persistence (significant dependence of the current state on trends of states far removed in time) known as brown noise is interpreted as a complex system with component-interaction pathways predominating at slower temporal scales. Between the temporally random (white) and robust (brown: $1/f^{\beta}, \beta = 2$) is a specific structure of fluctuations known as pink noise. When assessed in the frequency domain, pink noise presents power law ($1/f^{\beta}, \beta = 1$) relations in which fluctuation trends are nested proportionally across relevant scales.

The assumption follows that the dynamical self-similarity across scales is representative of an "optimally" complex system. That is, there is an abundance of component interactions operating across a myriad of scales, and any perturbations within nested levels provide the possibility for abrupt reorganization of the system qualitatively observed in macroscopic behavior. Numerous groups functioning within this framework have proposed that any deviations from $1/f^{1}$ temporal relations (be it toward randomness or order) is a consequence of degradation within the system. Moreover, this assumption has led to the reciprocal view that complexity measures have diagnostic potential over more traditional statistical analyses. Advocates within this framework follow the hypothetical premises generally attributed as the "Loss of Complexity" (LOC) or "Optimal Variability" (OV) approach in human systems control (Lipsitz & Goldberger, 1992; Stergiou, Harbourne, & Cavanaugh, 2006).

An alternative interpretation of complexity as it pertains to system adaptability is the capacity to modulate underlying behavioral dynamics according to relevant constraints embedded in the motor task (Vaillancourt, Sosnoff, & Newell, 2004; Sosnoff & Newell, 2009). Specifically, behavioral output in a healthy adaptive system will exhibit complex interaction-driven dynamics ($1/f^{\alpha}$) (Sosnoff & Newell, 2009), however the degree of complexity in behavioral output will map to, for example, the dimensionality or temporal patterns necessary to perform a specified behavior. Subsequent support of this proposed dynamical flexibility is evidenced by comparisons of output complexity in the young healthy and aged populations (Vaillancourt & Newell, 2002, 2003).

Discord regarding the adaptive value of variations in complexity (abundance and interaction of relevant system components) represented in collective dynamics is seemingly predicated on the desire to impose or eliminate external constraint while assessing behavior. The majority of studies following the loss of complexity or optimal variability hypothesis assess minimally constrained behavioral output (ie. self-selected walking pace, abstemious heart rate dynamics), and relate the temporal structure of specific output parameters with indirect indices of adaptive capacity (ie. index of fall risk) between cohorts (Hausdorff et al., 1997). Conversely, those following the loss of adaptability approach have directly imposed external constraints to examine the unique dynamics that emerge as a function of, for example, age and neuro-motor health (Vaillancourt, Sosnoff, & Newell., 2004; Sosnoff, Valantine, & Newell, 2009).

There is an abundance of literature that describes system complexity across many behavioral paradigms. However, these same studies exemplify the theoretical discrepancies that can arise when competing perspectives function with empirical autonomy. It is imperative to examine the compatibility of the LOC/OV and LOA frameworks, or whether either approach demonstrates superiority in terms of predictive power on indices of adaptive motor control. As an added benefit, assessment of unconstrained and constrained behavior would promote a more tangible understanding on how system dynamics relate to more traditional metrics of motor ability (ie. performance outcomes).

Proponents of the pink noise as optimum accounts endorse system assessment under minimal constraint. However, in spite of this, contemporary studies suggest that it is possible to re-establish pink noise fluctuations in minimally constrained behavior. Ironically, this calls for interventions that implement task constraints to facilitate a phenomenon known as "complexity matching" (West, Geneston, & Grigolini, 2008).

Essentially, interacting systems show an affinity to match complexity as a means to optimize the exchange of information. Empirical studies show that this is accomplished through the combined contributions of local synchronization and global tuning processes (Fine et al., 2015; Almurad, Roume, & Delignières, 2017). So far this technique has primarily generated interest from advocates of the LOC/OV approach. However, studies have also shown subjects can modify their behavioral complexity according to the task demands, that of which has included the degree of complexity in a visual tracking task (Sosnoff et al., 2009). Thus, complexity matching may hold more diverse application than is currently proposed.

The core of this dissertation is to better characterize the relationship between behavioral complexity and adaptive motor performance. Specifically, we will assess distributional properties of young healthy individuals system complexity in both minimally constrained, and task constrained behavioral conditions. While there is theoretical evidence to suggest that system dynamics (constrained and unconstrained) provide a window into its adaptive potential (Vaillancourt, Sosnoff, & Newell, 2004; Van Orden, Kloos, & Wallot, 2011), our goal is to determine whether these dynamics can directly predict individual’s capacity to facilitate adaptive perceptuo-motor control. As an extension, we investigate whether individual's initial behavioral complexity influences whether/how their dynamics change with practice, and whether task demands are additional factors that influence the direction/magnitude of dynamical change. Lastly, there is proposed benefit to generating intervention protocols according to these theoretical tenets. However, the predicted benefits of complexity matching on adaptive control are still unsubstantiated by empirical study. To this end, critical evaluation of the proposed superiority of this technique is a supplemental aim.

CHAPTER 2

Literature Review

Classical Approach to Variability

Variability of motor performance based on tenets from traditional statistics has been prevalent, albeit originally of minimal foci, in empirical research for well over 100 years (Woodworth, 1899). Original statistical inference was traditionally focused on central tendency of group distributions in the absence of task manipulation, as deviations within and between individual outputs across identical conditions were perceived to be an expression of measurement/experimental error. Naturally, the corresponding assessment of alterations in averaged output (and subsequent disregard for variance in the response variable distribution) with experimental manipulation was of primary importance for determining individual performance capacity within the classical literature.

Nevertheless, the aforementioned research from Bernstein (1967) brought about a shift in perspective on variability through illustration of redundancies that can arise both intrinsically (i.e. joint relations to the same effector ends) and extrinsically (multiple trajectories to the same ends) to collectively provide numerous means for behavioral success. Thus, the notion follows that certain types of variability hold inherent value in providing a family of solutions for achieving a task with a high level of efficiency. Contemporary research has expanded these concepts through assessment of temporal dependencies of variability originally discussed through the lens of econometrics (Box et al., 2015). Specifically, time dependent fluctuations in macroscopic behavior are believed to illustrate organization of relevant degrees of freedom contributing to motor control at levels that are underpinning the biomechanical and task level.

A reductionist extension into assessing intra-individual variability within biomedical (specifically aging/disease) literature has generally assumed that neurobehavioral sub-systems can be partitioned into smaller, more tractable units. This is in large part based on the belief that these sub-systems and their levels of analysis operate under relative spatio-temporal autonomy (Mevedev, 1990). Such a perspective is enticing in that one can attribute any causal breakdown of behavioral function to limitation/degradation of redundant components originally contributing to healthy behavior. Note that an additive system is capable of redundancy, and in fact additive dynamics would imply that a healthy biological system is composed of many independent yet redundant component pathways. In which case this redundancy can be exploited as a means to produce approximate equivalence in behavioral output. Provided that the system can exploit these independent pathways within/between movements, the successive variations in outcomes would conceivably lack temporal structure. Thus, the inherent variations in human time series were thought to exhibit an output representative of white noise.

The opposing view on system organization stems from the concept of degeneracy and complexity, in which inter-dependent interactions between components across systems/levels/scales lead to emergent system organization with high degree of context sensitivity. That is, according to the relevant constraints, numerous inter-dependent components may interact along the same pathway. However, changes in constraint may demonstrate a characteristic change in functional role/interaction between the same components, thus leading to different pathway interactions (for synopsis on redundancy, complexity, and degeneracy, see Kay, 1986; Deliginieres & Marmelat, 2013). Given the interaction-dominant dynamics of a complex system (Van Orden, Holden, & Turvey, 2003), the temporal structure of the system would presumably demonstrate long-range correlations.

Synonymously, complex system analysis in the frequency domain would illustrate colored ($1/f^{\beta}$) noise in behavioral output, as the dominant pathways are dependent on the component elements functioning according to the specified constraints imposed on the system. Thus, complexity science stipulates that $1/f^{\beta}$ dynamics is a phenomenon reflective of a complex, interaction-driven system. That of which is supported by the pervasive nature of these scaling relations across a myriad of cognitive (Gilden, 2001) and motor tasks (Chen, Ding, & Kelso, 1997; Wing, Daffertshofer, & Pressing, 2004; Torre et al., 2011). Beyond this conclusion, however, lies a great deal of debate in regards to whether the differences in health and skill can be determined by variations in output along the white-brown noise continuum.

Loss of Complexity and Optimal Variability

Research on autonomic cardiac function was fundamental to the development of analysis techniques devoted to understanding dynamical change with aging and pathological degeneration (Lipsitz & Goldberger, 1992; Peng et al., 1995; Ho et al., 1997; Marwan et al., 2002). Traditional statistical measures of cardiac time series (µ/sd HR) were insufficient in differentiating healthy cohorts from those with congestive heart failure (CHF) in spite of the qualitatively observable differences in trends between their time series fluctuations. Consequently, studies began to implement non-linear analysis of heart rate time series in the time and frequency domain, and found that CHF cardiac dynamics were more deterministic than the young healthy population (Peng et al., 1995; Ho et el., 1997). They argued that increased temporal structure with aging or disease progression is a direct result of either: 1) a loss or impairment of component interactions prevalent to adaptive cardiac regulation (ie. endocrine, neuro- autonomic, local cross bridge cycling, etc.) or 2) alterations in the non-linear coupling between components at specific spatio-temporal scales. The breakdown of components interacting as a means to adaptively modulate cardiac function was interpreted as a systems "loss of complexity". The characteristic increase in determinism (shift to brown noise) with disease inferred that the system possessed insufficient component interactions pathways vital to sustaining healthy cardiac output.

While a number of subsequent empirical results have been consistent with the loss of complexity hypothesis, a number of studies have reported instances where task difficulty, normal aging, and neural degeneration demonstrate an output that moves towards completely random fluctuations (Hausdorff et al., 1997). Provided there is a shift to random fluctuations in individual time series where it is assumed that individuals would once have demonstrated a complex behavioral output, it is argued that certain situations can cause a breakdown in interdependence between components. This breakdown observed in minimally constrained activity is believed to be an illustration of a system with a diminished coordination and stability in the observed behavior. It is assumed that proximity to pink noise (fractal scaling) in terms of behavioral output represents a system that is near optimal complexity. These premises stem from the original attempts to explain the relative ubiquitous nature of 1/f noise across natural systems in a range of scientific domains (Bak, Tang, & Wisenfield, 1987; Bak, 1996).

Statistically speaking, a system that demonstrates a brownian structure indicates fewer component-interactions that predominate behavior, and thus the system within such a regime is considered relatively robust. As previously mentioned, a system that lacks statistical structure (white noise) is believed to lack functional stability. Bak and colleagues (1996) provided the conceptual framework of "Self-Organized Criticality" (SOC) in which a system organizes near a critical threshold. SOC supposedly illustrates a state where interactions between components at all relevant scales are at their highest, and even the most miniscule perturbations within the system at any scale can cause abrupt, macroscopic reorganization (Okkels, & Jensen, 1998; Wagenmakers, Farrell, & Ratcliff, 2005). Thus, the system is in a state of minimal stability (many components, can cause abrupt macroscopic change), in which the behavioral benefit relates to availability of nested degrees of freedom contributing to stable yet sensitive coordination. SOC models have demonstrated organization near criticality across natural systems (Davidsen & Lüthje, 2001) and neural network populations (Bak & Chialvo, 2001; Chialvo, 2010), with temporal structures demonstrating self-similar (fractal) pink noise fluctuations.

Provided the assumed benefits of criticality (for information on the operationally synonymous construct of meta-stability, see Kelso, 2012), along with a number of empirical studies showing $1/f^1$ dynamics in young healthy individuals, a number of research groups are now working under the "optimal variability framework". Here it is assumed that $1/f^1$ dynamics in behavior is the structural optimum for a stable yet flexible system. Thus, any deviation away from the optimum is considered to be contraindicative (Goldberger, Peng, & Lipstiz, 2002; Stergiou & Decker, 2011). Subsequently, studies have focused on the development of clinical interventions that attempt to enhance complexity of motor characteristics ranging from fractal ventilation (Boker et al. 2002), to fractal auditory stimuli as a means to alter gait dynamics in the elderly (Hunt, McGrath, & Stergiou, 2014).

There is very little argument with the notion that complexity measures hold inherent value for providing information about behavioral dynamics otherwise inaccessible through more traditional statistical analysis techniques (i.e. global performance indices). Furthermore, the relative consistency in which $1/f^{\beta}$ noise presents itself across many natural systems provides a strong case that temporal dynamics are functionally relevant to system control. However, while research in the domains of human movement and cognition has demonstrated numerous cases where individuals show $1/f^{1}$ structure in an output of interest, direct proof of functional significance in deviating away from the presumed optimum has proven to be ancillary at best. For example, Goldberger and colleagues (2002) provided empirical results of heart rate dynamics where the temporal structure in young healthy, elderly healthy, and heart failure patients was represented as pink, brown, and white respectively. This is in direct contrast with seminal findings from Goldberger (1996), Kim (1997), and colleagues, where heart failure patients showed a temporal composition that was highly deterministic in nature.

In addition to heart rate analysis, Goldberger and colleagues (2002) presented gait dynamics (stride) data from healthy and Huntington's patients in which the afflicted showed a structure corresponding to white noise. It should be noted that a number of studies have shown this same trend of gait patterns in healthy elderly subjects (Almurad et al., 2017). There is a legitimate argument that complexity measures tend to lack predictive power in terms of how individual temporal structure deviates from the hypothesized optimum based on conditions (or degree of progression) eliciting an inconsistent bi-directional shift depending on the study. Such an issue is all the more relevant when considering that the original gait studies indirectly related brownian characteristics to a higher standardized fall risk score (Hausdorff et al., 1995, 1996, 1997).

The aforementioned discussion cannot discredit the interpretations of those advocating pink noise structure as the behavioral optimum across behavioral tasks. Indeed, to their credit all aforementioned studies provide consistency in terms of the fact that the average behavioral complexity of young healthy groups do show a structure more correspondent to $1/f^1$ noise. A rare point of discussion, however, is the observed variations in within- and between-subject complexity observed in the young healthy population (Den Hartigh et al., 2015, 2018). Moreover, studies have shown how tasks (even minimally constrained) can significantly alter behavioral structure in populations expected to consistently show optimally complex output (Wijnants et al., 2009; Hollis, Kloos, & Van Orden, 2009; Athreya, Van Orden, & Reilly, 2012). It comes as no surprise then, that papers discussing behavioral complexity stipulate its apparentness in simple, over-practiced, repetitive (if discrete) tasks for young healthy individuals. In other words, one is expected to consider providing minimal task constraints in order to ensure that output reveals an optimum in temporal complexity.

As a reminder, assumptions about pink noise fluctuations representing optimal adaptability is predicated on the position that perturbations at any scale can cause an abrupt reorganization of the system. In other words, there is greater contribution and control of degrees of freedom pertinent to stable/flexible behavior. This begs the question as to why one would most generally exhibit the greatest complexity in situations where the necessity for adaptive behavior is least prevalent.

Loss of Adaptability

In light of the aforementioned issues in the LOC and OV hypotheses, Vaillancourt and Newell (2002) developed an alternative framework focused on the adaptive value of modulating individuals isometric force dynamics according to differential external constraint. In brief, 3 cohorts (young adults, old, older-old) performed both a constant and sinusoidal isometric tracking task based on the supposition that each task represents a fundamentally different coordinative regime embodied within the individual's intrinsic dynamics. That is, constant and sinusoidal force output correspond respectively to a fixed point or limit cycle attractor (for a comprehensive discussion on attractor dynamics, see Kaplan & Glass, 1995). They hypothesized that optimal tracking of a fixed point is predicated on coordinating and controlling many functional degrees of freedom as a means to mitigate system oscillation. Conversely, optimal performance in the limit cycle (oscillatory nature) task would require a reduction in degrees of freedom, especially those operating at faster time-scales. This would hypothetically facilitate higher synchrony with a perfectly regular structure embedded in the limit cycle condition. While not explicitly discussed, their results demonstrated a strong relation between force structure and task in young healthy individuals. Conversely, progressive aging apparently limited individual's ability to differentiate their force dynamics according to each task. Additionally, the overall task performance (Root Mean Squared Error) was progressively worse with age across all tracking conditions.

The premise behind their hypothesis and subsequent findings is predicated on the importance of individuals capacity to modulate the relevant DoF's according to dimensional constraints embedded in the task. It was expected that young healthy individual's retain this capacity, whereas aging is responsible for the decline in ability to modulate force dynamics in response to external constraint. Thus, a condition that evokes functional limitation (i.e. neural degradation) could logically result in temporal structure that corresponds with their stable intrinsic dynamics in the event that they cannot meet the dynamics required by external task constraints.

An extension from this paradigm was introduced by Sosnoff and colleagues (2009), where young healthy subjects were asked to perform a number of tracking conditions of varying temporal structure (constant, sine, black noise, brown noise, pink noise, white noise targets). They found that young healthy individuals were able to roughly match the structure of both the pink and brown noise targets, whereas they produced outputs that were more structured than the white noise signal and more irregular than the black noise signal, respectively. These findings again provide empirical evidence that young healthy individuals have the capacity to modulate their force structure (DoF's) based on the dynamics of the task constraints. However, it appears that there are limitations to dynamical modification within the confines of the structured/colored noise continuum (brown to pink).

In another example outside of an isometric force paradigm, Hoos and colleagues (2014) assessed dynamics of various gait parameters between competitive marathon runners. They found that runners who posted a significantly lower race time actually exhibited brown noise stride dynamics, whereas those who finished with a longer race time demonstrated patterns that were more correspondent with pink noise fluctuations. One can infer that an advanced runner is no less complex than their less adept counterparts, and thus there is an effect of behavioral strategy impacting emergent dynamics as a means to optimize task performance.

To re-iterate, there is a collective agreement on the inherent value to structure in a complex system based on the framework of interaction-dominant dynamics. Advocates of LOC and OV frameworks suggest that $1/f^1$ is the optimum of intrinsic dynamics in a minimally constrained system. There is generally minimal emphasis on how the system adaptively functions according to the task constraints. Even so, the majority of studies employing this framework for rehabilitative purposes have attempted to implement interventions (i.e. implementing fractal timers in gait studies, task interaction with young healthy subjects) with hopes that subjects retain a more complex output upon post assessment of minimally constrained behavior (Hove et al., 2012; Hunt et al., 2014). Conversely, the LOA approach emphasizes the value of assessing behavioral dynamics according task-imposed constraints, as they argue that adaptability should not be inferred according to observed behaviors requiring the lowest degree of adaptability (i.e. minimally constrained behavior).

Nevertheless, it is fair to state that while the LOA framework lends awareness to the limitations in reproducibility of $1/f^1$ structure across varying behavioral conditions, there is a lack of clarity on determining whether or not there is still a relation to individuals minimally constrained dynamics, and capacity to modulate system dynamics when task constraint arises. More importantly, while both literatures stress the prospective benefits of specific behavioral dynamics, there is little emphasis on how individuals go about systematically accomplishing this phenomenon. Regardless, contemporary literature has extended to the domain of practice and intervention according to a specific framework relying on dyadic interaction or complex stimulus coupling. That of which has the potential to provide novel insight into: 1) two key underlying processes that may contribute to alterations in individual dynamics; and 2) possible explanations in component interactions determining how individuals are matching complexity according to task or intervention technique.

Complexity Matching

Complexity matching (West et al., 2008) is predicated on the notion that inter- and intra-system interactions demonstrate the highest degree of information exchange when they share a high degree of similarity in terms of their respective temporal structure. Furthermore, there is a working conjecture that complex systems possess the capacity to synchronize/attune output complexity as a means to promote the optimal degree of collective information exchange. An exemplary study in dyadic conversation (for more examples on dyadic behavioral matching, see Pickering & Garrod, 2004) found that there is a preference in complex structure of verbiage for linguistic expression/interpretation, and as such complexity matching holds inherent value to efficient communication.

As an extension, contemporary studies on human movement have found that a strong correlation in terms of temporal structure can be accomplished in two distinct ways. First, individuals have demonstrated the capacity to match complexity indices (i.e. DFA scaling exponent) by way of shorter time-scale local synchronization (Torre et al. 2013; Fine et al. 2015). The second process is attributed to individuals showing a global tuning in output (complexity matching) which is suggestive of optimal coordination between the two systems (Stephen & Dixon, 2011).

The complexity matching phenomenon requires both coordinating systems, or the system and perceptuo-motor stimulus to exhibit complex 1/f scaling in their output. An extended hypothesis within the complexity matching view states that, in the event that the interacting systems differ in degree of fractal scaling, the system that exhibits a lower complexity in their behavioral dynamics will act in subordination, and mimic the dynamics of their more complex counterpart (Mahmoodi, West, & Grigolini, 2018). Recent studies advocating the pink noise as optimum approach have subsequently developed studies according to the premise that the combination of complexity matching and system subordination may be a viable option to facilitate highly specific alterations to individuals minimally constrained dynamics (Almurad, Roume, Delignieres, 2017, 2018).

Interestingly, a complexity matching study by Almurad and colleagues (2017, 2018) found that dyadic matching of gait dynamics between young and elderly exhibited a distinct contribution of both local-synchrony, and global-matching processes. They provided evidence that local-synchrony appeared to be a prevalent factor for matching scaling exponents early in practice, with global matching increasing in proportional contribution as subjects progressed in the study. Most importantly, they found that subjects were able to retain a more complex gait structure (from white noise) in retention test where they performed alone.

The viability of complexity matching/subordination in intervention paradigms has been proposed primarily through the pink noise optimum view on behavioral complexity. However, we argue that there is enough evidence- in terms of possible complexity matching beyond pink noise, and possible benefit of deviations from pink noise in certain contexts- to warrant more comprehensive assessment of complexity matching as a facilitator of dynamical change.

This evidence may be crucial to better understanding causal changes in individual dynamics according to adaptive (or lack thereof) regulatory means. Nevertheless, on the whole we are still lacking empirical evidence that baseline intrinsic dynamics directly relate to performance characteristics (i.e. performance indices, proportion of synchrony process contributions). Furthermore, the newfound capacity to assess how individuals are actually matching task dynamics necessitate a greater investigation into how individual strategies promote similar behavioral outcomes in accordance with their distinct minimally constrained outputs. Lastly, there is still a pressing issue as to whether $1/f^1$ behavior demonstrates the best task solution, or whether practice may elicit a shift within the fractal continuum that corresponds to more efficient behavior according to the context of individual, environment, and task interaction.

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CHAPTER 3

Experimental Focus

Behavioral complexity is a key issue that continues to be explored both clinically and theoretically in motor behavior research. $1/f^1$ fluctuation's arguably express individual capacity to organize a more abundant set of relevant degrees of freedom according to task requirement. Within this framework, any deviations from $1/f^1$ fluctuations are viewed as a negative, and thus behavioral interventions have been constructed with this desired output in mind. Alternatively, several groups exemplify adaptive capacity according to behavioral dynamics corresponding to contextual constraint.

There is no argument that a more complex output may represent an adaptive optimum in particular situations. There is, however, the possibility that it may not represent an optimum in *all* behavioral situations. Still, there has been little attempt to understand whether minimally constrained dynamics, along with their proximity to $1/f^1$ scaling, hold any predictive power for adaptive neuro-motor control. Furthermore, there is little understanding whether or not there is a direct relation between complexity measures and a more traditional indices of motor ability.

The aforementioned issues hold additional significance provided the inherent relations between practice, learning, and contemporary approaches to behavioral/rehabilitative intervention. There are advocates for promoting optimal complexity in individuals through these interventions. However, given the possibility that a shift in the colored noise continuum according to task holds benefit, it is important to consider whether or not young healthy individuals alter their intrinsic dynamics according to practice in tracking a specific force structure.

Purpose Statement

The purpose of this study is to determine how intrinsic control of relevant DoF's impacts task specific alterations in isometric force dynamics, and its relation to direct indices of performance in the young healthy population (Experiment 1). Furthermore, we want to determine whether practicing conditions at opposite ends of the colored noise spectrum cause persistent change to an individual's intrinsic isometric force dynamics, and whether specific practice regimes are comparable in terms of adaptive performance and control (Experiment 2).

Experiment 1:

The goal of Experiment 1 is to empirically illustrate both minimally constrained, and task relevant behavioral dynamics across a series of isometric tracking tasks. We aim to illustrate the relationship between intrinsic dynamics and task relevant shifts in force complexity. Additionally, a major aim of the study is to determine whether minimally constrained and task relevant dynamics hold any predictive power of adaptive control as indexed by measures of tracking performance. Baseline minimally constrained conditions consist of a self-selected force output with no visual target, force trace, or performance measure after any trial. In an attempt to limit extraneous constraints (i.e. non-preferred force) we will use their minimally constrained data to determine the force at which they will track targets with varying spatio-temporal properties.

Hypothesis 1: Based on recent pilot data, and results from previous studies (Athreya et al., 2012; Ducharme, & Van Emmerik, 2018, Novak & Newell (in preparation), 2018) young healthy individuals intrinsic force dynamics will vary within the colored noise spectrum.

Hypothesis 2: Young healthy individuals will exhibit similar directional shifts in their task relevant force dynamics according to the specified tracking task. However, the magnitude of shift will depend on proximity to their minimally constrained force output.

Anticipated findings and their significance: It is anticipated that young healthy individuals intrinsic dynamics will vary in complexity, however their output will fall within the colored noise spectrum (pink to brown). Regardless of their intrinsic force complexity, subjects will show characteristic changes in force dynamics specific to the force target. An added question that holds major significance is determining whether force dynamics are related to adaptive capacity as indexed by traditional tracking performance measure across task conditions.

Experiment 2:

The goal of Experiment 2 is to determine whether practice according to specified task constraints (temporal complexity) results in alterations to individual's minimally constrained force structure. Additionally, this experiment is designed to test how practice elicits change in the relative contribution of processes (local error corrective, global complexity matching) relevant to temporal matching based on their assigned practice regime. The final aim of this study is to determine whether either practice regime demonstrates superiority in terms of adaptive tracking performance through implementation of a transfer tracking condition.

Hypothesis 1: Post assessment of minimally constrained dynamics will show a shift in force output complexity corresponding to dynamics of the practiced task.

Hypothesis 2: Local synchrony will be most prevalent early on in practice, however global complexity matching will continue to increase throughout practice for both groups.

Hypothesis 3: While individuals will show a characteristic shift in their intrinsic dynamics, there will be no differences between practice groups in terms of performance outcome of a transfer task given their ability to utilize synchronization process at both the global and local level of the task.

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CHAPTER 4

INTRINSIC DYNAMICS AND THE ADAPTABILITY OF VISUO-MOTOR COUPLING IN ISOMETRIC FORCE TRACKING[1]

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[1] Novak, T. S. & Newell, K. M. To be submitted to *Nonlinear Dynamics, Psychology, and Life Sciences*

Abstract

The aim of this study was to investigate the relationship between preferred tendencies of isometric force dynamics, alterations to these dynamics according to various force-tracking demands, and adaptive perceptual-motor performance as indexed by isometric tracking accuracy. Participants initially produced and maintained their preferred force level without visual feedback for 30 trials. This was followed by isometric tracking of three visual force targets (constant, pink noise (≤ 12 Hz.), sine wave (1 Hz.)) for 30 trials (each) according to their preferred force range. Subjects demonstrated long-range correlations in all experimental conditions, however, their self-selected force complexity (indexed by DFA) was not representative of pink noise dynamics as is generally expected in minimally constrained behavior. Alterations to both the average and between trial distribution of a subject's DFA scaling coefficient was dependent on task constraints. The intrinsic dynamics assessment predicted tracking performance according to a generalize-able U-shaped function over the range of between-subjects preferred force DFA. Tracking performance was also predicted by an individual's dynamical flexibility, as indexed by the magnitude of difference between their task-relevant DFA exponents. These findings provide further evidence of a relationship between behavioral dynamics and adaptive performance. Intrinsic and task-relevant dynamics were both influential factors, and thus their collective assessment may expand our understanding of system organization and adaptive motor control.

Introduction

It is generally accepted that humans are inherently complex entities. By definition, a complex system consists of many interacting components (or elements) functioning across numerous scales in space and time (Mitchell & Newman, 2001; Delignieres & Marmelat, 2012; West, 2006). The pervasive phenomenon of long-range serial correlations in behavioral time series is considered to reflect functional complexity underpinning the dynamics of an individual's system (Van Orden, Holden, & Turvey, 2003; Diniz et al., 2011). That is, temporal properties of behavioral fluctuations are thought to represent both the degree of stability in terms of emergent coordination between functional elements, and the flexibility to re-organize said elements according to factors that critically perturb the system in its current state (Van Emmerik & Van Wegen, 2000).

A contemporary research agenda aims to identify general principles driving functional alterations to intra-individual coordination dynamics across many phenomena (ie. aging, adaptation, disease, etc) (Peng et al., 1995; Goldberger et al., 2002; Hausdorff et al., 1995, 2005). Several approaches, most notably the Loss of Complexity (LOC) and Optimal Variability (OV) hypotheses, operate according to assumptions that behavioral and physiological dynamics demonstrate the highest degree of complexity when time and/or frequency domain analysis exhibit $1/f^1$ scaling, also known as fractal or pink noise fluctuations (Torre & Wagenmakers, 2009; Kello et al., 2010; Delignieres & Marmelat, 2012; Wijnants, 2014). Provided $1/f^1$ scaling best accommodates stability and flexibility of the system, the LOC and OV approaches hold it to be representative of optimal adaptability (Torre & Balasubramaniam, 2011). Thus, any shift towards more random (white noise) or deterministic ($1/f^2$; brown noise) fluctuations in output is a consequence of pathology, mal-adaptation, or sub-optimal control (Hove et al., 2012; Washburn et al., 2015; Ducharme & Van Emmerik, 2018).

A major criticism of the LOC and OV approach stems from instances where behavioral output in otherwise young healthy individual's deviates from $1/f^1$ scaling (Chen et al., 1997, 2001; Kello et al., 2007). Proponents of the LOC/OV frameworks contend that scaling relations underpinning behavior are dictated by the balance between the flexibility of task and inherently intrinsic constraints (Van Orden, Kloos, & Wallot, 2011; Washburn et al., 2015). Pink noise fluctuations are thus exhibited when task constraints are sufficient for realization of a specified behavior (ie. individuals must walk) yet marginal so as to allow the system to coordinate the optimum contribution of component-interaction processes (ie. individuals should walk at their preferred pace) (see Van Orden et al., 2011 for extensive discussion). Consequently, advocates of this framework generally minimize task constraints while studying behavioral dynamics as a function of, for example, aging (Almurad et al., 2018), pathology (Hove et al., 2012), and developmental disorder (Stergiou et al., 2013). In the instances where task constraints are imposed and manipulated to explore alterations in behavioral dynamics (ie. speed vs. accuracy paradigm), the overarching theme is exploration of movement parameters that exhibit pink noise fluctuations (Athreya et al., 2012; Hunt, McGrath, & Stergiou, 2014; Washburn et al, 2014).

An alternative interpretation, known as the Loss of Adaptability approach, proposes that adaptability is better represented by the neuro-motor system's capacity to re-organize in response to any multitude of context specific constraints (Ganz et al., 1996; Vaillancourt & Newell, 2002; Newell et al., 2003). This extends from the premises of coordinative structures, in which the organization of the functional DoF's underlying macroscopic behavior is in large part constrained according to dimensional properties demanded by the task (Kay, 1988). Vaillancourt and Newell (2002) provided supporting evidence to this interpretation in an aging study (young healthy, elderly, older-elderly groups) utilizing isometric force tracking. While not expressly discussed, their data clearly demonstrate that young healthy individuals significantly shifted their force complexity according to unique properties of each target (approximately pink noise in constant target tracking; brown noise in oscillatory target tracking). Elderly subjects demonstrated a smaller shift in force dynamics, and the older-elderly group showed no shift in their force dynamics across conditions. Studies have further corroborated a shift from $1/f^1$ towards $1/f^2$ (brown noise) fluctuations as a function of, for example, specific force tracking demands (Sosnoff, Valantine, & Newell, 2009), stride parameters on marathon performance (Hoos et al., 2014), and stroke parameters on training in competitive swimming (adolescents) (Barbosa et al., 2015).

The aforementioned studies provide insight to the prospect that shifts in behavioral dynamics within the continuum of the colored noise spectrum (pink to brown) should not be immediately written off as a negative or spurious result. Nevertheless, the experimental scope of the studies just reviewed is limited in two capacities. First, the majority of studies within this framework assess individual dynamics corresponding solely to the specified experimental tasks. However, a constraints-based approach to motor behavior stipulates that stable coordination emerges according to a confluence of organismic, environmental, along with task constraints (Newell, 1986). Therefore, capturing individual’s intrinsic dynamics barring task constraints may still factor into how system organization is modulated when task and environmental factors are imposed (Kelso, 1995). Second, while studies with the capacity to report actual indices of individual or group performance have done so, the direct relationship between these measures and individual's within-trial dynamics remains unclear.

Regardless of interpretation, there is agreement that complexity measures may possess significant value as biomarkers for a system's adaptive capacity (West, 2006; Sturmberg & West, 2013). A generalized concept across definitions of adaptability is the ability to modify one’s behavior in accordance with novel constraints or conditions. Directly relating individual dynamics to adaptability necessitates a more direct approach on validating these measures according to their unique domain of study. A viable solution is to test whether dynamics hold predictive power in conjunction with domain specific ability scores (ie. performance scores, stability via perturbation). Most importantly, the field as a whole would benefit from studies across relevant paradigms providing a comprehensive characterization of intrinsic and task specific dynamics.

In the current study, we investigate how minimally constrained individual dynamics impact coordination and performance according to manipulations of the task dynamics. Specifically, we asked individuals to produce their preferred isometric force and we developed three tracking tasks corresponding to that preferred range. All subjects were required to match their force output to three tracking targets differing in dimensionality (constant force: fixed point; oscillatory force: limit cycle; pink noise force / $1/f^1$: chaotic). Our experiment was designed to investigate three primary questions.

First, do young adult healthy individual's exhibit a self-selected force output corresponding to $1/f^1$ pink noise? It is well established that continuous behavioral processes tend to function within the colored noise spectrum (pink to brown noise) (Collins & DeLuca, 1993; Sosnoff et al., 2009; Wijnants et al., 2012). However, there are few data on minimally constrained dynamics in the force domain, and thus the distribution of subject's force complexity is currently unknown. We expect that this population will fall within the colored noise continuum, as deviations towards random (white noise) behavior would infer a lack of stable coordination, and thus a breakdown in functional (multi-scale) element coupling relevant to continuous force production. As an extension, we predict that subjects will vary across the colored noise continuum (ie. pink to brown noise) in their minimally constrained force output. This prediction is based on the assumption that complexity of behavioral output does not necessarily reflect the absolute peak of complex coordinative possibilities available to individuals. Individuals can differ significantly in lifestyle activity, and thus their individual dynamics may differ according any number of factors ranging from skill to metabolic efficiency (Cavanagh & Williams, 1982; Hoos et al., 2014).

Second, does an individual’s intrinsic force dynamics (preferred tendencies) impact how force complexity shifts according to dimensional (spatial and temporal) properties of the task? The previous literature suggests that task dynamics elicit a general shift in average force complexity. Additionally, there appears to be change in magnitude of the force complexity shift as a function of task according to age groups (Vaillancourt & Newell, 2002; Sosnoff et al., 2009). However, provided the expectation that there will be differences in individuals self-selected force complexity, we wish to explore whether self-selected force complexity impacts the direction and magnitude of the force complexity shift as a function of task. We predict that subjects will demonstrate similar shifts towards more random and deterministic force output according to the specified force target. However, the magnitude of their force complexity shift will depend on their intrinsic dynamics as reflected in their self-selected force output.

Third, does the intrinsic force dynamics and/or task relevant complexity relate to traditional outcome measures of performance? Whether $1/f^1$ intrinsic, or specific criterion (task) dynamics predict better tracking performance is unclear. Intuitively, one could argue for both cases, as they could represent either the ability to exploit more relevant DoF's in a generalized manner, or the ability to reorganize DoF's optimally according to task demands. To our knowledge, there have been no attempts in the isometric tracking literature to illustrate the direct influence of force complexity characteristics on tracking performance.

Methods

Subject's

30 self-reported right-handed subjects (age: 23 ± 5 years, 16 Male) from the university population participated in this study. The subjects were not trained in fine manual tasks, were not competitive weight lifters, and had no previous history of neurological disorder. Written informed consent was obtained from all participants in congruence with the IRB approval from The University of Georgia. Two subjects (1 male) could not complete testing, and subsequently were removed from all analysis.

Procedures

Subjects were given approximately 5 min of familiarization with procedures related the experimental protocol before testing. They were instructed to apply force on a load sensor via abduction at the distal phalanx of the index finger on their dominant hand. During familiarization, subjects were provided feedback of all three forces (Fx, Fy, Fz)and moments (Mx, My, Mz). Subjects were instructed to attend to feedback of their normal force (Fz), and asked to manipulate different force levels in order to explore their force preference. That is, subjects were asked to search for a force range that they could: a) perform and maintain comfortably for an extensive duration, and b) perceivably modulate with the greatest precision. The non-dominant hand was to rest in a homologous position during testing. Upon familiarization individual maximum voluntary contraction (MVC) was calculated by having subject's produce their maximum force over 3 trials at 6 s per trial. While MVC was not utilized in any way for experimental setup, we collected their absolute force capacity in order to determine whether this was a contributing factor to individual differences in force characteristics.

Before any tracking tasks were introduced, all subjects were asked to produce 30 trials (20 s duration) of their preferred force. Subjects were not provided visual feedback of their output during any portion of the trial, however, they were notified on screen when each trial was completed. Upon trial block completion, individual force properties were assessed to match each experimental target to the confines of their preferred force distribution. Specifically, their average preferred force output corresponded as the mean force value for all experimental conditions, while their force distribution (between trial) dictated the boundary range for fluctuation magnitudes (± 2 SD) for all relevant targets.

Target order of the constant, sine wave, and pink noise conditions was randomized for each participant. A total of 30 trials within each target condition was performed before proceeding to the next task. Subjects were instructed to produce force on the load cell so that a yellow feedback line matched a red target line located on the center of the screen. Upon completion of a trial, participants received knowledge of results (KR) of root mean square error (RMSE) related to their force output. The duration of each trial was 20 s. The first 3 s of each trial were removed from RMSE calculations in order to remove any negative impact on their KR score. In order to reduce any transient effects of fatigue, the subjects were provided with as much time as they needed to recover between trials, and were given at least 5 min of rest between each block condition. The duration of testing for each subject was approximately 1.25-1.5 hours.

Apparatus

Subject's sat in a stationary chair approximately 23 in (58 cm) away from a 20 in (51 cm) LCD computer monitor. In front of the monitor were two ATI Entran ELFS-B3 force load cells spaced approximately 7.5 in (19 cm) apart. The output from each trial was amplified and sampled at (640) Hz by a 16-bit Coulbourn A/D board.

Although no physical constraints were applied during testing, subjects were asked to maintain the same posture and keep their elbows, forearms, wrists, and palms flat on the surface throughout the experiment. Feedback of the force output was given to subjects through a 20 in (51 cm) HP monitor with a resolution of 1920 x 1080 pixels. The force trace on the screen was set at a pixel-to-Newton ratio of 64 p/N.

Data Analysis

The first 3 and last 2 s of each trial were removed from the data of each trial in order to remove any transient gradations in force that precede target matching. Data processing was performed with Matlab 8.1 (Mathworks Inc.). Subject's normal force (Fz) output was recorded at 640 Hz. and subsequently decimated by a factor of 5 (128 Hz) prior to analysis. Data were filtered using a fourth-order zero-lag Butterworth filter with a cutoff frequency of 20 Hz.

Descriptive Measures: Subject's mean absolute (N) and relative (%MVC) force output were calculated in the self-selected force condition. Relative force was calculated by dividing subject's mean absolute force (N) over their absolute MVC (N).

Force Variability: Intra-subject force variability was assessed by within-trial standard deviation (N).

Force Accuracy: Subject's tracking accuracy was assessed by their absolute Constant Error (CE) of force output (N) within each trial (Schutz & Roy, 1973; Guth, 1990). The equation for absolute CE is:

$$\left| \frac{\sum(x_i - T_i)}{N} \right| \tag{1}$$

where x is subject's force, T is the corresponding target force, and N is the total number of discrete data points used for calculation. Absolute CE indicates the average amount in which subject's deviate from the target, and thus measures force accuracy irrespective of differences in force variability (force SD (N)) according to each task.

Structure of Variability. The time dependent force structure in the self-selected force condition and as a function of force target was assessed by Detrended Fluctuation Analysis (DFA) (Peng et al., 1995). DFA integrates raw time series data, divides this integrated series into boxes with equal window length, and within each box least squares fit line is applied. In order to detrend the data, each linear fit is subtracted for each window. The root mean square (RMS) variability is calculated within each window, and averaged across windows of the same size. These calculations are repeated at a range of window sizes, in which a regression slope (α) of the log-log relation between RMS variability and window size (time scale) captures the degree of self-similarity in a signal. DFA α values correspond to different deterministic structures on the force signal (white noise: $\alpha = 0.5$, pink noise: $\alpha = 1.0$, brown noise: $\alpha = 1.5$).

Model: Model fitting was performed prior to regression analysis via the *fit* function in MatLab 8.1 (Mathworks Inc.). Tracking accuracy (individual's average CE) as a function of self-selected DFA for all force targets (constant, pink, sine wave) was fitted to 1st, 2nd, and 3rd order polynomial models. The model selected for further analysis was determined ultimately by the lowest Bayesian Information Criterion (BIC) value.

Inferential Statistics: Based on model fitting, 2nd order polynomial regression analysis was performed on tracking accuracy of each target (constant, pink, sine target | CE |) (dependent variables). The aim was to determine whether intrinsic force dynamics predicted tracking accuracy in a manner specific to each tracking condition. The independent variable (Self-Selected DFA) was standardized prior to model fitting and regression analysis. In the event that assumptions of homoscedasticity were violated, a bi-square weighted regression was supplemented to our analysis.

A linear bi-variate regression was performed on the magnitude of shift between intrinsic and task relevant force dynamics (SS x CN, PK, SN target shift in DFA) as a function of the individual's self-selected DFA. Magnitude of shift was calculated by subtracting subject's average task specific DFA from their average self-selected DFA.

The aforementioned analysis techniques focus primarily on the unique relation between force dynamics and performance according to the task demands. As an extension, we investigated the generalize-ability of force dynamics, both intrinsic and task relevant, on overall isometric tracking ability. Thus, individual's average between task absolute CE was calculated as our dependent variable of interest. We performed the same model fitting techniques on our independent variables of interest that characterize both intrinsic force dynamics and dynamical flexibility. From here we performed a multiple regression on average absolute CE, where a stepwise selection process compared models with differing variables of interest.

Repeated Measures: The Shapiro-Wilk test of normality was performed prior to any repeated measures analysis. If assumptions of normality were met, a traditional one-way repeated measures ANOVA was performed. In the event that the assumption of normality was violated, a Friedman non-parametric K-related samples test was implemented.

A one way (4 target condition) repeated measures ANOVA was performed using subject's average between trial DFA output for every condition to determine how individual force dynamics shift as a function of tracking conditions.

A Friedman non-parametric test was run on standard deviation of individual's DFA output in order to determine how force dynamics are constrained as a function of task condition.

A Friedman non-parametric samples test was also run on average SD and absolute CE in order to determine how each tracking task impacts subject's overall force variability in conjunction with their tracking accuracy (| CE |).

All statistical analyses were considered to be significant when the probability of making a type 1 error was less than 5% ($p < .05$). If the assumption of sphericity using Mauchly's test was violated in the repeated measures ANOVA, a Huynh-Feldt correction was used to adjust the statistical degrees of freedom. Only those main effects that reach significance ($p < .05$) are reported. Model fitting and regression analysis were first performed in MatLab 8.1 (Mathworks Inc.). The remaining analyses were performed using IBM SPSS software.

Results

Figure 4.1 provides an illustration of a single trial from one participant’s force-tracking time-series in the constant, pink noise, and sine wave tracking tasks, respectively. Young healthy subjects produced an average absolute force (af) of 2.4 Newton's (SD: 1.3 (N)), along with an average relative force (rf) of 13% MVC (SD: 8%). Neither force characteristic showed a clear relationship with individual's self-selected DFA output (af x ssDFA (R: .097), rf x ssDFA (R: -.11)).

Force Accuracy and Variability

The distributions of between subject CE and SD according to each tracking condition are illustrated in Figures 4.2A and 4.2B, respectively. The Friedman test found no significant differences in absolute constant error across all tracking conditions, $X^2(2)$ 0.64, p = 0.73. The Friedman test did, however, find significant differences between subject's force standard deviation (N) as a function of tracking condition, $X^2(2)$ 42.64, p < 0.001. Post Hoc analysis using Wilcoxon signed-rank tests revealed that the sine wave target showed significantly higher force variability compared to the constant (Z = 4.62, p < 0.001), and pink noise (Z = 4.62, p < 0.001) targets, respectively.

Complexity of Force Output (DFA)

Figure 4.2C illustrates the distribution of between subject DFA scaling coefficient according to each testing condition. Figure 4.2D provides the same illustration in terms of individual's between trial standard deviation (SD) of their DFA output.

The 1 way (4 target condition) repeated measures ANOVA revealed significant shifts in subject's mean DFA output as a function of force tracking conditions, (F(2.29, 61.91) = 118.91, p < 0.001, η_p^2 = 0.82). Post Hoc analysis found significant differences in DFA between all conditions. The order of average DFA output from most complex to most deterministic was the constant target (M: 1.17, SD: 0.08), pink target (M: 1.20, SD: 0.05), self-selected force (M: 1.32, SD: 0.07), and sine target (M: 1.4, SD: 0.07) conditions, respectively.

The Friedman non-parametric test revealed that the distribution of individual's between trial DFA (SD) significantly differed according to tracking condition, $X^2(3)$ 42.81, p < 0.001. Post Hoc analysis using Wilcoxon signed-rank tests revealed that DFA

SD significantly differed between all conditions except for the constant target and pink target tasks. Specifically, SD of self-selected DFA was significantly larger than the constant (Z = -3.006, p = .003), pink (Z = -3.96, p < .001), and sine (Z = -4.33, p < .001) tracking conditions. SD of DFA was also significantly larger for both the constant and pink noise conditions when compared respectively to the sine wave target condition: CN (Z = -4.39, p < .001), PK (Z = -4.14, p < .001).

Tracking accuracy as a Function of Self Selected DFA

As shown in all panels of Figure 4.3, tracking accuracy (|CE|) followed a U-shaped function (also, see Table 1), in which the cluster of most accurate subject's across tracking tasks corresponded to a DFA scaling coefficient of approximately 3.0-3.5. Both the standard model fitting procedures and the bi-square re-weighted fittings determined that a U-shaped function was the best representation of the data compared to linear and cubic models.

Shift in Force DFA as a Function of Self Selected DFA

Figure 5.4 illustrates the impact of individual's intrinsic force dynamics on the magnitude of their shifts in force complexity according to task constraint. Simple regressions showed a significant relationship between self-selected DFA and subsequent changes to mean DFA across all tracking conditions, SS x CN (p = 0.015), SS x PK (p < 0.001), SS x SN (p = 0.001). Figures 5.4a and 5.4b show the collective shifts towards a more complex force output in the constant and pink noise tracking conditions, whereas figure 5.4c shows the sine wave condition eliciting shifts to a more regular output. Correspondingly, we found that the magnitude of changes in force complexity according to task constraint was predicted by proximity to individual's self-selected force dynamics.

A Generalized Function of Force Dynamics on Tracking Ability

Results from our analysis of force dynamics on average absolute CE can be found in both Table 2 and Figure 4.5. Intrinsic force dynamics were characterized according to individual's self-selected DFA. Dynamical flexibility refers to the magnitude with which individuals are able to shift their dynamics between tasks, thus representing their flexibility in control of the relevant degrees of freedom in visuo-motor force coupling. Depending on the individual, the largest shift in DFA was seen between the sine wave condition and either the constant or pink noise task. In all cases there was a much greater shift between the sine task and both conditions, and thus we calculated the magnitude of shift between sine/constant and sine/pink. The average between these values was found to be the most appropriate variable indexing dynamical flexibility.

Multiple regression found that self-selected force DFA and individual's average shift in DFA were both significant predictors of their general tracking accuracy (|CE|), ($F(3,27) = 9.40$, $p < 0.001$), in which both variables accounted for 54% of the variance in performance. There was a generalizable u-shaped function between accuracy and self-selected DFA, with the optimum scaling coefficient interval between 1.30-1.35 (~1.32). There was a linear relationship between average DFA shift and tracking accuracy, where improved performance was predicted by a larger magnitude of difference between task relevant DFA scaling coefficients.

Discussion

This study investigated the influence of healthy adult individual's intrinsic dynamics, and flexibility of their task-relevant dynamics, on adaptive control across a range of visuo-motor tracking tasks. Specifically, we tested the theoretical position that pink noise fluctuations represent the optimum in system coordination, and thus: a) is an ubiquitous characteristic of unperturbed/unconstrained behavior in the healthy adult population (Lipsitz & Goldberger, 1992; Kloos & Van Orden, 2010; Van Orden et al. 2011), and b) directly relates to system adaptability (Stergiou & Decker, 2011; Ducharme, 2018; Ducharme & Van Emmerik, 2018). Our findings demonstrate that young healthy subject's do exhibit long-range correlations in their intrinsic force output, however, the distributional properties within this condition differ from the conventional expectations of pink noise behavior. Our findings also revealed considerable flexibility of individual's force output in terms of coordination and performance in visuo-motor coupling. Most importantly we provide robust evidence for a generalized relation between intrinsic dynamics and adaptability, as indexed by tracking performance over the range of force tracking tasks.

Force Variability and Tracking Performance

As expected, the inherent spatiotemporal properties of our tracking tasks required individuals to manipulate the variability of their absolute force output (SD). The isometric tracking literature has quantified performance in terms of absolute (ie. standard deviation (SD)) and relative (ie. coefficient of variation (CV)) force variability as an index of consistency, or utilized a combined index of tracking accuracy and consistency (ie. root mean square error (RMSE)) (Loscher & Gallasch, 1993; Slifkin & Newell, 1999, 2000; Vaillancourt & Newell, 2001; Christou et al., 2002). Subsequent reports of these outcome measure show significant changes in performance according to manipulations in the task force requirement, visual information, or a combination of both. While subjects produced the same average force, the unique spatial and temporal variations between tracking conditions required alterations to force consistency (SD) (See Figures 4.1 & 4.2b).

Nevertheless, young healthy subjects were able to sustain their force accuracy across all tasks. Similar studies have reported performance differences as a function of target according to subject's RMSE scores (Sosnoff et al., Newell, 2009; Studenka & Newell, 2013). Our results, however, suggest that consistency and accuracy measures require distinct assessment in the event that task manipulations are disproportionately related in terms of, for instance, force consistency. In fact, the capacity to modulate force variability to preserve accurate visuo-motor coupling may be an exemplary marker of flexible adaptation in and of itself. In which case future studies on aging, pathology, and rehabilitation could investigate how the force variability/accuracy relationships manifest, both general and task specific, according to each population of interest.

Force Dynamics

We adopted a self-selected force condition by virtue of the constraints-based approach to within system coordination (Newell, 1986; Kay 1988). Specifically, emergent coordination of the neuro-motor system results from a confluence of intrinsic, environmental, and task constraints acting on it. By prescribing minimal imposition of environmental and task constraints (ie. self-selected force as opposed to prescribed force, no visual information) we aimed to provide the conditions necessary for a system to freely express the intrinsic dynamics. The continuous nature of our force-time paradigm in conjunction with extensive trial repetitions within conditions also allowed a more comprehensive outline of the average and distributional properties of individual's dynamics according to relevant constraints.

The DFA results from the self-selected force condition support the notion that healthy adult neuro-motor output exhibits long range correlations associated with interaction dominant dynamics. However, there were no instances where subject's exhibited pink noise fluctuations, and the majority of force dynamics were closer in proximity to brown noise. We cannot explicitly state why this was the case, however we can speculate several possibilities that relate to several findings in the relevant literature.

A possible explanation for a more regular output in young healthy adults corresponds with a theoretical proposal that degree of long-range correlation is proportionally related to energetic efficiency (Ahn & Hogan, 2013; Dotov, Bardy, & Dalla Bella, 2016). A recent study by Marx (2019) monitored college student’s daily activity with accelerometers. They found that subjects who consistently performed endurance exercise demonstrated higher DFA values compared to all other sub groups (ie. weight lifters, controls). Another possibility is the nature of activities involving manual dexterity. Specifically, manual control in many situations involves a continuous shift from oscillatory/rhythmic behavior, to fixed-point precision-based control (Mathiowetz et al., 1985). In a motor control sense, it is plausible that these force dynamics are an expression of a lifetime of task relevant constraints driving the system to stable shifts in interactive processes, and thus reflecting a balance between more random and more deterministic dynamics.

The results from the force tracking conditions supported our second hypothesis, in that individual's force complexity was driven by the dimensional properties of each task.

Athreya and colleagues (2012) found that feedback of force output alone increases force complexity, in which they proposed that a "whitening" of the signal was a consequence of visual information affording the facilitation of visuo-motor error correction. However, our findings show that further constraint in the task dimension is a driving force in the organization of interacting control processes, thereby producing a bi-directional shift along the range of 1/f like force fluctuations. It is bi-directional in the sense that, when compared with their intrinsic force complexity, subject's force output shifted towards pink noise in the constant and pink noise tracking conditions and towards brown noise in the sine wave tracking task (see Figure 4.2C).

Adaptive shifts in force complexity according to task demands have been previously reported in a young healthy population (Vaillancourt & Newell, 2002; Sosnoff et al., 2009). Our results show just how these shifts correspond to their 1/f dynamics, in that there is a direct relation on both the direction and magnitude in which they shift from these dynamics according to task-imposed constraints. Individuals with intrinsic dynamics near $1/f^1$ show a larger shift towards $1/f^2$ in the sine wave condition, whereas those who are intrinsically near $1/f^2$ show a larger shift towards $1/f^1$ in the constant and pink noise tracking conditions (see Figure 4.4). Intuitively, this relation is to be expected, however, an explicit reporting of these results is necessary when considering previous findings (Vaillancourt & Newell, 2002), where the magnitude of change in force complexity decreased according to age. Future studies could examine whether the relative rigidity of elderly subject's task relevant dynamics relate proportionally with their intrinsic tendencies. In which case adapting manual force modalities to expand on their dynamical range may be a key factor for the development of therapeutic modalities.

The current study is unique to the isometric tracking domain in that we: a) outlined individual's intrinsic force dynamics, and b) provided a comprehensive illustration of the distributional properties of subject's force dynamics across experimental conditions (30 trials compared to typically no more than 10). A much larger sample size per condition allowed us to expand on how task demands constrain dynamical properties of individual force output. That is, how visual information and corresponding spatio-temporal properties of each condition constrain variations in force complexity from trial to trial. The self-selected force condition showed the greatest degree of variation in between trial complexity compared to all other conditions (see figure 4.2D). Furthermore, the sine wave tracking condition showed a significant reduction in how subjects vary their complexity compared to all other tasks.

A well-established hypothesis holds that 1/f like output represents a system driven by interaction-dominant dynamics, and subsequently the degree of system complexity is contingent upon a more weighted contribution of faster timescale processes available for action (Sosnoff et al., 2008, 2009; Ofori, Samson, & Sosnoff, 2010). Vaillancourt and Newell (2002) proposed that the dimensional properties of the task at hand dictate how force complexity is modulated. Essentially, an oscillatory task requires attenuation whereas a fixed-point task requires augmentation of faster time scale control processes to optimize goal-oriented behavior.

However, our findings reveal that an individual's average force complexity alone provides an incomplete picture to how different tasks constrain behavioral dynamics. Apparently, conditions that require attenuation of faster timescale processes are also more rigid in how individual's coordinative regimes may vary. That, or healthy individuals have developed a highly stable coordinative regime in controlling their force oscillations, thus limiting the amount in which their force complexity needs to vary (Serrien, 2008; Snapp-Childs, Wilson, & Bingham, 2015). In any case, the added dimension of individual's complexity distribution requires consideration for future experimental inquiry.

Force Dynamics Predict Task Performance

The idea that intrinsic dynamics provides important insight into how the system functions, performs, and evolves has been established through extensive research on bimanual rhythmic coupling (Kelso & Zanone, 1992; Zanone & Kelso, 2002; Kostrubiec et al., 2002, 2012). We provide supporting evidence that this premise can be generalized to studies using different movement paradigms, along with different metrics of system coordination. However, we also show the necessity for a more comprehensive and critical understanding of intrinsic dynamics in a manner that is specific to each experimental paradigm. In our case, there was a clear and general u-shaped function between tracking accuracy and self selected DFA. The most adept subjects were clustered at a force complexity that can be approximated as central to the colored noise continuum. More importantly, they were centered in terms of the interval that may approximate the bounded range of complexity in minimally constrained force output of humans. In which case this range does not corroborate with the frameworks suggesting that optimal system dynamics should be universally characterized through pink noise behavior.

Studies have also established a flexible range in 1/f behaviors according to task demands on visuo/auditory-motor coupling in force tracking and gait (Sosnoff et al., 2009; Hunt et al., 2014). However, to our knowledge this is the first study to show a direct relation between dynamical flexibility and adaptive task performance. Specifically, average tracking accuracy was better in subjects who showed a larger range in between task DFA output. These findings provide preliminary evidence for a number of research directions. Future studies could expand our understanding of influential factors such as aging and pathology on dynamical flexibility. Furthermore, learning and rehabilitation paradigms could examine how affected populations can go about increasing their dynamical flexibility. These prerequisite steps could influence how practitioners instantiate future interventions for adaptive behavior.

The perception that adaptive capacity is explicitly reflected by the emergent dynamics of a system performing under ideal conditions is, in our estimation, fundamentally erroneous. Such an approach infers that the only relevant constraints governing adaptive coordination and behavior come from the system itself (ie. organismic). This also extends to the assertion that optimal behavioral dynamics can be universally characterized as a $1/f^1$ process, as this undervalues how a lifetime of environmental and task constraints shape system dynamics in the service of adaptive behavior.

Thus, a metric for adaptability requires the implementation of contextual constraint so as to estimate individual’s dynamical flexibility in relation to behavioral performance. This in turn also provides insight into causal factors describing the plausible deviations in intrinsic dynamics from paradigm to paradigm that may predict optimal performance. For example, we speculate that the nature of manual dexterity requires a continual modulation of the degrees of freedom relevant to kinetic output. In which case the necessity to either switch or shift from rhythmic to fixed point control may have be responsible for resultant intrinsic dynamics. Furthermore, proximity of intrinsic dynamics to each task may relate to flexibility. Figure 4.5 clearly shows that the most adept subjects exhibited self-selected force DFA ~ 1.30 in conjunction with a greater range in between task DFA. While such an explanation is speculative at best, we contend our general approach holds inherent value to advancing insights into complexity and adaptive behavior.

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Tables

Table 4.1

Regression equations describing isometric tracking accuracy (|CE|), and shifts in DFA (α) as a function of self-selected force DFA (α)

	Polynomial regression equations			Goodness of fit
Dependent variables	a	b_1X	b_2X^2	R^2
Standard model:				
Constant Target CE	0.0248	0.0085	0.0213	0.34
Pink Target CE	0.0276	0.0114	0.0188	0.29
Sine Target CE	0.0398	0.0067	0.0152	0.43
Weighted model:				
Constant Target CE	0.0223	0.0031	0.0088	0.78
Pink Target CE	0.0231	0.0302	0.0246	0.72
Sine Target CE	0.0339	0.0077	0.0450	0.41
Standard model:				
SS x CN Shift	0.434	-0.442	---	0.21
SS x PK Shift	0.583	-0.533	---	0.43
SS x SN Shift	1.042	-0.726	---	0.37

Note: The first standard model section and subsequent weighted model sections represent regression equations describing force tracking accuracy as a function of force complexity. The presence of heteroscedasticity within functions was addressed in the weighted model section, where we fitted models utilizing the bi-square weight method for robust least squares regression. This method implements an iteratively reweighted least-squares algorithm for calculation. Unique weights are applied to every data point according to their proximity with the fitted function, thereby limited the impact of extreme outliers. The third standard model section represent linear regression equations for the shift in mean DFA as a function of self selected DFA.

Table 4.2

Multiple regression equation describing overall isometric tracking accuracy (|CE|) as a function of self-selected force DFA, and average shift in task relevant force DFA ($R^2 = 0.54$)

	B	SE *B*	*t*	*p*	*VIF*
Constant	4.719	1.463	3.225	0.004	---
SS-DFA	-7.111	2.221	-3.203	0.004	1012.514
SS-DFA^2	2.722	0.839	3.245	0.003	1016.025
Av. DF-Shift	-0.196	0.071	-2.777	0.010	1.113

Note: The dependent variable for regression was individual's averaged |CE| between tracking conditions. SE = standard error for *B*. VIF represents the collinearity statistic variance inflation factor. Significant structural collinearity was expected between both self selected DFA terms, however the primary variable of interest in this statistic is average DFA shift.

Figures

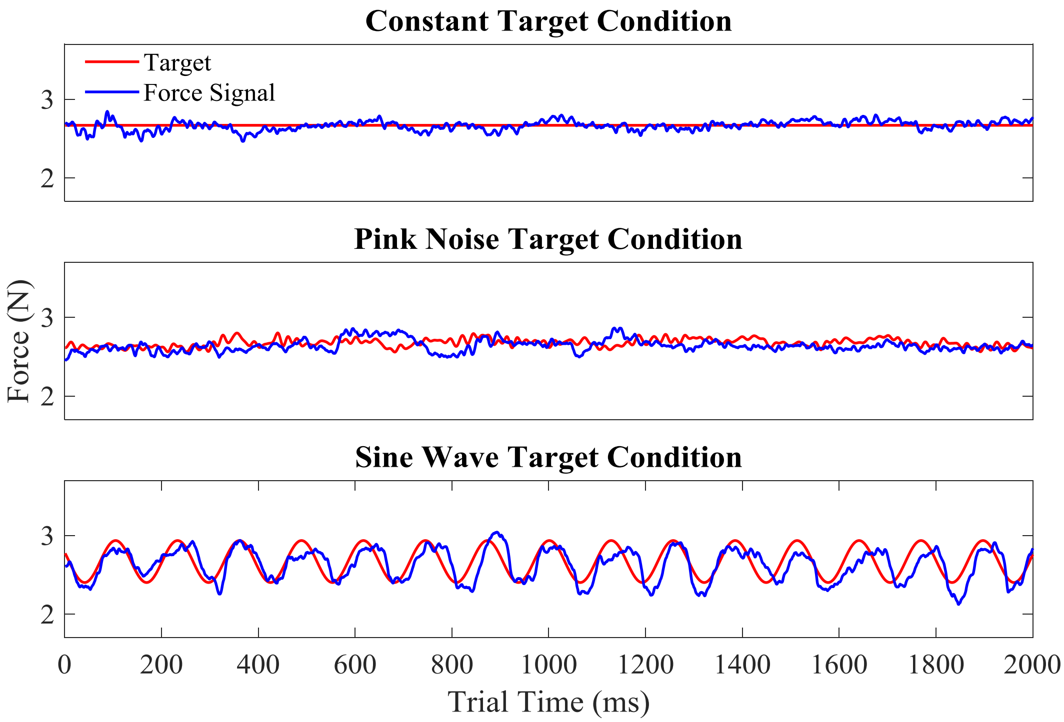

Figure 4.1. Example of force-time series in the constant, pink noise, and sine wave tracking conditions. All trials are the 15th trial from the same subject across conditions.

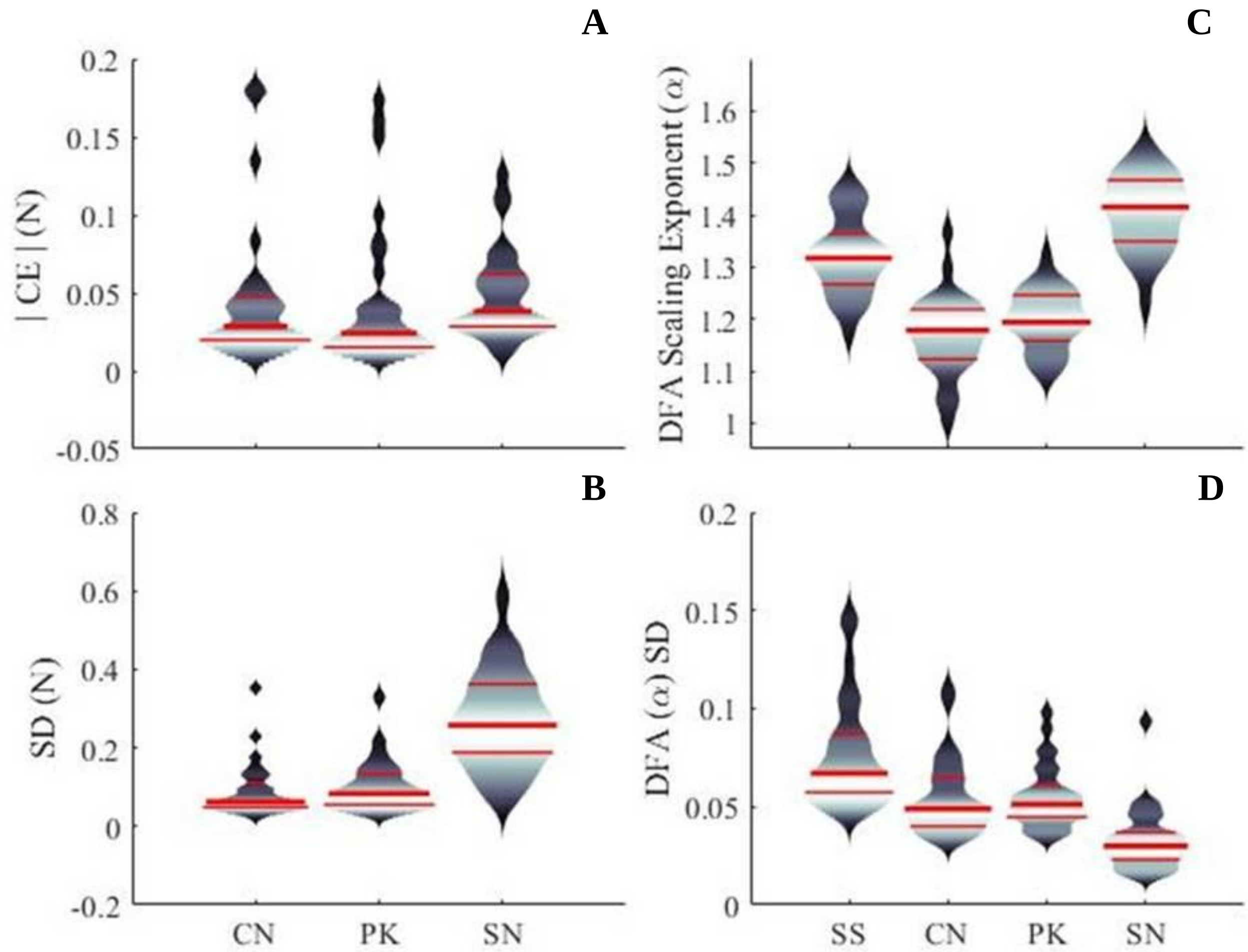

Figure 4.2. Violin plots demonstrating changes in young healthy subject's mean absolute CE (A), mean SD of force output (B), mean DFA scaling exponent (α) (C), and subject's between trial SD of their DFA scaling exponent (α) (D) as a function of force tracking conditions (SS= Self Selected Force, CN= Constant Target, PK= Pink Target, SN= Sine Wave Target). Each condition distribution is presented, in which color spectrum corresponds to frequency cluster. The higher a frequency of occurrence, the lighter the color under the curve. The red lines correspond with each conditions Interquartile Range (IQR).

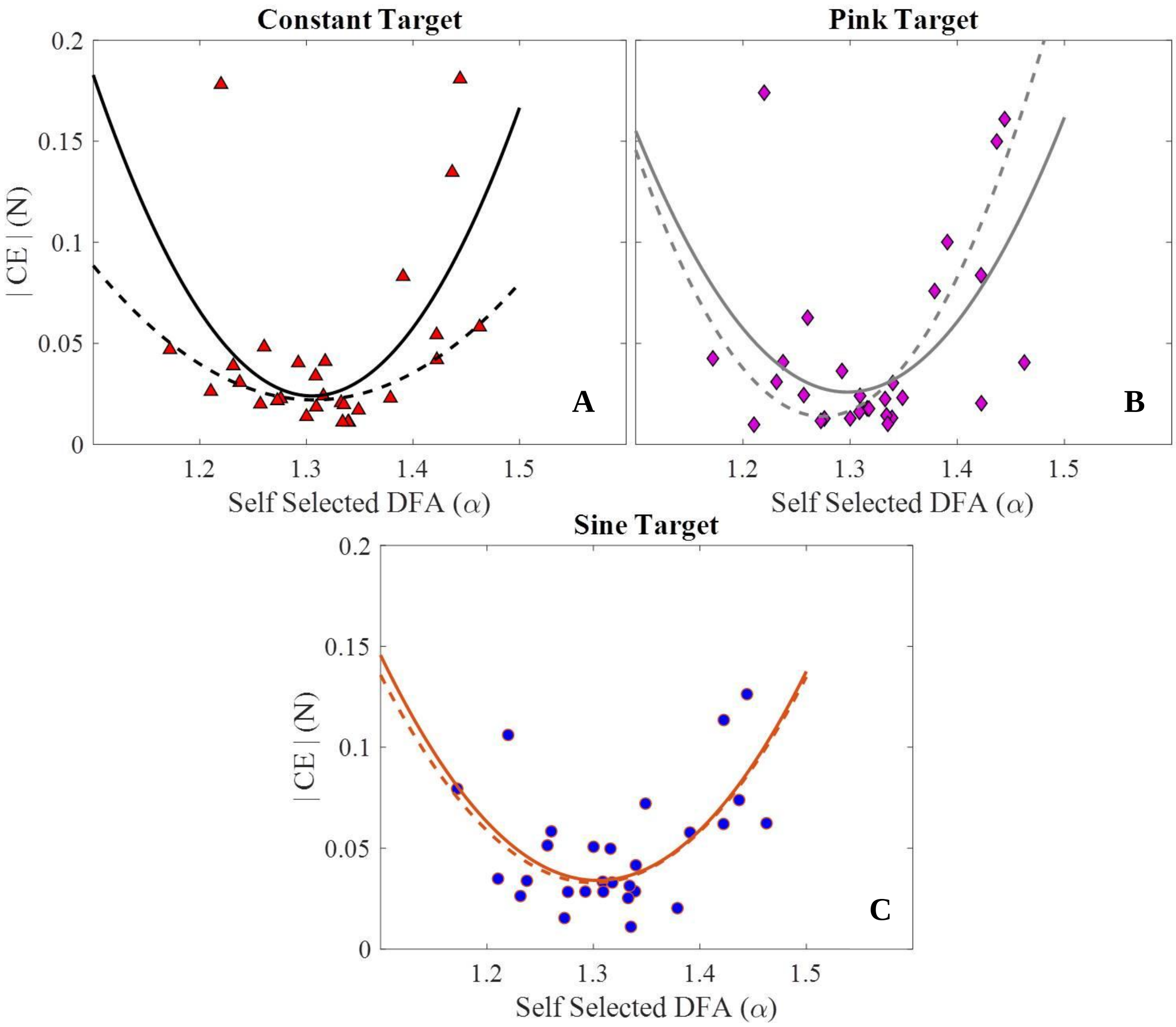

Figure 4.3. Individual's mean tracking accuracy (|CE|) as a function of mean DFA scaling exponent across all tracking conditions. The solid line represents a 2nd order polynomial least squares fit. The dashed line represents a 2nd order polynomial least squares fit when a bi-square reweighting algorithm is implemented. The corresponding regression equations for all fitted functions can be found in the first and second sections of table 1.

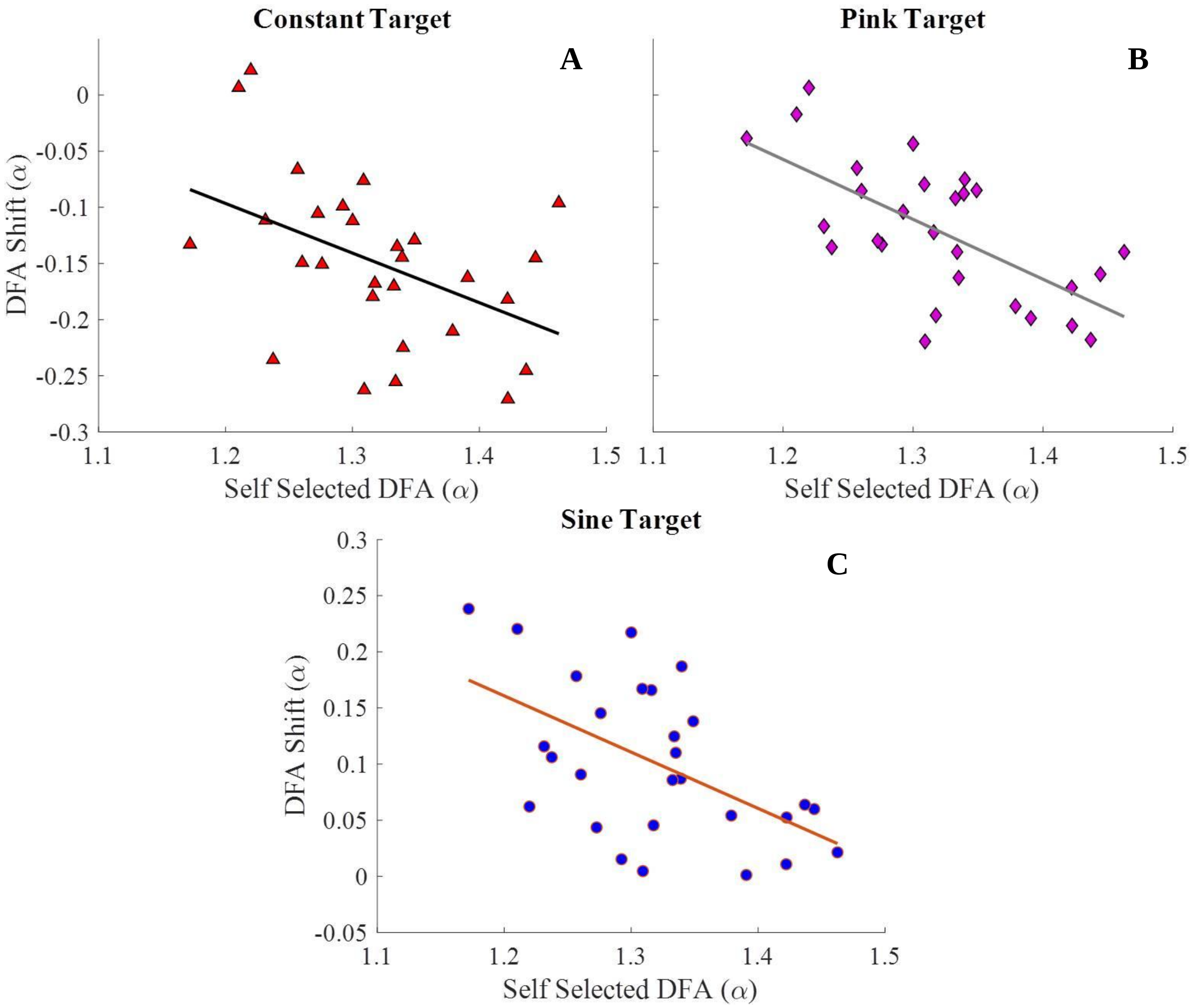

Figure 4.4: Shift in mean DFA scaling exponent according to tracking task as a function of self selected DFA. The regression equations for all fitted lines can be found in the third section of table 1.

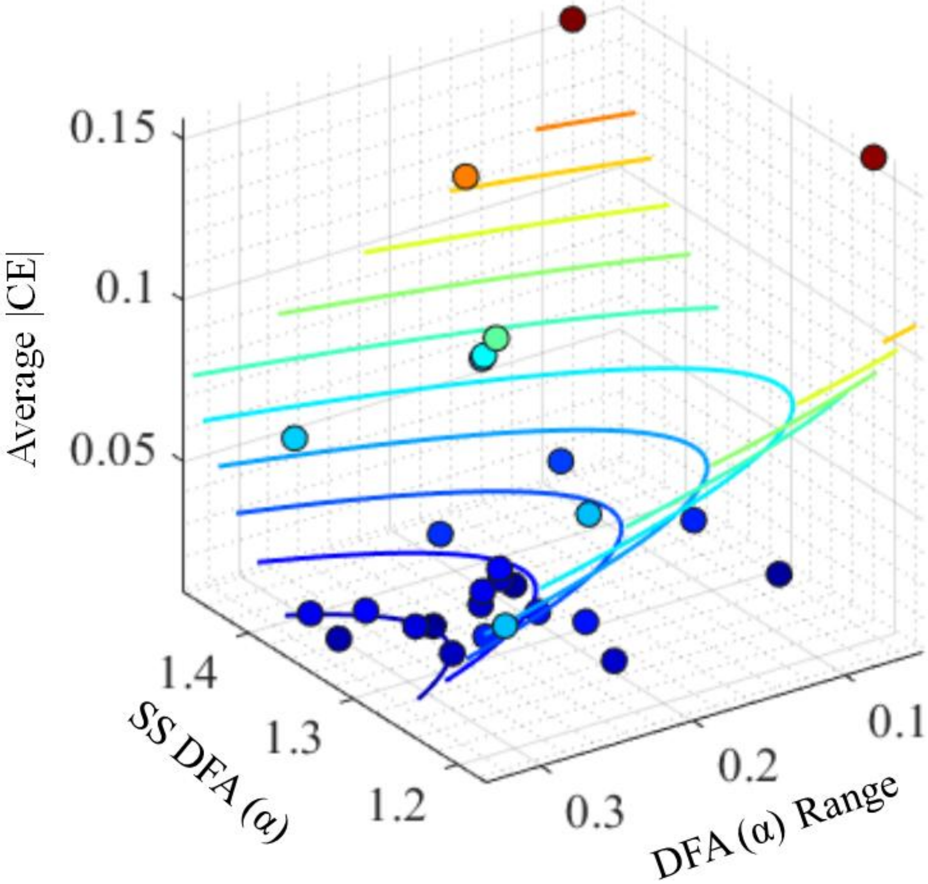

Figure 4.5: General tracking accuracy (average |CE|) as a function of intrinsic force dynamics (self-selected DFA) and dynamical flexibility (average difference between sine/constant & sine/pink target DFA). The contour surface corresponds to the multiple regression equation in Table 2.

CHAPTER 5

THE ROLE OF COMPLEXITY MATCHING ON INTRINSIC, AND TASK SPECIFIC ISOMETRIC FORCE DYNAMICS: A PRACTICE STUDY[2]

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[2] Novak, T. S. & Newell, K. M. To be submitted to *Nonlinear Dynamics, Psychology, and Life Sciences*

Abstract

Previous research has developed opposing perspectives on the role of system dynamics, and more specifically the degree of temporal complexity in these dynamics, as an index of adaptability. Based on these views, current literature is also extending beyond the level of system description to the domain of rehabilitative intervention. An active hypothesis is that $1/f^1$ dynamics represents an optimally adaptive system, and thus intervention studies should strive to elicit this output in individuals minimally constrained behavior. Recent findings suggest that the complexity matching phenomenon is a viable approach to establishing greater complexity in behavioral dynamics according to dyadic interaction, or perceptuo-motor coupling. This study tested whether the degree of complexity embedded in a visual stimulus led to unique alterations in complexity of force output with practice. Furthermore, we tested the hypothesis that practicing a $1/f^1$ target was superior in facilitating adaptive force control. Twenty subjects were instructed to perform 5 days of tracking practice in either a pink noise ($1/f^1$) or brown noise ($1/f^2$) tracking target. Their preferred-force dynamics were assessed prior to the start of practice, and directly upon its completion. Furthermore, a transfer condition was implemented where the pink group switched to a brown target, and the brown group tracked a pink target. Both groups preferred-force dynamics were more complex after practice, however, their force dynamics in the tracking task could be differentiated according to their target assignment. No differences in transfer performance were found between the two practice regimes. Together, these results suggest that complexity matching may facilitate unique changes to force dynamics according to visuo-motor

constraint, however differing temporal patterns may lead to similar changes in minimally constrained behavior.

Introduction

Essentially all observable actions and outcomes from a biological system are fundamental expressions of the coordination of a complex system. Behavioral dynamics in human movement is exemplary to this concept, as even the most mundane activity necessitates coherent coupling of system components functioning through a nested array of spatio-temporal scales (ie. neural, musculoskeletal, biomechanical). To that end, a growing body of literature has established that measures of time and frequency dependent fluctuations in human output lend insight to underpinning dynamics contributing to intrapersonal coordination (Passos et al., 2009; Rhea, & Kiefer, 2014). Specifically, long memory $1/f^{\alpha}$ fluctuations often exhibited in human output are representative of a system coordinated via interaction-driven dynamics. However, the functional significance of $1/f^{\alpha}$ fluctuations in human behavior, that is the quantified expression of system complexity, continues to be a point of scientific conjecture (Wijnants, 2014).

Reliable description of a systems coordination dynamics has been historically limited to studies on bi-manual rhythmic coupling (Haken, Kelso, & Bunz, 1985; Kelso, 2012; Tognoli, & Kelso, 2014). However, contemporary research in motor behavior and neurophysiology is expanding to a variety of movement paradigms according to the premise that temporal correlations of human time series describe: a) the adaptive state of an individual's coordinated behavior (Den Hartigh, Cox, Gernigon, & Van Yperen, 2015), and b) how these properties change with breakdowns in coordination as a result of, for instance, frailty (Lipsitz & Goldberger, 1992; Lipsitz, 1994), pathology (Goldberger et al., 2002), and mal-adaptation (Thurner, Mittermaier, & Erhenberger , 2002). Current trends in complexity research point to prospective influence in the domain of applied rehabilitation (Uchitomi et al., 2011; Manor, & Lipsitz, 2013; Marmelat et al., 2014; Hove, & Keller, 2015). However, at present there are two distinct interpretations regarding the relationship between complexity of system dynamics and adaptive capacity. While there is relative autonomy between these approaches in empirical study, their general aims correspond with developing future intervention paradigms to improve an individual's neuro-motor function.

Advocates of the *loss of complexity* (LOC) (Lipsitz & Goldberger, 1992) and *optimal variability* (OV) (Stergiou & Decker, 2011) frameworks operate according to the premise that $1/f^1$ fluctuations, also known as fractal pink noise, is the optimum in system adaptability. This logic stems from the notion that pink noise dynamics represents a system that best accommodates stability and flexibility in their dynamical organization (for extensive review, see Van Order, Kloos, & Wallot, 2011; Harrison, & Stergiou, 2015). More structured output (~ $1/f^2$, brown noise) is indicative of increased stability at the expense of flexibility, as fewer component-interaction pathways are predominating in behavior. However, a more robust system presumably limits the capacity for adaptive reorganization of the system when appropriate. Uncorrelated output (~ $1/f^0$, white noise) indicates a lack of system stability, presumably via breakdowns in component-interaction pathways.

A key point of debate on this approach, however, is the lack of concrete understanding as to why long-range correlations in behavior are so inclined to modification with varying degrees of constraint on action (Wijnants, 2014). Marginal attempts have been made to explain this phenomenon (Van Orden, Kloos, & Wallot, 2011), however, the more prevalent approach consists of experimental paradigms implementing minimally constraining tasks to compare populations of interest (Kello et al., 2007). Nevertheless, this method has successfully illustrated $1/f^1$ fluctuations in minimally constrained behavior of young healthy subjects across a number of neuro-motor tasks (Kello et al., 2008, 2010; Van Emmerik et al., 2016).

The *loss of adaptability* (LOA) framework (Vaillancourt & Newell, 2002, 2003) emphasizes adaptive capacity according to an individual's ability to reorganize system dynamics in accordance with dimensional demands of a specified task. This premise is built on the interpretation that cross-scale elements and processes embedded in the system represent degrees of freedom (DoF's) (ie. neural pools, motor units, joint relations, etc.) operating across multiple system levels. Furthermore, a confluence of individual, environmental, and task constraints govern the dynamical organization of a system as a means to facilitate appropriate behavior (Newell, 1986). The ability to modify functional degrees of freedom according to task dimensionality- be it towards a more or less complex behavioral output- is thus considered to be a better reflection of system adaptability. This requires experimental studies to expressly modify task constraint, and in doing so have found differences in flexibility of behavioral dynamics as a function of aging and degeneration in health (Sosnoff & Newell, 2008; Sosnoff, Valantine, & Newell, 2009; Studenka & Newell, 2013).

To reiterate, the distinguishing factor between frameworks studying complexity as adaptability is their focus on system dynamics according to imposition or limitation of constraint. The LOC/OV frameworks are essentially emphasizing system adaptive capacity through observation of an individual's intrinsic dynamics. Conversely the LOA approach emphasizes the role of constraint on action, and subsequently the ability to modulate system dynamics in response to task manipulation. In either case, a primary objective beyond description of adaptive capacity is to optimize practice/training interventions and integrate them into contemporary rehabilitative modalities. A relatively novel perspective on complex system coordination provides rationale for functional modifications in system complexity, and is currently considered a viable basis for intervention development.

The *complexity matching* approach is being used to characterize inter- and intra-system coordination across a range of perceptuo-motor paradigms. This includes dyadic interaction (Coey, Washburn, Hassebrock, & Richardson, 2016), coupling to complex stimuli (ie. dynamical timers) (Rhea, Kiefer, D'Andrea, Warren, & Aaron, 2014), intra-system coordination (ie. autonomic and central nervous system processes) (Rigoli, Holman, Spivey, & Kello, 2014) and explanation of neural network structures (Mafahim et al., 2015). The overarching principle predicting complexity matching is predicated on system(s) capacity and inclination to coordinate or synchronize their behavioral dynamics as a means to optimize information exchange (West, Geneston, & Grigolini, 2008) (for extended discussion, see Sokolov, Klafter & Blumen, 2002). An ancillary extension of this premise proposes that in the event that two systems differ in their respective complexity, the less complex system will act in subordination and subsequently alter their dynamics according to output of its counterpart (Mahmoodi, West, & Grigolini, 2018).

Support for complexity matching beyond theoretical conjecture is based on empirical evidence of convergence in $1/f^{\alpha}$ fluctuations of interacting systems (or system levels) in several movement paradigms (Hunt, McGrath, & Stergiou, 2014; Coey et al., 2018; Schloesser, Kello, & Marmelat, 2019). Detailed analysis within these studies has found that dynamical convergence is accomplished through a culmination of two neuro-motor processes. There is a local synchrony, which is representative of short time scale coordinated behavior. An example of this would be dyadic mimicking, in which an individual adjusts their movement according to short time-scale observations of their partners behavior. The second process, known as global complexity matching, is believed to occur when the system itself begins to inherently shift behavioral dynamics in correspondence with its counterpart (Fine, Likens, & Amazeen, 2015; Deligniéres, Almurad, & Roume, 2016).

Recent studies advocating the pink noise optimum approach have tested whether complexity matching is a viable option for "re-establishing" individual dynamics. Specifically, researchers have implemented fractal ($1/f^1$) stimuli (auditory timers) (Hove, Suzuki, Uchitomi, Orimo, & Miyake, 2012), or used dyadic interaction (between young and elderly) (Almurad, Roume, & Delignieres, 2017; Almurad, Roume, Blain, & Delignieres, 2018) paradigms to assess coordinative shifts within and between individual outputs. Almurad and colleagues (2018) studied minimally constrained gait dynamics of the elderly, followed by an intervention where they walked side by side with young subjects over a course of 12 testing sessions. As a follow up, subjects performed a retention session where they walked individually. The study found that elderly subjects shifted parameters of their gait dynamics towards $1/f^1$ fluctuations (from white noise) with practice, and to some extent exhibited a degree of retention in complex gait dynamics. Furthermore, they found that both local synchrony and global complexity matching remained present in a subject's behavior across practice.

The general assumptions of the complexity matching approach coincide with tenets of LOC and OV. They theorize that the true optimum of information exchange is directly reflected in $1/f^1$ behavior (Mahmoodi, West, & Grigolini, 2018), and thus subsequent intervention should attempt to re-establish pink noise fluctuations in an individual's behavioral dynamics. However, in our estimation such a rigid view blatantly disregards the evidence suggesting that movement dynamics emerge as a consequence of constraint on action (Newell, 1986; Kugler, & Turvey, 1987). This is exemplified by studies that show unique changes in subjects behavioral dynamics according to specific spatio-temporal properties embedded in perceptuo-motor tasks (Vaillancourt & Newell, 2002; Newell, Broderick, Deutsch, & Slifkin, 2003; Studenka et al., 2014). Thus, the confluence of constraints that pervade coordinated behavior could logically alter intrinsic dynamics across the complexity continuum if there is adaptive benefit according to prevalent factors beyond information exchange. For example, Hoos and colleagues (2014) found that total marathon race times were lower in individuals who's stride dynamics were closer to $1/f^2$ brown noise fluctuations. A plausible explanation on the relation behind better performance and more regular behavior could be reflected by dynamical economy that emerges in the service of bio-energetic efficiency. In such a case, it is logical to assume that adaptable individuals who train with more established partners could act in subordination, thereby exhibiting less complex stride dynamics. Moreover, there is no reason to believe that this case would not also show a combination of local and global matching processes contributing to adaptive coordination and control.

The purpose of this study is to examine whether a subject's intrinsic force dynamics can be changed with practice, and if so whether the direction of change is proportional to the complexity embedded within the respective task. To test this, subjects practiced an isometric tracking task according to a force target that had a temporal structure corresponding with either $1/f^1$ pink noise (DFA = 1.0), or $1/f^2$ brown noise fluctuations (DFA = 1.5). We tested the hypothesis that subjects will show shifts in their intrinsic force complexity, where the direction of change will relate their assigned practice target.

Empirical evidence suggests that the complexity matching phenomena observed in the motor control literature results from a combination of local synchronization and global complexity matching processes. Provided the theoretical position that complexity matching is beneficial for adaptive coordination, a primary question is whether these phenomena can be harnessed by way of complex system-system or system-stimulus interaction. However there is limited understanding on the complementary relation of both processes, in addition to how their contributions to coordinated behavior changes with time. As an extension, complexity matching is exclusively discussed in terms of the proposed ideal circumstance where at least one system or corresponds with $1/f^1$ dynamics. However, adaptability relates to the capacity to coordinate and perform in circumstances that may not fit this criterion. Thus, a supplementary aim is to test whether there are differences in both local and global matching processes over time according to the target complexity in which they are assigned. We hypothesize that global complexity will continue to change over practice for both groups, whereas changes in local synchronization will be exhibited primarily in the beginning stage of practice.

Perhaps the most important question along this line of research is whether we can distinguish a specific practice regime as superior for developing adaptive behavior. We believe that adaptability in this paradigm is represented by the combination of flexibility in force dynamics according to tracking demands in conjunction with the ability to perform each task with a high degree of tracking accuracy. Thus, a transfer task was implemented in our study to test whether tracking groups differed in their ability modulate force dynamics, and accurately track a force target with a novel dynamical pattern. We hypothesized that both groups would show a characteristic shift in their force complexity according to the temporal demands of the transfer task, and in doing so there would be no difference in their capacity to accurately track the transfer target. Global complexity matching processes appears to be the primary focus in much of the contemporary literature. However, our hypothesis of no differences in group tracking performance is based on the assumption that early adaptive coordination is in part reliant on changes to local synchronization processes. We do not know whether the proportional contribution of local correction processes is driven by interaction dynamics (task constraint) or if there is a generalized pattern exhibited across testing conditions. Thus, an exploratory component of this paper addresses whether we see differences between groups in terms of local synchronization at the beginning and end of practice, in addition to in the transfer tracking condition. If this process is a generalized feature, we would expect local synchrony patterns to relate on day 1 of practice and transfer of both conditions. Conversely, we would expect to see groups diverge in the transfer condition if local synchrony is driven according to task constraint.

Methods

Subjects

Two groups (n=10 per group) of self-reported right-handed subjects (Group 1: age: (26) ± (4) years, 5 Male; Group 2: age (27)± (5) years, 5 Male) from the University of Georgia population participated in this study. The subjects were not trained in fine manual tasks, were not competitive weight lifters, and had no previous history of neurological disorder. It should be noted that six participants from Experiment 1 also took part in this study. Written informed consent was obtained from all participants in congruence with the IRB approval from The University of Georgia.

Procedures

Subjects were given approximately 5 min of familiarization with procedures related the experimental protocol before testing. Participants were instructed to apply force on a load sensor via abduction at the distal phalanx of the index finger on their dominant hand. During familiarization, subjects were provided feedback of all three dimensions of force (Fx, Fy, Fz) and moments (Mx, My, Mz). Subjects were instructed to attend to feedback of their normal force (Fz), and asked to manipulate different force levels in order to explore their force preference. The non-dominant hand rested in a homologous position while testing commenced. Upon familiarization, individual maximum voluntary contraction (MVC) was calculated by having subjects produce their maximum force over 3 trials at 6 s per trial. While MVC was not utilized in any way for experimental setup, we collected absolute force capacity in order to determine whether this was a contributing factor to differences in individual and group force characteristics.

Before any tracking tasks were introduced, all subjects were asked to produce 15 trials (20 s duration) of their preferred force. Subjects were not provided visual feedback of their output during any portion of the trial, however, they were notified on screen when each trial was completed. Upon trial block completion, individual force properties were assessed to match each experimental target to the confines of their preferred force distribution.

Participants were pseudo-randomly assigned to one of two experimental groups: pink noise target (DFA: $\alpha = 1.0$), or brown noise target (DFA: $\alpha = 1.5$) tracking conditions. Subjects tracked their assigned target for 5 consecutive days at 30 trials per session. The first testing session took place after subjects produced their 15 self-selected force trials. During the tracking task, subjects were provided knowledge of results (KR) at the end of each trial providing them with their Root Mean Squared Error (RMSE). In an effort to limit any influence of fatigue, subjects were required to take a minimum 1 min break after every 5 trials until the testing session was completed. Subjects were asked to match the target to the best of their ability, while attempting to continually minimize the RMSE score within every trial.

Upon completion of their 5th practice session, subjects performed the same preferred force protocol specified on testing day 1. Thereafter, subjects performed a transfer task, in which the pink noise practice group performed 15 trials of the brown noise target condition, and the brown noise practice group performed 15 trials of the pink noise target condition.

Force Variability and Accuracy: Task performance was assessed through within trial standard deviation (SD), and absolute constant error (|CE|) of the subjects force output in all trials and tracking conditions (practice (days 1-5), transfer (day 5) target conditions).

Structure of Variability. Detrended Fluctuation Analysis (DFA) (Peng et al., 1995) was used to calculate force complexity of every trial for individual's self-selected force (days 1 & 5), practice (days 1-5), and transfer (day 5) conditions. Subjects average DFA scaling coefficient (α).

Force Synchrony: Wavelet cross-coherence was used to assess how subjects synchronized their force output to each tracking target. Within this technique, each signal (ie. 1/f target and subjects force output) undergoes spectral decomposition, which then allows for assessment of the strength of synchrony between subject force and target oscillations across the continuum of relevant frequencies (for extended review, see Grinsted, Moore, & Jeverejeva, 2004). Much like DFA in the time domain, wavelet cross-coherence is a robust analysis technique when working with non-stationary datasets. A Morlet wave of order 12 was used for our analysis. We assessed coherence at 6 frequency scales by partitioning all coherence time points within the 0-2, 2-4, 4-6, 6-8, 8-10, and 10-12 Hz frequency bands. Point to point coherence values were averaged across time within each frequency band, followed by an averaging of all values within each 2 Hz band of interest. This analysis was performed on all trials for the practice and transfer tracking conditions.

It is important to note that we illustrated the contribution of local synchrony and global matching according to the changes in DFA (global) in addition to alteration in wavelet cross-coherence (local). It is extremely difficult to partition both processes, however if changes to both variables are non-proportional, we can infer a shift in their relative contributions over time.

Inferential Statistics: In order to assess how each dependent variable of interest changed as a function of practice (both within and between days) the average output across 10 consecutive trials was calculated prior to inferential analysis. A three-way (2 group x 3 block x 5 day) mixed between-within subject repeated measures ANOVA was performed on the dependent variables DFA, | CE |, and SD.

The effect of practice on changes to individual force complexity was assessed with a two-way (2 group x 2 day (day 1 & day 5 SS force conditions) mixed between-within subject repeated measures ANOVA on subjects averaged DFA.

A two-way (2 group x 2 tracking condition) mixed between-within subject repeated measures ANOVA was performed on the dependent variables | CE |, SD, and DFA. This was done to assess practice regime revealed differences in ability to modulate force dynamics and tracking performance according to novel tracking constraints. For each dependent variable, the last 15 trials on practice day 5 were averaged and compared to the transfer condition.

Two separate ANOVA's were used on wavelet-coherence measures. First, a three-way (2 group x 5 day x 6 frequency band) mixed between-within subject repeated measures ANOVA was used to assess how local synchrony processes evolved over 5 days of practice. Another three-way (2 group x 3 day x 6 frequency band) mixed ANOVA was used with the first 15 trials of practice day 1, last 15 trials of practice day 5, and the 15 transfer task trials. This explored whether local synchronization processes operate in a generalized fashion, or if task constrain drives proportional contributions across the relevant frequencies.

All statistical analyses were considered to be significant when the probability of making a type 1 error was less than 5% ($p < .05$). If the assumption of sphericity using Mauchly's test was violated, a Huynh-Feldt correction was used to adjust the statistical degrees of freedom. Only those main effects and interactions that were significant ($p < .05$) are reported. Analyses were performed using IBM SPSS software.

Results

Figure 5.1 provides an illustration individual's force time-series according to both the pink noise (1a) and brown noise (1b) tracking conditions, respectively. Subjects produced an average absolute force of 3.1 N (SD: 2.2 (N)) in the initial self-selected force testing condition, followed by 2.9 N (SD: 1.8 (N)) in post-practice self-selected force. Subjects preferred force output remained stable after testing, as indexed the strong positive correlation between subjects pre and post self-selected force exhibited in Figure 5.2 ($R=0.83$).

Force DFA as a function of practice

Figure 5.3a illustrates how DFA changed as a function of practice for both tracking groups. The corresponding ANOVA revealed a significant main effect of group, ($F(1, 18) = 4.64$, $p < 0.05$, $\eta_p^2 = 0.82$) with the brown noise practice group exhibiting a larger DFA scaling coefficient throughout practice (brown noise group ($\alpha = 1.15$), pink noise group ($\alpha = 1.09$)). The main effect of day was nearly significant ($p = 0.053$), in which the pink noise tracking group showed a consistent decrease their DFA scaling coefficient across practice days. The brown noise tracking group generally exhibited a steady DFA scaling coefficient across all days of practice.

Tracking performance as a function of practice

Tracking accuracy: There were no significant main effects or interactions on tracking accuracy as indexed by | CE |.

Force Variability: Analysis of group force variability (SD) as a function of practice revealed significant main effects of day,(F(1.43, 25.67) = 6.82, p = 0.008, η_p^2 = 0.28), testing block, (F(1.56, 27.85) = 9.69, p < 0.001 , η_p^2 = 0.04), in addition to a significant day x block, (F(2.33, 41.85) = 4.19, p < 0.05, η_p^2 = 0.19) interaction. Post-hoc analysis found that subjects SD was highest in the first 10 trials (block 1) for the first three days of practice (all p < 0.05). After three days of practice force variability became consistent across trial blocks. Both groups showed the greatest decrease in force variability within the first three days of practice.

The results of both tracking accuracy and force variability are illustrated on figure 5.3c. As stated the results, subject's in both groups showed the highest SD in the first block of the early practice days. Otherwise the performance measured remained relatively stable for both practice groups.

Self-selected force dynamics

Figure 5.4a illustrates how practice regime influenced individuals self-selected force DFA. The corresponding ANOVA revealed a significant main effect of day, (F(1, 18) = 12.13, p = 0.003 , η_p^2 = 0.40). Both groups exhibited a decrease in their DFA scaling coefficient in their post testing preferred-force condition (pre: α = 1.30, post: α = 1.23).

Transfer

DFA: Force dynamics as a function of practice group, and condition (practice vs. transfer) are illustrated in figure 5.4b. The corresponding ANOVA revealed a significant group x condition interaction, (F(1,18) = 18.10, $p < 0.001$, η_p^2 = 0.50). Post-hoc analysis found a significant divergence in DFA scaling coefficient in the practice condition (pink: $\alpha = 1.06$, brown: $\alpha = 1.14$)($p = 0.02$), however there was a convergence in scaling coefficient between groups when they performed the transfer task. Additionally, the pink noise practice group showed a larger shift in DFA between the practice and transfer condition compared to the brown group (practice: $\alpha = 1.06$, transfer: $\alpha =1.11$, $p < 0.001$).

Tracking Performance: Significant group x day interactions were found for both tracking accuracy (| CE |), (F(1,18) = 9.16, $p < 0.01$, η_p^2 = 0.34) and force variability (SD), (F(1,18) = 6.60, $p < 0.05$, η_p^2 = 0.27) between the day 5 of practice and transfer. Post hoc analysis revealed that the major differences in tracking performance were on day five of practice (both $p < 0.05$). It should be noted that there was a slight increase in tracking error for the brown noise group on the fifth day of practice compared to day's 1-4. However, in the transfer condition, accuracy and force variability converged between the two groups.

Synchrony

Figure 5.5 illustrates the between-groups differences in cross-coherence across the partitioned bandwidths according to practice days 1, 5, and transfer. Line colors coincide with the colored noise structure that each group/individual practiced. This was maintained in the transfer condition, and so the pink line still represents the pink group performing the transfer task, and vice versa. The wide solid lines represent group averages, while the smaller lines show individuals average coherence within each band.

Practice: Analysis of variance revealed significant main effects of frequency, (F(1.51, 27.10) = 25.78, $p < 0.001$, η_p^2 = 0.59), and day, F(4, 72) = 6.10, $p < 0.001$, η_p^2 = 0.25), in addition to significant frequency x group, F(1.51, 27.10) = 3.90, $p < 0.05$, η_p^2 = 0.18) and frequency x day, F(7.22, 129.94) = 4.18, $p < 0.001$) interactions in wavelet-coherence as a function of practice.

A comprehensive report of pair-wise comparisons can be found after the reporting of transfer coherence. However, here we highlight that both groups showed the greatest alteration to their force synchrony over practice days in the 0-2 Hz. frequency band. Specifically, 0-2 Hz. coherence increased significantly ($p < 0.05$) in the first three days of practice. Thereafter coherence stabilized for both practice groups.

Transfer: A significant main effect of frequency, (F(1.89, 33.95) = 23.36, $p < 0.001$, η_p^2 = 0.57), along with significant day x group, (F(1.42, 25.62) = 6.19, $p < 0.05$, η_p^2 = 0.26), day x frequency, (F(4.64, 83.47) = 2.71, $p < 0.05$, η_p^2 = 0.13), and day x frequency x group, (F(4.64, 83.47) = 7.51, $p < 0.001$, η_p^2 = 0.29) interactions were revealed in wavelet cross-coherence as a function of transfer.

The brown noise practice group only showed significant shifts of coherence in the 0-2 Hz. frequency band between all days. There was a large increase in coherence at this band when comparing days 1 and 5 of practice ($p = 0.04$). However subjects decreased their coherence in the transfer condition (tracking pink noise target) to a level of synchrony that corresponded to the first practice day.

The pink noise practice group showed significant changes in coherence between days in the 0-2, 2-4, and 4-6 Hz frequency bands (all $p < 0.05$). Coherence increased between days 1 and 5 of practice in the 0-2 Hz band, and in the transfer condition synchrony increased to an even greater degree. A similar effect of practice was exhibited in the 2-4 Hz. band, however coherence significantly decreased when subjects performed the transfer task. The 4-6 Hz. band was relatively stable over practice, but this value also decreased significantly in the transfer task.

Observable differences in tracking synchrony were found between practice groups as a function of both practice and transfer. On day 1 of practice, the brown noise group showed a significantly higher coherence in the 0-2 Hz. frequency band ($p = 0.05$). Statistical significance was nearly reached in the 2-4 and 8-10 Hz. bands. Differences in group coherence were non-significant on day 5 of practice, however, the largest differences were still observed at the 0-2 Hz. band. Significant group differences in the transfer condition were found at the 4-6, and 8-10 Hz. frequency bands. While the 0-2, 2-4, and 10-12 Hz. bands were not statistically significant (all $p < 0.09$), Figure 5.5 shows the qualitative changes to group coherence when they tracked the opposite groups practice regime target as a transfer task. There was a switch in the 0-2 Hz. band, where the pink noise practice group showed a higher coherence there in the brown noise target condition. However, in this same condition, the pink group also showed greater coherence at the high frequency bands (6-12 Hz.).

Discussion

The present experiment examined the role of temporal complexity of a visual target on force coordination while subjects practiced an isometric tracking task. Furthermore, we assessed whether practice in one of two distinct targets ($1/f^2$ brown noise; ($1/f^1$ pink noise) led to unique alterations in the temporal complexity of subject's preferred force output. Current literature is emphasizing the adaptive value of "re-establishing" complexity in behavioral dynamics, and the complexity matching phenomenon appears to be a viable factor for achieving this result. It is necessary, however, to expand on practical applications of complexity matching and whether it warrants consideration beyond coincidental occurrence. Thus, the motivation of this experiment was to determine whether the degree of complexity in a perceptuo-motor stimulus influenced characteristics of system coordination, along with adaptive capacity in isometric force control.

The results show partial support for our first hypothesis in that isometric tracking practice did elicit a change to subject's preferred force dynamics. There was a strong correlation between subject's average force output on both days of practice. When instructed to produce their preferred force after day 5 of practice, we made it clear that this did not mean they should try to mimic their force output from the first testing session. Studies show that young healthy individuals demonstrate relatively stable kinematic and kinetic output (ie. stride length and frequency in normal over-ground walking) under minimally constraining movement conditions (Malatesta et al., 2010; Raburn, Merritt, & Dean, 2011). Our results extend this evidence to the force domain, and while there was relative stability of subject's absolute preferred force, they exhibited a notable change to their preferred force dynamics.

However, contrary to our expectation, practice regime did not influence the direction of change in subject's preferred force complexity. Average preferred force dynamics were more complex on day 5 for both groups, with their DFA coefficients converging to a value that fell directly between pink and brown noise fluctuations (pink DFA= 1.0, brown DFA= 1.5, pink/brown self-selected DFA= ~1.25). Thus, in our case the results do not support a bi-direction complexity matching effect. We cannot discount the possibility of a complexity matching effect on minimally constrained output for the pink noise group, however, an alternative explanation that predicts similar outcomes as those found in this study limit our capacity to clearly support it as a causal factor.

Previous isometric tracking studies have found that subjects increase their force complexity over practice when the visual target is a fixed point, or has temporal structure with specific asynchronous fluctuations (ie. white, pink) (Ranganathan & Newell, 2008; King & Newell, 2013). Spectral decomposition consistently shows increased contributions of faster frequency control processes with practice. It is suggested that this increase in spectral contribution at faster timescales illustrates the release and exploitation of redundant degrees of freedom available to the system as subjects practice force tracking (Hu & Newell, 2010; Studenka, King, & Newell, 2014). To our knowledge, this is the first study to provide evidence that this phenomenon could extend to minimally constrained force dynamics.

More importantly, these findings exemplify the necessity to differentiate whether complexity matching holds any value over interventions that can also facilitate exploitation of system DoF's in behavior over practice. Complexity matching requires a complex output from interacting systems, or both the system and perceptuo-motor stimulus (West et al. 2008). While many studies show that behavioral complexity is directly affected by task constraint, there is little data that compares how minimally constrained dynamics change with practice according to a variety of task regimes. Future studies could investigate this while expanding on their specific impacts on change and retention of the systems behavioral dynamics.

While complexity matching cannot be confirmed as a primary factor of change in subject's preferred force dynamics, this phenomenon was certainly apparent in the force tracking conditions. Overall, there were clear differences in force complexity between both practice regimes. As expected, the brown noise group showed more deterministic force output compared to the pink noise group. These results corroborate numerous studies that show differences in force dynamics according to tracking demands (Vaillancourt & Newell, 2002; Sosnoff, Valantine, & Newell, 2009). An unexpected finding, however, was the unique complexity functions over practice observed between the two groups. Specifically, the pink noise group showed a consistent decrease in their DFA output as they progressed through 5 days of practice. Conversely, DFA was consistent across all days for subjects practicing in the brown noise condition.

The aforementioned findings may hold important insight into the unique contributions of local synchrony and global complexity matching processes according to task demands. Both conditions showed consistently stronger synchrony with the longer time-scale fluctuations embedded in the force target. Moreover, changes in synchrony were most prevalent in the first three days of practice for both groups, with no changes occurring thereafter. While there was a plateau in local synchrony contributions, average DFA for the pink noise group continued to shift through the remaining session, thereby provide supporting evidence for our second hypothesis. That is, local synchrony processes increased their proportional contributions in the early to middle stages of practice. Thereafter, subjects force dynamics continued to shift towards that of the target. Thus, force dynamics continued to align with the target without relying on local synchronization, presumably through global complexity matching.

While the same trend in local synchrony was found for the brown noise group, there was never a change in their DFA output. Although the brown noise group did show a higher DFA output within the tracking condition across days of practice, the actual scaling exponent was still more proximal to pink noise than brown. We speculate that this is in part because temporal structure may interact significantly with the magnitude of fluctuations to change the actual degree of complexity matching in manual force control. Numerous studies have found the largest differences in subject's force complexity when they're performing fixed point (constant line) (DFA ~ 1.0), and rhythmic (sine wave) (DFA ~ 1.5) tracking behavior (Vaillancourt & Newell, 2002; Newell et al., 2003). There is a more deterministic pattern of rhythm in the brown noise target compared to pink, however, the predominance of very low frequency oscillations in conjunction with the relatively low wave magnitude suggests that there was still a high degree of precision control in the task. This does not discredit a complexity matching effect, as the brown noise group was sensitive to the force structure enough to maintain a more deterministic output. However temporal-structure alone may not drive global changes to system dynamics in a bi-directional manner. Manual coordination functions across a continuum of tasks that emphasize varying degrees of fine motor and rhythmic behaviors. Future studies could examine the influence of both magnitude and structure of system/stimulus fluctuations on complexity matching, and whether there is a change in coordinative behavior according to their interaction. If so, there is still a possibility for a bi-directional complexity matching effected as proposed in hypothesis 1.

To reiterate, a transfer condition was implemented in this study to determine whether practice of a specific target influenced subject's adaptive capacity. Specifically, we wanted to test whether assumptions that the pink noise condition is a superior training modality could be substantiated.

As expected, there was an interaction effect on DFA between groups when comparing day 5 of practice and the transfer condition. Average DFA for the pink noise group shifted to a higher value in transfer, while average DFA decreased for the brown noise group. What is interesting is the fact that while the direction of shift was as expected, the absolute value of average pink group DFA was higher when tracking the brown noise target than average brown group DFA was when tracking the pink target. This was not statistically significant, however, it did also correspond with the pink noise group showing higher coherence of the faster frequency bands in the transfer (brown noise) condition. It is possible that the pink noise condition did allow subject's to better attune to the faster frequencies in both tracking conditions. However, this did not correspond with any changes in their ability to accurately track the transfer target. Performance was comparable for both groups, which suggests that in terms of traditional adaptive performance, neither condition showed superiority.

It is apparent that local synchronization at slower frequencies predominates in force control. We found that there was a switch in pattern coherence strength between practice groups in the transfer task. Essentially, local synchrony patterns appear to be highly task specific in the young healthy population. While previous studies suggest that overall dynamical flexibility under varying constraint is predictive of adaptive behavior (Vaillancourt & Newell, 2002; Novak & Newell (in preparation)), it is yet to be determined how local and global matching processes are altered according to adaptation, mal-adaptation, or system degradation.

Conclusion

In conclusion, we provide supporting evidence that practice facilitates change in minimally constrained force complexity. Complexity matching patterns differed between practice groups during force tracking, in which the contribution and evolution of global matching was unique to the complexity embedded in the force target. However group differences in task-relevant dynamics did not extend to the minimally constrained condition. Instead, both groups showed similar increases in minimally constrained force complexity. Moreover, ability to perform in the transfer condition was not dependent on the assigned practice regime. These results show that complexity matching measures may be a valuable asset for future assessment of adaptive control. However, it is important to distinguish whether complexity matching is a causal factor for dynamical change, or just a variation of intervention techniques that facilitate a generalized increase of system degrees of freedom with practice.

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Figures

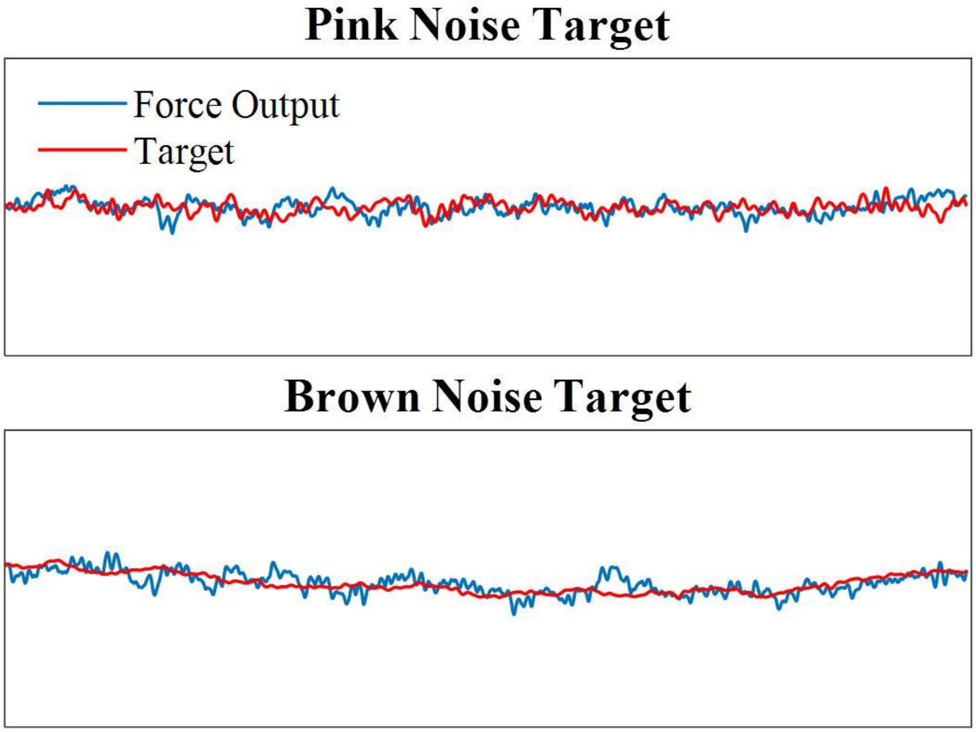

Figure 5.1: Example of the force-time series of one subject tracking the pink noise (a) and brown noise (b) force target. Both figures represent the 10th trial on day 1 of practice (a) and transfer (b).

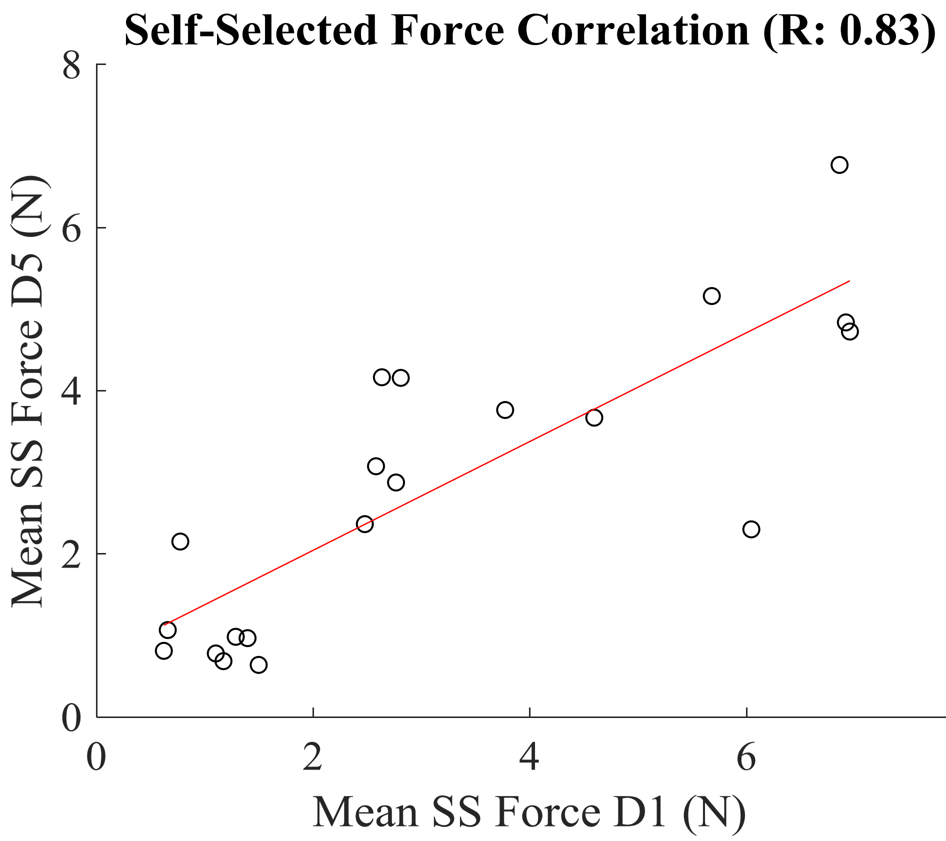

Figure 5.2: Correlation of subjects average self-selected force output (N) at baseline (x-axis) and after the 5th day of tracking practice (y-axis). Each dot represents one subject, and the corresponding red line represents the least squares fitted line.

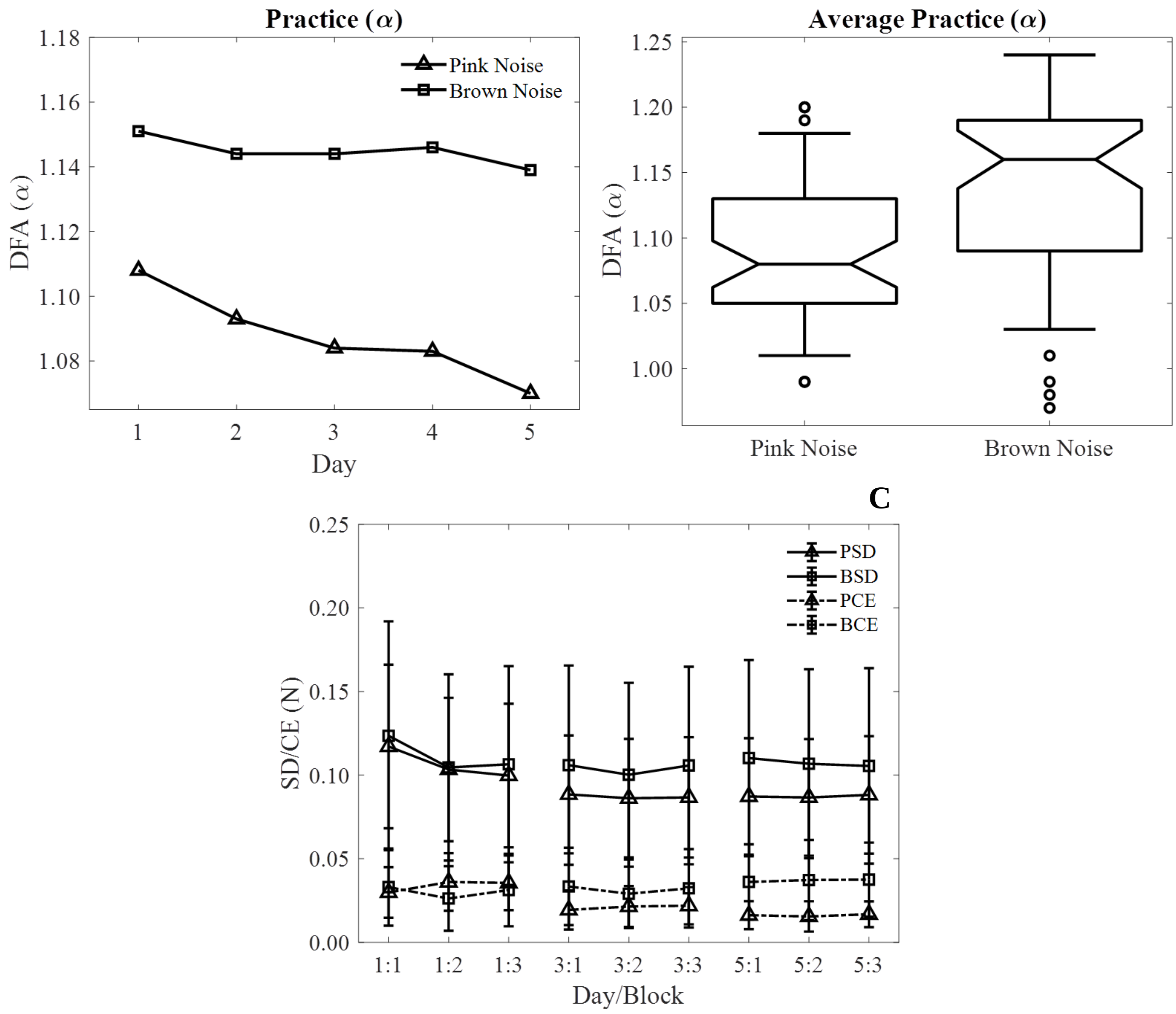

Figure 5.3: Figure 5.3a illustrates the qualitative change in average group DFA (α) as a function of practice. 3b illustrates the overall differences in average group α which reached statistical significance. 3c illustrates group standard deviation (SD), and absolute constant error (|CE|) as a function of trial block and day of practice. For better clarity, days 1,3, and 5 were selected for plotting. Note that the x-axis has two numbers separated by a colon. The first number represents day, and the second number represent the corresponding trial block. Triangles represent the pink noise practice group, while squares represent the brown noise practice group. Solid lines correspond with SD, while the dotted lines show |CE|.

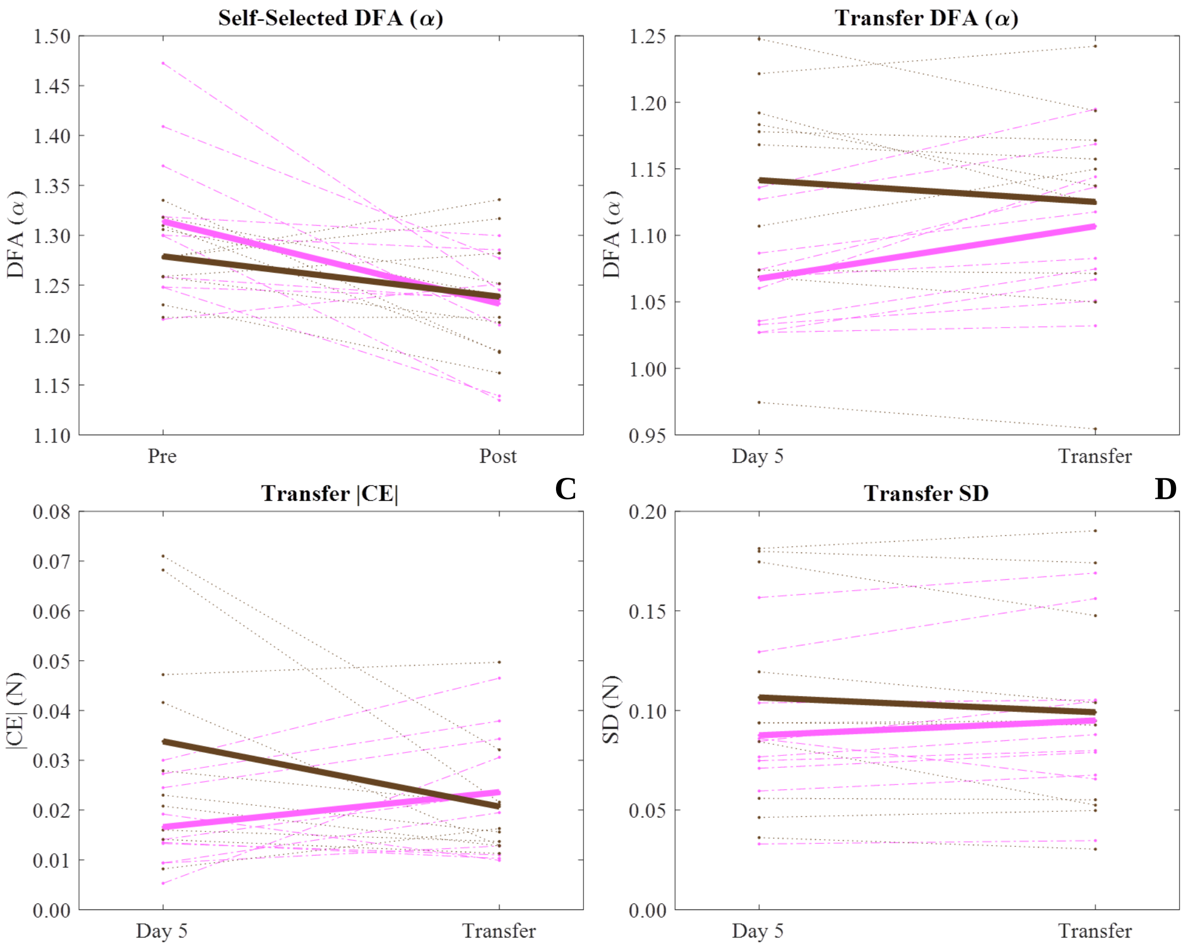

Figure 5.4: Figure 5.4a illustrates both group and individual shifts in self-selected DFA (α) at baseline, and after 5 days of tracking practice. The remaining figures illustrate characteristic differences in DFA (α) (4b), |CE| (4c), and SD (4d) between the last 15 trials of practice on day 5, and all 15 transfer trials. Pink lines correspond with the group that practiced with the pink noise target, and brown correspond with the brown noise practice group. Thick solid lines represent group averages, while the thin dotted lines show individual averages.

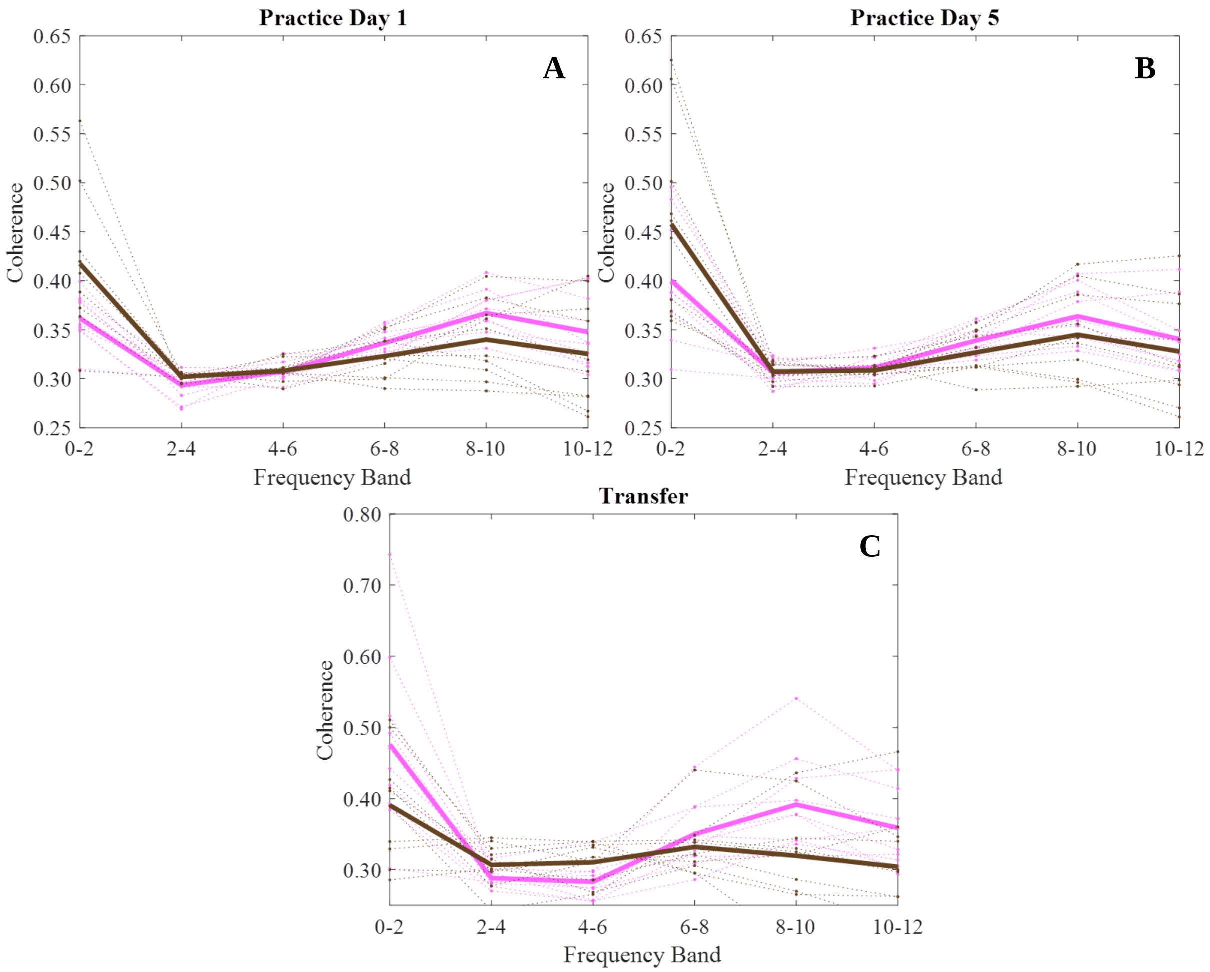

Figure 5.5: Wavelet cross-coherence on practice day 1 (5.5a), practice day 5 (5.5b), and transfer (5.5c). Coherence range is between 0-1. Higher coherence values correspond with stronger coupling between force and target at the specified frequency (Hz) band. Pink lines represent the pink noise practice group, and brown represents the brown noise practice group. Thick solid lines are the group mean, while thin dotted lines are individual averages in coherence at each frequency band.

CHAPTER 6

General Discussion

The general aim of this dissertation was to provide a more comprehensive examination of the role of complexity in adaptive motor control. Separate isometric force tracking experiments were designed to address key theoretical issues in this area of study on two fronts.

Experiment 1 addressed several ambiguities that stem from historical accounts of system complexity and adaptive behavior. A supplemental aim was to assess the compatibility of central tenets from the Loss of Complexity (Lipsitz & Goldberger, 1992)/ Optimal Variability (Stergiou et al., 2006) hypotheses with those of the Loss of Adaptability framework (Vaillancourt & Newell, 2002; Sosnoff, Valantine, & Newell, 2007). Experiment 2 examined the role of external constraint on change in minimally constrained dynamics according to tracking practice. There is a working conjecture that the complexity matching is a viable technique to elicit specific change to system dynamics (West et al. 2008; Mahmoodi et al., 2018). However, the majority of empirical study is aligned with the central premises of the LOC/OV frameworks. Thus, we also tested the assumption that complexity matching according to pink noise dynamics provides a discernible advantage in adaptive tracking performance. Together, these studies highlight the necessity for a unified approach in systematic examination of system complexity in future study.

The following sections will expand on the theoretical relevance of our experimental findings. This discussion will also consider future research directions necessary to expand on the current view.

Collective Assessment of Isometric Force Dynamics

As previously discussed, there is a dearth of literature that illustrates minimally constrained dynamics in conjunction with dynamics according to multichotomous task constraint. This is especially true in the isometric tracking literature, in spite of its popularity for assessing motor learning/control through the combined lens of traditional performance and non-linear analysis (Slifkin & Newell, 1999; Christou, Grossman, & Carlton, 2002; Lodha, Coombes, & Cauraugh, 2012; Jin et al., 2019).

As previously stated, both experiments found that young adult's minimally constrained force output was not distributed around $1/f^1$ scaling, and instead varied near the middle of the pink-brown noise continuum. Even after 5 days of practice in conditions that exhibited task-relevant dynamics near pink noise, their minimally constrained dynamics shifted directly central to the pink-brown noise continuum.

These findings are still compatible with the position that minimally constrained force output exhibits dynamics representative of a complex, degenerate, self-organizing system (Edelman & Gally, 2001; Prokopenko, Boschetti, & Ryan, 2009). However, this challenges the position that brown noise behavior (in young/healthy) is a consequence of external constraint provoking exaggerated intrinsic control (Van Orden et al., 2011; Washburn et al., 2015). Both experiments followed suggestions made for empirical studies attempting to mediate intrinsic and external constraint (to show pink noise), and found that subjects who exhibited the most complex preferred-force dynamics were still more deterministic than pink noise behavior.

Alternative interpretations predict that increases in external constraint and/or volition on behavior will lead to a "whitening" of individual's output (Dingwell & Cusumano, 2008, 2010). Support of this in the isometric force domain stipulated that visual information increased force complexity in a condition that did not necessitate tracking behavior (Athreya, Van Orden, & Riley, 2012). However, our findings show that increased volition and/or perceptual information exhibited a bi-directional shift from subject's preferred force DFA depending on the specific force target.

Perhaps a more pragmatic approach to understanding behavioral complexity is assessing the system according to both minimal constraint and representative conditions pertinent in everyday life. We contend that, specific to manual force control, emergent coordination falls along a continuum of behaviors that require both static and rhythmic control. Their emergent force complexity under minimal constraint falls between the complexity exhibited in either behavior. It is possible, then, that the observed intrinsic dynamics function as a middle ground to the emergent dynamics that continually arise according to pervasive static and rhythmic function. We do not argue that the quantitative results may be relatively unique to our paradigm of interest. However collective observation is feasible for the majority of relevant paradigms. To do so may provide valuable insight about the nature of minimally constrained dynamics in relation to the multitude of emergent behaviors observed with everyday constraint.

An alternative discussion point on force complexity relations pertains to hypothesis 2 of experiment 1. Our motivation was to expand on the flexibility of behavioral dynamics observed in numerous movement paradigms (Vaillancourt & Newell, 2002; Hunt, Mcgrath, & Stergiou, 2014). Vaillancourt and Newell (2002) framed the LOA approach according to the alterations in static or rhythmic force dynamics as a function of age. They argued that the constant and sine wave tracking tasks correspond with unique intrinsic attractor dynamics available to the system (fixed point/limit cycle). In which case, the direction of change in force complexity was believed to co-vary differently with age/disease according to the dimension of the corresponding intrinsic attractor.

As discussed in chapter 3, these findings provided indirect evidence that young healthy subjects showed a greater degree of dynamical flexibility compared to the elderly group. Moreover, the relative consistency in elderly subject's force complexity allude to the possibility that they were functioning according to their intrinsic force tendencies. Our findings align with the results from Vaillancourt & Newell (2002) in terms of the differences in force complexity between both constant and sine tracking tasks. However, we also found that these differences also correspond with predictable shifts from their preferred-force dynamics. While they showed the same direction of change, the magnitude of shift depended on how much their intrinsic dynamics corresponded with the specific task.

The location and relative rigidity of elderly subjects force complexity begs the question as to whether this corresponds with their intrinsic dynamics. This was a motivating factor for outlining dynamical change in young healthy subjects, as this preliminary evidence provides a unique perspective on dynamical change in the complexity literature. Future study is necessary, however, to corroborate this function in other modalities, and determine its functional significance on neuro-motor health.

Force Complexity on Adaptive Control

The specific distribution of force dynamics in both experiments did not align with predictions from the LOC/OV frameworks. However, our findings provided the much needed empirical support for a tangible relationship between behavioral complexity and adaptive motor control. More importantly, we provide evidence that both minimally constrained dynamics and dynamical flexibility (task relevant) are relevant for predicting isometric tracking performance. Thus, the unique assessment of dynamics according to opposing frameworks are not only compatible, but a more united approach according to both tenets is worth consideration in future study. It appears the customary attitude of empirical autonomy may inhibit a more comprehensive account of complexity as an adaptability index.

The prediction of better performance according to greater dynamical flexibility is an important finding from a unique perspective. However, this does correspond with broader tenets that stipulate the relevance of dynamical sensitivity in effective perceptuo-motor control (Nishimoto & Tani, 2004). The generalized U-shaped function found between minimally constrained force DFA and tracking performance, however, remains somewhat confounding. A U-shaped function in and of itself is conceivably aligned with the tenets of LOC/OV, however the vertex would expectedly align with pink noise behavior. As discussed in chapter 4, we speculated that the observed function (and location) relates in part to the coordinative regimes relevant in manual force control. In which case, intrinsic force dynamics that are centralized in respect to the dynamics that emerge according to static and rhythmic behavior may possess a coordinative composition that affords better overall performance. In which case, this may reflect a sort of goldilocks paradigm in the enabling/attenuation of the DoF's relevant in isometric force control.

In general, there is still a pressing need to further examine the relationship between complexity measures and adaptive control. This is relevant in terms of both experimental paradigm (ie. gait, postural control), and adaptability measures (ie. stability, various perceptuo-motor performance metrics). Specific to force tracking, it is necessary examine the relationship between minimally constrained dynamics and dynamical flexibility in different populations of interest. There is obvious benefit to understanding the unique changes to both functions according any number of intrinsically constraining factors. Moreover, it is important to examine whether unique intervention techniques can address the specific deficiencies exhibited on an individual basis.

Complexity Matching and Future Interventions

Study of complexity matching along the lines of adaptive behavior have put a premium on the sub-premise of system subordination (Mahmoodi et al., 2018). Obviously, this is a product of the central assumptions from LOC/OV, and thus this technique is prevalent due to the prediction that it can facilitate very specific changes to system dynamics. However, our results show that relevant practice literature (our second experiment included) may operate with too narrow a view in terms of how task constraints predict/cause specific change in emergent behavior.

Let us consider that emergent coordination is a product of the momentary confluence of individual, environmental, and task constraints (Newell, 1986). Provided there are many elements that define a task constraint (ie. type/degree of information, temporal structure, kinetic parameter) it is reasonable to assume that manipulation of single element within the task limits the capacity to predict and facilitate coordinative change. Take for example the findings from Almurad and colleagues (2017), where subjects in the experimental condition matched/retained a degree of loco-motor complexity after matching the gait of a young healthy person. Control subjects were required to walk alone, and did not show change in their gait complexity. A reasonable question is whether complexity matching was the source of change to behavioral dynamics, or whether this was simply a consequence of differences in terms of the degree of information presented to each group over practice.

The same can be said for our experiment, where the primary manipulation was the dynamical complexity embedded in subject's visual target. Manipulation of this single element did elicit differences in force dynamics between the tracking conditions, although both groups were still closer in proximity to pink noise compared to brown. This finding, in conjunction with identical shifts in both groups’ minimally constrained behavior may imply that the temporal structure alone is not sufficient to facilitate bi-directional changes in minimally constrained complexity. This is supported by evidence presented in a study by Marmelat and colleagues (2014), where the degree of complexity matching was contingent upon a minimum threshold of variation (coefficient of variation ≥ 3%) embedded in complex auditory-motor stimuli.

At present, our findings suggest that complexity matching may be useful to determine the means by which individual's coordinate and couple their behavior to an external system or stimulus. However, the effectiveness of this technique on relatively sustained alterations to system dynamics is still unknown. There is a possibility that this phenomenon interacts with other elements of task constraint, which in and of itself is an interesting avenue for future research. In a broader sense, questions about relevant elements of task constraint are at the heart of numerous findings from the current work. Two of which include the functional significance of you healthy subjects force complexity location/distribution, and its corresponding U-shaped function on adaptive tracking performance. In any case, these findings highlight the necessity for an integrated approach on assessing system complexity.

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