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SHORT REPORT

The relationship between task difficulty and motor performance complexity

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Abstract
Difficult tasks are commonly equated with complex tasks across many behaviors. Motor task difficulty is traditionally defined via Fitts' law, using evaluation criteria based on spatial movement constraints. Complexity of data is typically evaluated using non-linear computational approaches. In this project, we investigate the potential to evaluate task difficulty via behavioral (motor performance) complexity in a Fitts-type task. Use of non-linear approaches allows for inclusion of many features of motor actions that are not currently included in the Fitts-type paradigm. Our results indicate that tasks defined as more difficult (using Fitts movement IDs) are not associated with complex motor behaviors; rather, an inverse relationship exists between these two concepts. Use of non-linear techniques allowed for the detection of behavioral differences in motor performance over the entire action trajectory in the presence of action errors and among neutrally co-constrained effectors not detected using traditional Fitts'-type analyses utilizing movement time measures. Our findings indicate that task difficulty may potentially be inferred using non-linear measures, particularly in ecological situations that do not obey the Fitts-type testing paradigm. While we are optimistic regarding these initial findings, further work is needed to assess the full potential of the approach.

Keywords Fitts' law · Motor behavior · Non-linear analysis · Complexity · Task difficulty

Introduction

Across the field of behavioral research, task complexity is equated with difficult tasks, such that the two terms have been used interchangeably (Bernard-Demanze, Dumitrescu, Jimeno, Borel, & Lacour, 2009; Gajewski & Falkenstein, 2012; Olivier, Cuisinier, Vaugoyeau, Nougier, & Assaiante, 2010; D. J Serrien & Spapé, 2009; Deborah J. Serrien, 2009; Vander Velde & Woollacott, 2008). In terms of performance, complex tasks have been typically viewed as tasks in which there are two or more competing goals (Fait et al., 2011; Gooijers et al., 2011; Krishnan & Jaric, 2010; R. Schmidt & Lee, 2011; van den Berg, Swinnen, & Wenderoth, 2011; Van Impe, Coxon, Goble, Wenderoth, & Swinnen, 2009). Despite the use of the phrase "task complexity" in over 400 publications, there is no standard definition or method to evaluate how complex a task may be. Instead we rely on vernacular, custom, and personal experience to say that one task is more complex than another.

Circa 1954, a method to evaluate task difficulty in motor behavior emerged from the application of information theory to behavioral psychology (Fitts, 1954). By applying Shannon's 17th theorem regarding channel capacity (Shannon & Weaver, 1949) to information transmission in the human body, it was hypothesized that movements requiring more information from the environment to flow into the central nervous system (CNS) would require longer execution times (Hick, 1952). This relationship between movement time minimization and movement characteristics for spatially constrained actions was established empirically via Fitts' law (Fitts, 1954; Fitts & Peterson, 1964; Guiard & Olafsdottir, 2011; Schmidt & Lee, 2011). Fitts' law has been validated for a wide range of tasks ranging from simple tapping actions (Fitts, 1954; Fitts & Peterson, 1964) to movements made under water (Kerr, 1978) (for overview, see (Plamondon & Alimi, 1997)).

According to Fitts' law, the time needed to complete a motor task is dependent on the size of the end target, such that

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smaller targets are associated with more environmental information and thus longer task completion times. The classical interpretation of this phenomenon is that the neuromuscular system requires more time to resolve the spatial uncertainty, choose the appropriate response from a set of possible solutions, and implement the motor response using an initial-impulse and current-control approach (Crossman & Goodeve, 1983; Woodworth, 1899).

Despite consistent evidence in favor of Fitts' law, some components of the original model have been disputed. Several studies have countered the deterministic current-control point of view of the original model, with evidence that human motor performance involves stochastic processes (Meyer, Abrams, Kornblum, Wright, & Keith Smith, 1988; Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979). Acknowledgement of random noise inherent within the neuromotor system, which partially explains endpoint variability, is an important feature within the stochastic models (e.g., stochastic optimized sub-movements).

While inclusion of stochastic processes in movement models is an important step, other essential observations of human motor performance have not been well captured by previous considerations of Fitts' law. Features not accounted for in previous models include (but are not limited to): consideration of variability in overall movement/action trajectories (not just effector endpoints); consideration of action errors; systemic action biases; action hysteresis; inclusion of more than two sub-movements within an action; and differences in environmental situations (to which we adapt our motor actions).

As a consequence, traditional consideration of everyday actions using the Fitts-type paradigm is problematic. For example, we may pick up a cup of coffee with our non-dominant hand while opening a door with our dominant hand, or vice versa. In this case, one may encounter quite a few of the features not considered within previous models. Is it possible to determine which of those two combinations is more difficult or complex? As these tasks cannot be evaluated specifically via Fitts' law, this remains an important empirical question in the field of motor control.

Recently, the non-linear complexity of physical and numerical data sets has become of significant interest to researchers of human subjects. Several of these techniques have been applied to the field of neuroscience and motor behavior, including computational models of neural dynamics (Pernice, Staude, Cardanobile, & Rotter, 2011; Qi, Watts, Kim, & Robinson, 2012; Victor, Drover, Conte, & Schiff, 2011), evaluation of neural firing patterns (Lafreniere-Roula et al., 2010; Nowotny, Huerta, & Rabinovich, 2008; Park & Rubchinsky, 2011), and evaluation of basic motor and cognitive impairments (Bajo et al., 2010; Cignetti, Decker, & Stergiou, 2012; Deffeyes, Harbourne, Stuberg, & Stergiou, 2011; Huisinga, Yentes, Filipi, & Stergiou, 2012; Smith, Stergiou, & Ulrich, 2011). In this vein, complexity of data has been defined as highly variable fluctuations in physiological processes, such that these processes are better characterized by non-linear equations rather than more pervasive linear models. These non-linear models do consider the following as essential features: stochastic processes, trajectory variability, systemic biases, and trajectory hysteresis. Non-linear approaches are also able to include trajectories with multiple subcomponents as well as unusual observations (e.g., action errors) for consideration into the model of behavior.

Non-linear measures have been typically employed to evaluate changes in physical phenomena that are not discernible using traditional linear approaches, such as linear variability analyses. As traditional linear measures rely upon temporal or spatial averaging of data, subtle time-related changes in phenomena may be masked by averaging. By evaluating physical and behavioral phenomena using non-linear techniques, subtle time- and environment-dependent changes can often be detected within such data sets.

Given the overall potential strengths of non-linear techniques, we employed non-linear analyses of motor performance during a Fitts-type task to evaluate the relationship between task difficulty and motor performance complexity. We hypothesized that tasks with higher indices of difficulty would be associated with increased complexity measures of motor output. Such behavior would suggest that tasks perceived and referred to as "difficult" would indeed be related to complex behavioral patterns as measured via non-linear approaches.

Materials and methods

Performance of quick isometric finger force production between two force targets in an oscillatory manner in right-handed individuals using a Fitts-type task (Fig. 1) was evaluated. Force trajectories for six different indices of difficulty (ID) were evaluated, where ID represents the amount of encoded information via Fitts' Law (Fitts, 1954; Fitts & Peterson, 1964; Schmidt & Lee, 2011). Successful analysis of force production in a Fitts' law paradigm has been demonstrated in a number of recent publications (Bertucco, Cesari, & Latash, 2013; Kim, Wininger, & Craelius, 2010; Thumser, Slifkin, Beckler, & Marasco, 2018; Verros et al., 2018). Movement time (MT) was computed as the time difference between consecutive force production maxima and minima in the time series. MT was used to evaluate the traditional relationship between task difficulty and motor output. To evaluate behavioral features of the motor task, two non-linear measures were considered: (1) sample entropy, and (2) the largest Lyapunov exponent of the attractor. Both non-linear measures were calculated for the entire oscillatory force series produced by subjects. Sample entropy (SampEn) measures the

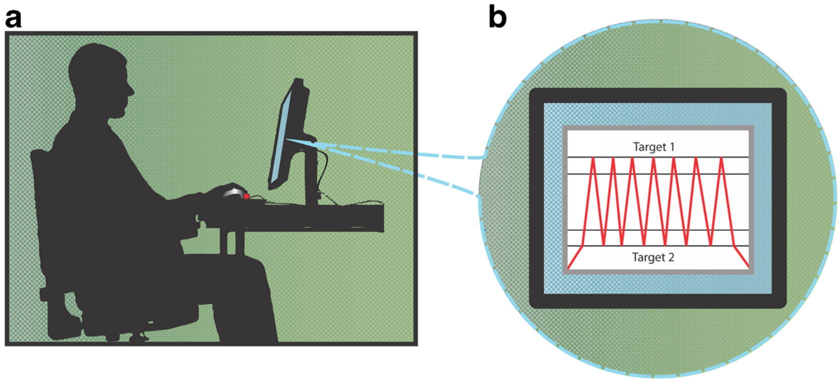

Fig. 1 Depiction of experimental setup. Participants sat upright directly facing a computer monitor. Force sensors were placed underneath the fingertips of the right hand, illustrated by red dot. **a** Profile view of setup. **b** Example of computer monitor providing feedback to study participants. Finger forces generated during the task were shown in real-time via a red line on the computer monitor. The red cursor moved from the left side of the screen at the beginning of the trial to the right side of the screen with time. Participants were instructed to produce finger forces between two targets (depicted as space between the lines on the screen) as fast as possible

unpredictability of the time series; greater values of SampEn indicates increased signal unpredictability. Lyapunov exponent (LyE) measures data complexity via divergence of the attractor trajectories during cyclic tasks (i.e., repeated observations). Greater values of LyE represent increased data complexity and reduced signal predictability/stability (Fig. 2).

In addition to the six ID conditions, force production was evaluated in three distinct finger combinations: index finger of the right hand (I_R), little finger of the right hand (L_R), and all digits 2 through 5 of the right hand acting together (index, middle, ring, and little fingers acting altogether, denoted by $IMRL_R$). These three finger combinations were chosen to evaluate the sensitivity of the computational method to changes in task performance. Computation of MT, SampEn, and LyE were performed on 18 continuous force production cycles within a trial. In many cases, force production errors were present in the 18-cycle set (over- and undershoots of the target), thereby violating the fourth condition of Fitts-type tasks.

Four male and four female students served as subjects in this study (total n = 8). Average data for the subjects were (mean ± *SD*): 27 ± 3 years of age, 1.71 ± 0.11 m in height, and 70.9 ± 12.8 kg in mass. All subjects were strongly right-handed according to their preferential use of the hand during daily activities such as writing, drawing, and eating. Subjects had no previous history of upper extremity trauma or neuropathy. Experimental protocols and written informed consent documents were approved by the Pennsylvania State University Institutional Review Board. The experimental

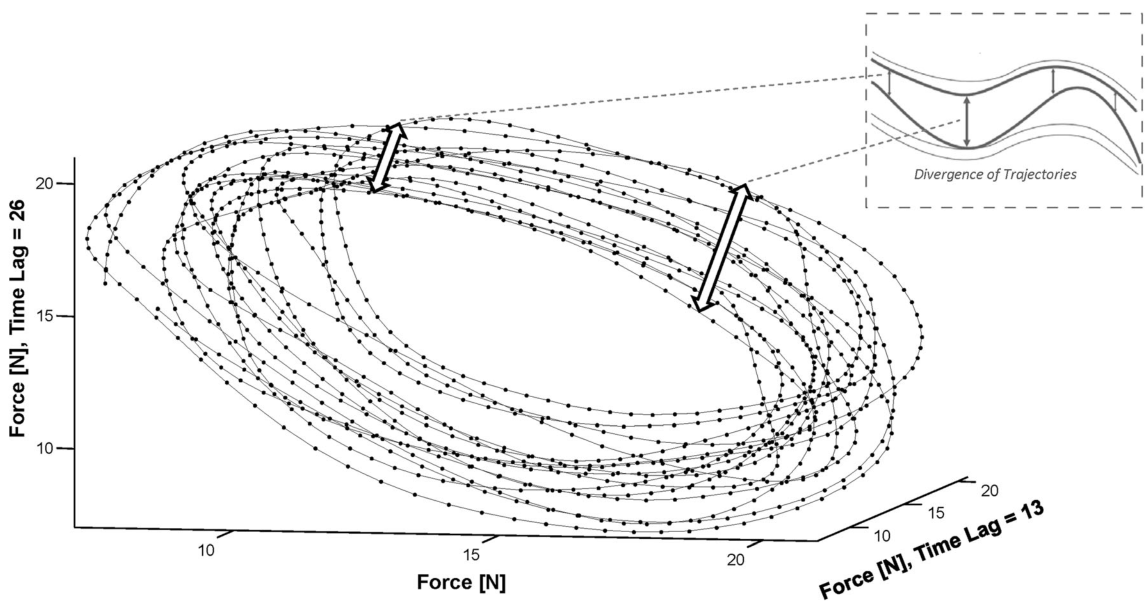

Fig. 2 A 3D state-space plot of force generated by one participant during the $IMRL_R$ task at ID = 1.5. A depiction of the trajectory divergence measured as by LyE is shown using the plot3 command in Matlab. The attractor for this data has been reconstructed using the delay technique (Cignetti et al., 2012); the data are plotted with respect to the original data series versus one and two times the corresponding time lags (13 and 26, respectively) associated with this particular data set to show the unfolded attractor space for this particular data set

procedures were conducted according to the Declaration of Helsinki. All subjects gave written informed consent according to the procedures approved by the Office of Regulatory Compliance of the Pennsylvania State University. Data presented in the figures are shown as means and standard errors.

Indices of performance were computed for the forces generated by one or more fingers of the right hand involved in a task. Tasks were similar to pressing and holding a key on a computer keyboard using various levels of force. Data were collected using unidirectional piezoelectric force sensors (208AO3; PCB Piezotronic Inc., Depew, NY, USA) and a National Instruments A/D board (NI PCI-6023E, National Instruments, Austin, TX, USA). Subjects were instructed to press with a specified set of fingers of the right hand such that the total force produced by the specific finger set oscillated between two target windows as quickly as possible. Subjects typically produced 18–20 oscillations per condition. Force feedback was available only for the fingers specified in the task via computer display (LabView 6.1, National Instruments, Austin, TX, USA). A sampling frequency of 200 Hz was used during data collection.

The distance between the centers of the two targets was set at 10% of the maximum voluntary force (MVF) produced by the finger set in each condition (Fig. 1b). A background force of 10% MVF was required in all trials in order to avoid floor effects of the target window. The targets were centered at 10% and 20% MVF, respectively. The width of the target windows displayed was chosen to correspond to six indices of difficulty (ID = Log2(2A/W)), such that ID = 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 were used. The order of tested conditions was block randomized across subjects. Prior to each trial, the subject sat relaxed with the digits of the right hand resting on the sensors. The computer generated two beeps (to prime the subject); at this point the cursor showing the force produced by the specified finger set was displayed on the computer monitor. The task was to oscillate between the two targets with the cursor as quickly as possible while making as few errors as possible.

Data were processed off-line using customized MATLAB software (Mathworks, Inc., Natick, MA, USA). Force data were low-pass filtered at 10 Hz using a second-order zero-lag Butterworth filter. The 10-Hz cutoff was verified using fast-Fourier transform of force production data in all conditions and subjects. MT was determined as the time between two consecutive extrema (minima and maxima pairs). SampEn was calculated as a predictability measure of the entire force-cycle time series. Wolf's algorithm for the Lyapunov exponent (LyE) (Huisinga et al., 2012; Smith et al., 2011) was calculated as the rate of divergence between force trajectories across the force-cycle series. Wolf's algorithm was selected for use here as it produces more sensitive estimates of LyE for small data sets as compared to other approaches (Cignetti et al., 2012). As a note, one orbit of the attractor within the phase space constitutes one individual cycle of force production (shaped similar to a sine function) in the current data set. Subject- and condition-specific embedding dimensions and time lags were used in LyE computation (Cignetti et al., 2012; Smith et al., 2011). Embedding dimensions were detected within Matlab as a means to identify the dimension in which the percentage of global false nearest neighboring data points approached zero. This dimension is considered the optimal embedding dimension as it will allow for the attractor to completely unfold within the phase space. Time lag values were determined using the first minimum average of the mutual information function. These time lag values maximize the information content of the time series in reconstruction. Across all subjects and conditions, the average embedding dimension was five dimensions and average time lag was 22 data points (see Fig. 2 for an example of a reconstructed attractor from our data set).

Repeated measures ANOVAs were performed on MT, SampEn, and LyE data with the factors of: *ID* (six levels; 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0) and *Finger Combination* (three levels; I_R, L_R, $IMRL_R$). Main effects were reported as no interaction effects were found. Pairwise *post hoc* comparisons were performed using Bonferroni corrections to analyze significant effects of ANOVAs. Linear regression among MT, ID, LyE, and 1/LyE were performed to determine the overall relationship among measures showing significant effects. Partial correlations were performed to determine the strength of the relationship between MT and 1/LyE while controlling for *ID* and *Finger Combination*.

Results

MT increased with larger ID values ($F_{5,20} = 7.5$, $p < 0.001$) across all finger combinations (Fig. 3a). *Post hoc* analyses indicated MT values for IDs 1.5 and 2.0 were lower than MT values for IDs 3.5 and 4.0 (where $^*p < 0.0033$, n = 15 unique *post hoc* comparisons ($p^* = p/n$)). LyE did not exhibit this trend (Fig. 3c); LyE decreased as ID increased (LyE; $F_{5,20} = 37.7$, $p < 0.001$). No *post hoc* differences were found among ID values for LyE data.

Differences in LyE produced by different finger combinations were found ($F_{2,20} = 29.3$, $p < 0.05$), *post hoc* analysis indicated LyE produced by L_R was significantly lower than LyE values produced by I_R (Bonferroni-corrected *post hoc*, $p < 0.01$; Fig. 3c). MT data did not indicate differences among finger conditions.

Further analysis indicated that MT was inversely related to LyE, such that 1/LyE explained a significant proportion of variance in movement time ($R^2 = 0.44$, $F_{1,138} = 106.7$, $p < 0.001$; Fig. 3b). The correlation between MT and 1/LyE remained significant when *ID* and *Finger Combinations* were controlled for ($r_{ID} = 0.56$, $p < 0.001$; $r_{FingerCombination} = 0.66$, $p < 0.001$). Separate regression

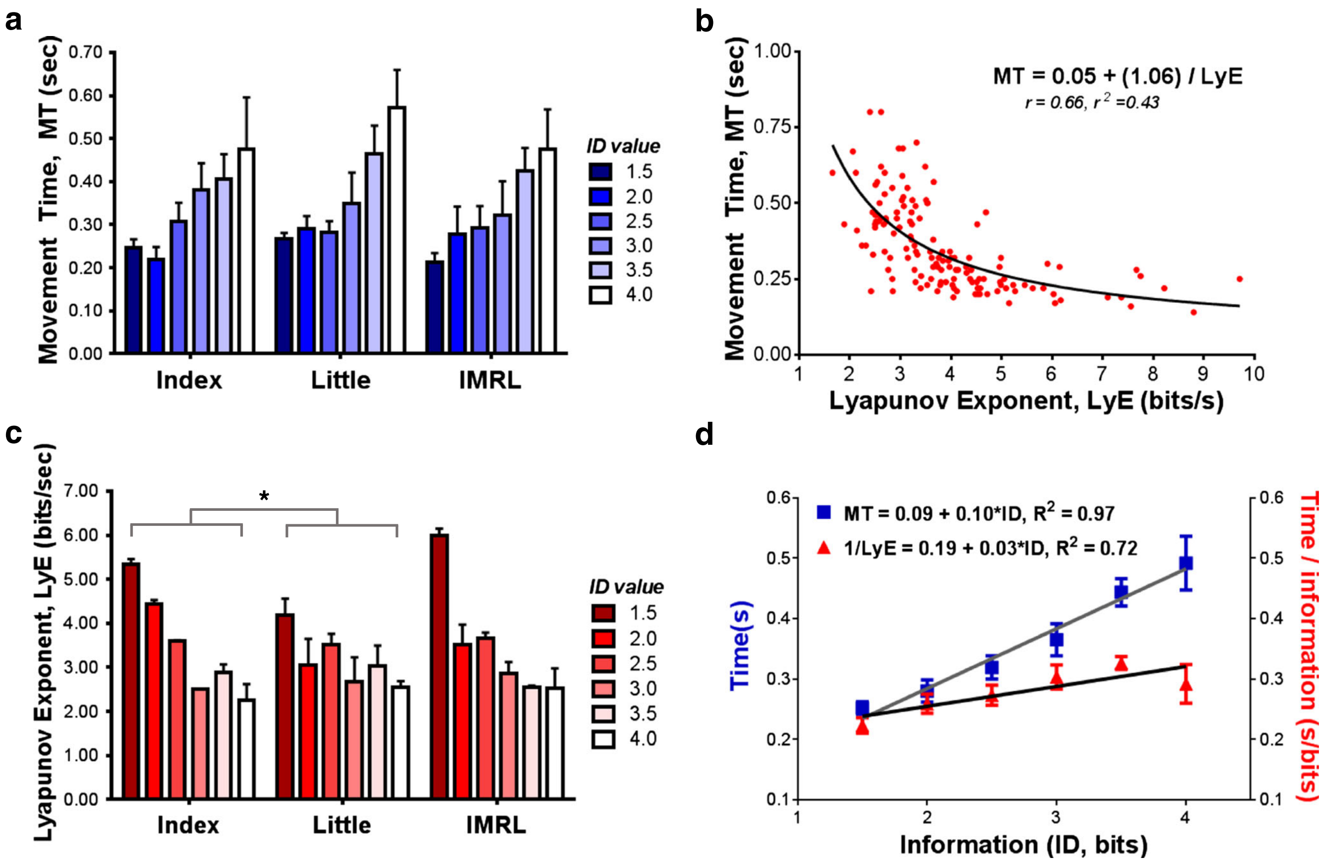

Fig. 3 Relationship between task difficulty and motor performance complexity. **a** Movement time (MT) increased with ID across all tested conditions. **b** MT was correlated with the inverse of LyE across all tested conditions. Values of r and r^2 shown for inverse relationship model indicated. **c** LyE decreased with ID across all tested conditions. On average, LyE in tasks performed by the index finger was higher than those performed by the little finger ($p < 0.01$), as indicated by *. **d** Regression of behavioral measures (MT and 1/LyE) on ID. Models were found to be significantly different from each other, $p < 0.001$

models of MT and 1/LyE on ID show significant positive linear trends (Fig. 3d). Each measure captured a significant portion of variability in task performance, (R^2(MT) = 0.97 and R^2(1/LyE) = 0.72), respectively. Models were found to be significantly different from each other, $p < 0.001$. No interaction effects were found within the data set for MT or LyE data ($p > 0.3$). As a note, SampEn did not exhibit any significant trends with respect to ID or finger combinations.

Discussion

Overall, Fitts' law was upheld in this experiment, such that larger ID values (e.g., difficult tasks) were associated with longer movement times without differences across finger combinations (Fig. 3a). Contrary to our hypothesis, actions with lower IDs were associated with larger Lyapunov exponents, indicating that easier tasks are linked to behaviors with higher indices of complexity (Fig. 3c). No significant *post hoc* differences were found with respect to ID levels in LyE data. We interpret the discrepancy between task difficulty and motor performance complexity as a reflection of the abundance of motor solutions for simple tasks (Latash, 2012; Scholz & Schöner, 1999), such that the neuromuscular system uses a flexible, yet broad, range of solutions to perform easy tasks. In the context of this study, the solution sets are the motor unit activation patterns utilized by the central nervous system to produce finger forces. This range of solutions is reflected by increased complexity of the resultant motor behavior observed, measured by divergence of solution trajectories (LyE). In contrast, difficult tasks were associated with reduced LyE values (Fig. 3b). Lower LyE values reflect a smaller range of behavioral solutions used by the CNS to perform difficult tasks, resulting in highly stereotyped motor behaviors.

Further evaluation of LyE revealed finger-specific differences in motor output such that forces generated by the little finger were on average associated with lower behavioral complexity values as compared to the index finger (Fig. 3c). Compared to the other non-thenar digits of the hand, the index finger possesses anatomical differences and exhibits higher indices of motor independence (Li, Dun, Harkness, &

Brininger, 2004; Zatsiorsky, Li, & Latash, 2000). As such, faster movements and higher behavioral complexity in the index finger output is not entirely unexpected. In contrast, considering the common source of neural input and mechanical linkage across the flexor muscle compartments of digits 2–5, the output of the little finger is highly enslaved at a neuromuscular level to the other digits of the hand (Li et al., 2004; McIsaac & Fuglevand, 2007; Zatsiorsky et al., 2000). We interpret the reduced behavioral complexity exhibited by the little finger as a reflection of this inherent neuromuscular and mechanical coupling of this particular digit.

Difficulty versus complexity

As a positive correlation between task difficulty and complexity in motor performance does not appear to hold, the relationship between the concepts of "difficulty" and "complexity" was further evaluated. In the field of motor behavior, the index of difficulty of a task (ID) represents the information required to resolve the uncertainty of a movement response (Fitts, 1954; Fitts & Peterson, 1964). Higher ID values indicate that more information is needed to choose a correct response from a set of solutions. This increase in information is reflected in longer movement times (MT) in tasks with higher ID values (Fitts, 1954; Fitts & Peterson, 1964; Schmidt & Lee, 2011). In contrast, to evaluate how complex a task or behavior truly is, we are concerned about the information an external observer gains from observing the system. As task complexity has been previously, albeit loosely, defined using behavioral observation, this approach is not in conflict with earlier approaches. If the action solutions arise from a small solution set, the observer gains little information during performance of the task, as the chosen actions will have low variability (e.g., highly stererotyped movements). This is consistent with our observation of stereotyped force production profiles and low LyE values exhibited for tasks in this study with high ID values. This is also consistent with the definition of LyE as related to signal complexity and predictability, as low values of LyE reflect increased signal/motor predictability. Thus, tasks with higher difficulty (high ID values) could be identified through lower LyE values of the observed motor actions. Such a shift in focus from the interval reference frame (information encoded and transmitted by the CNS) to an external reference frame (information gained by the external observer) suggests an inverse relationship between the perception of "difficulty" and "complexity" in behavioral tasks.

To evaluate this concept, the relationship between a behavioral measure traditionally identified as representing neutrally coded information (movement time, MT) and values representing behavioral complexity (LyE) was evaluated. It was found that MT is inversely related to LyE, such that 1/LyE explained a significant proportion of variance in movement time (Fig. 3b). Generally, lower MT and ID values were related to increased motor complexity measures, indicating higher indices of non-linear variability within the motor patterns produced. Such an inverse relationship is not entirely surprising, as power law relationships have been reported in previous stochastic models of Fitts' law (summarized in Meyer, Abrams, Kornblum, Wright, & Keith Smith, 1988). We do acknowledge that increased practice on a motor task may result in some amount of reduced variability across a set of actions, but it is likely that the shape of the attractor formed by the set of actions and the rate of divergence of the attractor trajectories (LyE itself) should remain fairly consistent. However, we do acknowledge that further investigation is needed in this area.

Surprisingly, assessment of movement predictability via entropy did not yield significant results in this study. Our previous work in entropy assessment of motor actions indicated that entropy values (reflecting movement predictability) were associated with changes in object properties (e.g., object fragility) (Madansingh & Gorniak, 2015). However, it is possible that Lyapunov exponent values are more sensitive to environmental constraints of movement/action versus intrinsic physical properties of an object handled during motor actions. It is also possible that Lyapunov exponents are more sensitive to attractor dynamics during continuous cyclical actions, as in the current project, whereas entropy values may be more sensitive to motor behavior changes during chained discrete actions (as in Madansingh & Gorniak, 2015).

With respect to Lyapunov exponents, less complexity (solution convergence) of behavioral signals in more difficult tasks was found in the present study. We found individuals perform "difficult" tasks in a stereotyped manner (low motor performance complexity). These findings also indicate that task difficulty may potentially be inferred using non-linear measures. As the majority of tasks performed in daily life do not obey the Fitts-type testing paradigm, this approach may allow researchers access to infer task difficulty in ecological actions. Use of non-linear measures of task performance (1/LyE) instead of traditional measures of task difficulty (MT) may permit interpretation of channel capacity and neural transmission. Our results also show that divergence or convergence in behavioral output can be assessed to detect differences among tasks that do not appear overtly different to an external observer – here, as in tasks performed by different fingers.

This proposed method may be used to evaluate a wide variety of behavioral data, provided that the behavior can be measured and repeated. This method may also be used to delineate performance among neurologically constrained effectors, such as co-agonistic muscles. Beyond the immediate practical utility of these methods for behavioral research, this method may also be used to evaluate behavioral development/aging and/or disease progression by comparing motor performance complexity in activities of daily living as compared to healthy individuals. Currently, we are exploring the expanded use of this computational approach in our laboratory. Further work is needed to assess the potential utility of the approach.

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