

HOW INDIVIDUAL DIFFERENCES IN PRE-DISPOSITIONS OF BEHAVIORAL
REPERTOIRES INFLUENCE MOTOR LEARNING AND PERFORMANCE

by

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(Under the Direction of Karl M. Newell)

ABSTRACT

This study investigated the effect of preferred behavioral dynamics on performance and learning of a target-based throwing task. Two experiments were performed, revealing that differences in pre-dispositions between individuals result in a large variety of movement solutions, while maintaining similar performance output across all individuals. In Experiment 1, participants demonstrated changes in preferred patterns of coordination in response to alteration of the target distance and/or throwing hand. The notion that these behavioral preferences are relatively stable across time was tested and confirmed in a sub-set of participants who performed the same task twice, in a behaviorally similar manner. This finding becomes particularly relevant considering that these preferences and their relative stability provide the background on which subsequent learning takes place. In Experiment 2, individuals were assigned to a prolonged practice intervention where they were instructed to maintain one movement pattern that was either congruent or incongruent to their initially preferred pattern. The results suggest that the strength of preference of this initially preferred pattern determines the learning pathway. Higher

absolute autocorrelation values were observed for individuals who were asked to learn a coordination pattern more dissimilar to their preferred pattern. Autocorrelation values provided insight into the structure of variability, with higher values suggesting a more directed exploration of the task space. This early exploration proved successful for transfer to other target conditions, as the overall performance improvement between PRE- and POST- test showed a strong relation with the amount of autocorrelation early in practice. These results provide a framework to more strongly consider the effect of initial differences in pre-dispositions of behavior and performance in both scientific and applied settings, as these differences have a clear effect on the learning pathway. Particularly, rather than using a retrospective approach to the issue of individual differences, the proactive approach employed in this study was successful in relating individual differences in preferences to learning pathways. Furthermore, the effect of additional instructional constraints is strongly determined by the predisposition of the individual, further substantiating the need for change agents to consider learning within the context of the individual.

INDEX WORDS: individual differences, motor learning, skill acquisition, intrinsic dynamics, throwing

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DEDICATION

This dissertation is dedicated to my grandfather, who taught me what it is like to work tenaciously to make yourself, and the people you care about, proud. Although your presence is missed greatly, your guidance was felt throughout this process and will continue to serve as an inspiration for me.

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CHAPTER 1

INTRODUCTION

The complexity of the human movement system has engrossed the motor control problem for the better part of the past century (Adams, 1987; Bernstein, 1967; Braun, Mehring, & Wolpert, 2010; Schmidt, 1975; Skinner, 1938; Thorndike, 1931; Warren, 2006; Woodworth & Schlosberg, 1938). Illustrative of the complexity is that even at the macro level of analysis, the human body consists of hundreds of potential joint motions and muscle actions (Meskell, 2010; Warren, 2006), each able to move in different ways. The complexity increases when different levels within the system are considered, such as the billions of neurons available at the neural level (Azevedo et al., 2009). This observed complexity has been argued to be an adaptive advantage and a result of evolution. It provides humans with the ability to perform a task with the same output using structurally and/or functionally different elements (Edelman & Gally, 2001; Todorov & Jordan, 2002). However, it makes a theory of motor control difficult to formulate and rationalize (Tseng & Scholz, Schöner, 2002).

In light of this complexity of the many degrees of freedom, it is relatively remarkable that at the output level human movement is coherent and coordinated (Kauffman, 1993, 1996; Kelso & Engström, 2006; Schöner & Kelso, 1988). The issue of maintaining control of movement despite the large number of variables to control was coined the Degrees of Freedom (DoF) problem by Bernstein (1967). Human motor learning is even more extraordinary when considering the constant but opposing need to be both flexible and stable in motor performance. We need to be

flexible in the sense that we are required to apply our wide range of movement skills in ever-changing environmental conditions. At the same time, many of the tasks and motor problems faced in daily life have a strong requirement for stable performance, especially at the behavioral output level. Therefore, understanding the acquisition, control and adaptation of stability and flexibility in human movement is essential in the domain of motor learning.

A key to understanding the processes of human motor learning might be the appreciation of individual differences in performance and learning pathways. Although attempts to find general laws of motor learning have often disregarded these differences, they might be essential in better understanding the degrees of freedom problem. Moreover, a more comprehensive framework of learning and performance that can integrate within- and between-individual differences of performance has the possibility to provide recommendations and direction for means to capitalize on individual differences, rather than disregarding them.

CHAPTER 2

THE CONTROL OF COMPLEX SKILLS: AN INTRODUCTION TO THEORIES OF MOTOR BEHAVIOR

Traditional Theories

Early attempts to study complex motor skills go back to the seminal experiments of Byran and Harter (1899) who studied Morse code operators and the acquisition of their skill. Through the tracking of changes in performance over time, they came to the conclusion that a complex skill like Morse code processing involved a combination of different skills. The learning of these different skills was represented in plateaus that were observed in the learning curves. The idea was that as an individual was learning to become a Morse code operator, they would go through phases where, in sequential order, they would learn subcomponents of the overall skill, from easy to most difficult. The plateaus in performance represented the moment at which the learner moved from one subskill to the next. Although more than a century has passed since their experiment and interpretation, certain elements, particularly that of transitions in learning and compartmentalizing of performance, are still viewed as relevant.

From this beginning, it was subsequently Thorndike's legacy that shaped the future of motor learning (Thorndike, 1931). Although his theoretical influence is noticeable in many aspects of motor learning, one issue is most notable for the scope of this overview: namely, the *Law of Effect*. The Law of Effect relates to the importance of *reinforcement* while learning a skill. His study on a line-drawing task revealed that when participants are instructed to draw a

line of a given length, their performance remains unchanged throughout the practice period if they were not given feedback about their accuracy. However, participants who received feedback quadrupled their performance at the line drawing task (Thorndike, 1927). This empirical evidence builds on the idea of stimulus and response in the sense that the feedback from the experimenter could strengthen (or weaken) the habit of the learner. Investigations of knowledge of results have continued well into the 20th century (Adams, 1971; Janelle, Kim, & Singer, 1995; Newell, 1976; Salmoni, Schmidt, & Walter, 1984; Schmidt & Lee, 2011).

In motor learning, the idea that feedback influences what an individual had already learned about a given movement became more influential. Empirical evidence that individuals used feedback to improve the cognitive structures (memories) of movement representations to solve the motor problem led to a development of theories of motor control towards that of *closed-loop theory*, that integrates the possibility of feedback into the traditional open-loop model of control (Adams, 1971). Rather than executing a fixed motor program, a closed loop feedback system is embedded, allowing for modifications to the movement in response to small perturbations and error signals. According to closed-loop theory, perceptual information of every movement is compared to a reference of correctness that is stored in memory. With practice, more of these *perceptual traces* are generated, improving performance as well as the reference, resulting in a higher frequency of correct movements and successful outcomes. In this closed-loop view, movements are selected by a different trace, the *memory trace* (Adams, 1971; Bower & Hilgard, 1981).

However, the closed-loop theory possessed several drawbacks, most notably related to the difference in error processing between ballistic and slow movements, which Adams' theory could not account for. Similarly, empirical evidence had demonstrated the effectiveness of

variable practice, that is, practicing different variations of trial conditions rather than repeating the same one (Braun et al., 2010; Schmidt, 1975). According to the closed-loop theory of control, variable practice should be less effective as it does not provide a defined modal perceptual trace (Adams, 1971).

To counter these critiques, *schema theory* of motor learning and control was developed (Schmidt, 1975). Although some elements of Adams' original theory remained, the schema theory was able to better explain robust findings from the motor control literature. Whereas the open-loop theory involved a perceptual trace and a memory trace for feedback reference and action selection, respectively, the schema theory referred to this as recognition memory and recall memory. Schema theory is largely based on the ideas of a General Motor Program from Keele (1968). Contrary to the motor program, representations of classes of actions, rather than a one-to-one mapping are formed and instead of emphasizing exact timing and control variables, the general motor program emphasized the relations between the variables (Schmidt, 1975). Whereas some features of the program, the *parameters*, can be varied depending on the task, the *invariant features* remain the same. Examples of parameters are the overall duration of the execution, the force and the muscle selection.

The postulates of schema theory were aimed to solve the storage problem and provided the foundation for a substantial body of experimental work in motor learning. In spite of that, the schema theory received substantial critiques, mainly related to the need for an 'intelligent' command that stores and executes motor programs (Van Rossum, 1990). As each set of actions or skills has its own program containing commands to muscles, these programs need to be stored somehow, with an obvious and elegant solution nonexistent (Schmidt, 1975; Turvey, 1977). Similarly, the motor program account does not have the ability to explain how new movements

are performed. In other words, what is the abstract representation for an action that has never been performed yet (relatively) successfully executed.

Related to this is the issue of similarity, or, variability, of movements. Subsequent trials of a complex skill are rarely identical, suggesting that there has to be differentiation in the motor program, which is not accounted for in the schema theory outside of 'motor noise'. Lastly, both the closed-loop and schema theories of motor learning hypothesize an exclusively positive relation between practice and performance. In other words, the assumption is that with practice the learner gains more knowledge about the parameters of the movement and that this accumulation can only improve performance (Adams, 1971; Gibson, 1979). However, both anecdotal and empirical evidence suggests that (temporary) decreases in performance are unexceptional.

The Dynamical Systems Approach

In response to the aforementioned matters, the motor control literature has focused on a dynamical systems account of motor performance and learning, largely built around the notions of ecological psychology (Fowler & Turvey, 1978; Kugler, Kelso, & Turvey, 1980; Turvey, 1977). Rather than simplifying the complexity of the system through motor programs, this account puts the complexity of the interaction between the different components of the system as the focal point (Kugler et al., 1980). The underlying concept in the dynamical systems account of motor control is that of the *degrees of freedom problem* (Bernstein, 1967). The degrees of freedom, in this case the joints and muscles of the body, need to be organized in a particular way in order to achieve a certain task goal. The solution to this problem is approached through *self-*

organization (Kugler et al., 1980; Turvey, 1977), a universal concept in physics and chemistry (Haken, 1977).

Self-organization is observable in many systems, either living or non-living (Kugler et al., 1980; Kugler, Shaw, Vincente, & Kinsella-Shaw, 1990), and is an attractive account of movement coordination because it reduces, or in some interpretations removes, the difficulty of handling the redundancy of the degrees of freedom in executive control. According to the theory, the degrees of freedom form temporary functional units called *collectives* or *coordinative structures* (Kugler et al., 1980; Kugler, Kelso, & Turvey, 1982; Turvey, 1977) influenced by informational properties of the environment that the organism is operating in. Informational properties, in its broadest sense, can involve intentions (Kugler et al., 1990; Schöner & Kelso, 1988), somatosensory information but also gravitational pull and energy. These coordinative structures consist of muscles and joints that operate together as a unit, but are considered to be dissipative, such that they would be formed and dissolved based on the information from the environment that the individual is acting in.

For humans and other organisms, the informational support coming from the environment needs coupling with an action system before the system can arrive at a goal state. For example, the location of food in the environment provides an informational cue to an animal without providing a force field or physical push and the animal's action system is required for the ant to move towards the location of the food (Guerin & Kunkle, 2004; Kugler et al., 1990). This linkage between movement and information, or action-perception coupling (Gibson, 1979) is at the core of the dynamical systems approach of motor control.

As a consequence, the environmental information that is available to the learner during skill acquisition is critical. By moving around and acting upon the environment, information

becomes available about both the movement and the environment, which can then support subsequent movements, creating a cyclic relation. Relevant examples of this are wielding an object to perceive its weight (Turvey, Burton, Amazeen, Butwill, & Carello, 1998), or using visual information to intercept an approaching ball (Lee, 1976). The non-stationarity of affordances plays an important role in the understanding of skilled performance and skill learning, as there are many processes on different timescales that influence the affordances, ranging from fatigue to injury and changes in muscle strength, etc. (Verhoeven & Newell, in press).

Attractors, stable states and constraints

Seminal studies demonstrating the workings of the concepts outlined above are those by Kelso (1981, 1984) and the theoretical model based on these results by Haken, Kelso and Bunz (1985). In the original study, participants were asked to oscillate their index fingers to the beat of a metronome (Kelso, 1981). During the initial phase of the experiment, participants were asked to move their fingers (or hands; Kelso, 1984) at a preferred frequency, and in an asymmetrical anti-phase pattern. However, as the frequency was scaled up an abrupt shift occurred for all subjects, whereby the movement transitioned from an anti-phase to an in-phase mode in which the fingers flexed simultaneously. Notably, both the preferred frequency and the frequency at which the transition occurred (*critical frequency*) were different for each subject, highlighting individual differences in preferences and performance.

The findings from this experiment provided insight in the workings of two coupled oscillators, and were the background for the HKB model on the dynamics of physical systems

(Haken et al., 1985). Several elements of the model are worth highlighting, as they provide a theoretical context for the experiments in this study. That both the in-phase and anti-phase patterns of coordination can be performed at low movement frequencies indicates that the system is in a *bi-stable* state at these frequencies. However, when the movement frequency is scaled up, only the in-phase pattern is stable. This transition from a bistable to *mono-stable* system is often referred to as a *phase transition*. Although in this experiment the system moves from two to one stable states, this is not the case for all systems: phase transitions can occur from mono-stable to multi-stable systems and vice versa (Kostrubiec, Zanone, Fuchs, & Kelso, 2012).

This paradigm is an appealing way to explain the concept of an *attractor*. In nonlinear dynamics, the attractor is considered to be a state of the system that a system moves toward (Kugler, Shaw, Vincente, & Kinsella-Shaw, 1990). In the literal sense, it attracts behavior towards a given state. In the example of bimanual oscillations, the attractors are the in-phase and anti-phase patterns of coordination. During the scaling of the frequency, the anti-phase attractor became less *attractive* (also, less stable), which led the system to move to another, more stable attractor, in this case, the in-phase pattern.

The HKB model advanced the conceptualization of human movement as a self-organizing system. Whereas traditional explanations of motor control argued that movement is controlled through cognitive operations, dynamical systems theorists argue that it is the interaction with the environment that organized the degrees of freedom. In the example of the bimanual oscillation, the speed of the metronome is the environmental information that is channeling the pattern of coordination that is observed at the behavioral level. A different example involves that involves a phase transition when a parameter is scaled up is that of the walk-to-run transition when scaling up the movement speed on a treadmill (Brisswalter &

Mottet, 1996). Although both walking and running patterns can be achieved by individuals, there is a movement speed where the preferred pattern switches from walking to running, or vice versa. This speed is not identical across individuals suggesting that there are differences between individuals that drive this preference.

Since the publication of the HKB model, studies in motor control have focused on establishing the stable states of behavioral patterns in individuals executing a skilled movement. The emergence of stable states of performance is the result of relations between the learner and the environment in which the learner is finding a task solution. These relations are determined by *constraints* (Newell, 1986) that either eliminate the occurrence of certain behavioral patterns or enable them to occur more frequently. Constraints can be seen as the boundaries to the possible movement outcome for a given system at a given time. Constraints can be physical, like the presence of a wall, or the limited range of motion around the shoulder joint, but constraints can also be informational, like proprioceptive information about the surface an individual is standing on or specifications about a particular task goal. The constraints, together with behavioral information (like memory and intentions), shape the behavioral patterns that we observe (Newell, 1986, 1991).

CHAPTER 3

THE SKILL ACQUISITION PROCESS: PATHWAY TO SOLVING THE DEGREES OF FREEDOM PROBLEM

Intrinsic Dynamics

The main goal of acquiring a complex, multi-joint, skill then becomes to learn how to plan and control a movement within the set of (task, individual and environmental) constraints (Scholz, Schöner, & Latash, 2000). For example, when catching a ball, the movement needs to be planned such that the position of the hand matches the position of the ball at a specific time. Secondly, the planned movement needs to be controlled. This control of movement becomes especially challenging when the number of to-be-controlled degrees of freedom increases, as previously discussed.

Generally speaking, the processes behind the acquisition of a complex skill are poorly understood (Anderson & Sidaway, 1994; Newell, Broderick, Deutsch, & Slifkin, 2003). This has largely to do with several factors. First, experimental work has focused on laboratory based-tasks, with a relatively low complexity level (Warren, 2006). Besides this, experimental paradigms have centered around the scaling of already known tasks, rather than learning a novel task (Newell, 1981). Thirdly, it is difficult to directly assess learning. The observed changes in behavior after practice are the result of multiple different processes associated with learning (Schmidt & Lee, 2011; Verhoeven & Newell, *in press*).

What exactly is being learned by an individual acquiring a movement skill has been at the heart of investigations in motor learning (Mitra, Amazeen, & Turvey, 1998; Newell, Liu, & Mayer-Kress, 2001). The account provided by dynamical systems is related to the dynamics of the attractors. As mentioned before, human behavior can gravitate towards certain stable states, called attractors. However, these attractors are not permanent and their stability is highly dynamic. If an attractor loses stability, or, if an additional attractor arises with a higher stability, the system will move away from the initial attractor towards the novel attractor, a phase transition.

Not only does the strength of the attractor change depending on the control parameter, as in the examples of bimanual oscillation and treadmill walking, but attractor layouts change as a result of experience and the acquisition of skills. The layout of attractors at a given time for a given individual is referred to as the *intrinsic dynamics* of the system and reflects the current state of the individual. From this point of view, learning is considered to be process of qualitative changes to the attractor layout.

A Scanning Probe

Phase transitions do not necessarily occur at the same control parameter value for each individual, and therefore it is essential to consider performance in the context of individual differences. A possible method to investigate the differences in behavioral tendencies of individual learners in relation to the task goal is that of a *scanning* procedure – in which performance is observed while the learner is asked to intentionally vary a parameter of the movement (Zanone & Kelso, 1992). This scanning procedure is a method to create a snapshot of

the attractor landscape for the individual, and provides a way to not only investigate the overlap between the intrinsic dynamics and the task demands, but also to assess a learner's progress over time. This method can be seen as the dynamical systems equivalent of skill identification, which is considered one of the key responsibilities of coaches and instructors in athletic and rehabilitation settings alike.

This method has been successfully employed by Zanone and Kelso (1992) to understand the spatiotemporal patterns of behavior in bimanual coordination. They argued that the establishment of the initial intrinsic dynamic is essential in understanding the learning process, as this would provide information about the initial state of the learner. Determining the intrinsic dynamics operationalizes the concept that individuals learn new coordination patterns in the context of previously learned skills and experiences, rather than ignoring these differences, or in an extreme case, assuming a *blank slate* approach (Pinker, 2003; Thorndike, 1931).

The experimental proceedings were similar to that of the original bimanual coordination experiments (Kelso, 1981; 1984), as participants were asked to move their fingers congruent with a visual metronome. During the experiment, the relative phase of the two fingers was gradually increased from 0 to 180 degrees, to probe the intrinsic dynamics. Through analysis of performance and stability (variance), stable states were determined for each participant. Whereas most individuals demonstrated bistable behavior (with a stable state at 0 and 180 degrees, or in-phase and anti-phase), several subjects showed evidence of three stable states (0, 90 and 180 degrees).

Subsequently, participants were placed in a practice regime, in which they were required to learn the bimanual coordination at a given phasing pattern that was different from the stable states already present in the initial layout (90 degrees for the bi-stable subjects, and 135 degrees

for the tri-stable subjects). After practice, the subjects in the bistable group had created a new stable state around the 90 degrees relative phase, thus moving from a bistable to a tristable system. Yet, the initially tristable participants failed to create a new stable state, and instead seemed to have shifted a stable state away from the 90-degree relation to the 135-degree pattern.

Consequential for this study is that the relation between the intrinsic dynamics and the to-be-learned pattern was guiding the learning process. In particular, whereas the original bimanual coordination experiment only reported a phase transition (Kelso, 1981; 1984), this study was able to show both phase transitions as well as a pattern *shift*. This shift occurred if the to-be-learned pattern was close to an existing pattern, whereas a phase transition was observed when there were no proximal competing stable states. This qualitative difference in learning pathways might be empirical evidence for the often-discussed distinction between adaptation and learning.

This suggestion was further strengthened by a follow-up study, in which the persistence of the newly stable states was assessed (Kostrubiec, Tallet, & Zanone, 2006). Again, participants practiced on a novel behavioral pattern and showed either a shift or a newly generated stable state as a result. However, the retention of the behavioral pattern and its stability were assessed up to 24 days later. Whereas the individuals that moved from a bi-stable to a tri-stable state (generating a new stable pattern at 90 degrees) showed persistent stability, that is, during a scanning probe they demonstrated that a 90-degree relative phase was still part of their repertoire, the group that had shifted from a 90-degree pattern to a 135-degree pattern showed weaker stability.

Given that experience and memory shapes the experiment, studies have investigated the effect of bimanual expertise (operationalized through musical experience) on the stability of

movement patterns (Verheul & Geuze, 2004), confirming the notion that experience in a bimanual coordination task increases the stability of the commonly found attractors.

The Solution to the Degrees of Freedom Problem

Although the dynamics of the attractor layout provide a framework to consider motor learning, it does not give a solution to the degrees of freedom problem offered by Bernstein (1967). The concept of intrinsic dynamics is an appealing approach to understanding the initial conditions of a learner facing a novel task. As was demonstrated in several experiments, the outline of the already-learned movement patterns was predictive of the success at the to-be-learned pattern (Kostrubiec et al., 2006, 2012; Kostrubiec & Zanone, 2002; Zanone & Kelso, 1992, 1994). That said, it does not outline the process of how the individual reaches the to-be-learned pattern and learns how to control the degrees of freedom.

The solution to the problem of motor control was to organize the degrees of freedom in structurally and functionally meaningful units, a process called self-organization. Although self-organization is thought to be an emergent process in the sense that it does not require executive control, it does not mean that the optimal organization emerges instantaneously. In fact, it is the process of finding a solution to the motor problem that is what is at the core of practice and learning. This process of practice was elegantly coined “*repetition without repetition*” and leads the individual to find a more appropriate solution to the task at hand (Bernstein, 1967).

Finding the solution to a complex, multi-joint motor problem is finding the solution to controlling the task-relevant variables (Bernstein, 1967; Fowler & Turvey, 1978; Newell, 1991). The search for finding more optimal solutions to the task has led to the development of the

notion of task-spaces, or perceptual-motor workspaces (Newell, 1989; Newell, McDonald, & Kugler, 1991). The task-space consists of the variables that influence the task at hand. For example, the task space of a free-throw shot in basketball is the combination of release height, angle and velocity that satisfy the criteria of getting the ball through the hoop (Verhoeven & Newell, 2016). Based on this, it has been suggested that rather than controlling all variables, an individual learns the organization of the task-relevant variables during practice (Saltzman & Kelso, 1987).

To investigate which variables the individual is learning to control in multi-joint tasks, several approaches have been introduced that are built around the notion of redundancy. More specifically, in tasks that allow for multiple behavioral solutions that results in the same performance output (for instance, throwing a ball at a target), the joint space is highly redundant. However, this does not mean that learners utilize the entire task space, and it has been postulated and demonstrated that joint configurations are restricted to a subset of the available space, and that the preferences in subsets are highly individual (e.g., Pacheco et al, 2017; Pacheco & Newell, 2015, 2017a)

Moreover, trial-to-trial changes in movement patterns (or, variability) can be used to identify the task relevant variables. One approach to this is the Uncontrolled Manifold (Scholz & Schöner, 1999), which separates goal-relevant from goal-irrelevant variability. In other words, variability along one axis of performance might not result in changes at the performance level, whereas variability along another axis might. Relating this back to the original degrees of freedom problem suggests that learners become aware of the relevant variables for a specific task, and that they only actively control those variables that directly influence performance output. The task-irrelevant variables are *released* and not controlled, reducing the need for

additional planning and control, while also limiting the risk of joint-level perturbations (Scholz & Schöner, 1999; Scholz et al., 2000).

In sum, learning can be considered the process of changing the coordination to accommodate the novel task requirements and with that, understanding the qualitative aspects of the changes taking place (Mitra et al., 1998). This is done through search of the perceptual-motor workspace (Newell et al. 1989), in which individuals explore the possibilities of how the task can be solved to find the movement pattern that is most optimal for the task at hand. Just as it is specific to the particular task, it is also specific to the individual learner. This dependency has been observed in several studies relating the individual differences in intrinsic dynamics to learning (Kostrubiec et al., 2006; Kostrubiec & Zanone, 2002).

CHAPTER 4

INDIVIDUAL DIFFERENCES: HOW THE CHARACTERISTICS OF THE LEARNING INFLUENCE THE SKILL ACQUISITION PROCESS

A History of Individual Differences

The difficulty with considering the background of an individual in studies of motor learning is to provide an adequate account of the individual's history, sufficiently thorough to capture the experiences that have contributed to the characteristics of the learner relevant to the skill. Moreover, the consideration of the intrinsic differences in performance has been further minimized by both theories and experiments in motor control that emphasized *general laws of learning*. Given that heterogeneity in performance weakens the interpretation of the power law, differences between individuals are often disregarded. In the discussion of the existing literature, we consider individual differences to be the inter-individual variability in behavior and performance.

Whereas this type of analysis has been the focus in certain areas of psychology, like research on personality, the variation around individual performance is often considered to measurement or execution noise in motor learning literature and ignored for subsequent analysis. That said, an analysis of individuals does not mean that systematic patterns across (sub-)groups should be ignored. If, for instance, half of the participants show a positive response to an intervention and the other half a negative response, these could reflect characteristic differences in individuals that

are worth exploring. Notably, these differences would have been ignored if response was averaged across all individuals, emphasizing the need for individual-based analyses.

The existing discussion around individual differences in learning and performance largely originates from the discussion of ‘nature’ versus ‘nurture’, or, in this case, genocentrism and environmentalism. The former, was advocated early on by Sir Francis Galton, suggesting that individuals with a high intellect were born with it, and that no training would influence this (Galton, 1869). The opposing argument is that individuals are able to achieve any level of performance, as long as they practice. Environmentalists believe that people begin as a blank slate, and everything else is learning and experience (Pinker, 2002). A prominent contemporary advocate of this idea has been Anders Ericsson, who studied expert violinists and concluded that deliberate practice is what leads to expert performance (Ericsson, Krampe, & Tesch-Romer, 1993). Although most contemporary theories of individual differences accept that behavior is a dynamic interaction of genetic contributions, environmental influences, experiences and random events (Ackerman, 2014), some discussions in both popular and scientific literature continue to emphasize either extreme view (Bray et al., 2009; Chassy & Gobet, 2010)

From a motor learning and performance perspective, the historical emphasis has been on finding ‘abilities’ that underlie individual differences in skilled performance. In other words, it was believed that these abilities, or capabilities, are traits specific to a given individual such that if two tasks require the same ability, an individual that would do well in Task A, would be successful at Task B. This introduces the issue of skill transfer, which has been a topic of interest for over a century in motor learning (Adams, 1987; Gagne & Foster, 1949; Salmoni et al., 1984; Schmidt, 1975; Schmidt & Lee, 2011; Shea & Morgan, 1979; Thorndike, 1931; Woodworth & Thorndike, 1901; Zanone & Kelso, 1997). At the heart of these investigations was the notion that

improving understanding of task conditions that lead to transfer, would reveal the underlying learning process. In other words, by assessing how much of a learned skill transfers to a different task, the question of *what* is learned during practice can be answered.

The approaches based on schema theory and dynamical systems theory suggest that the similarity between the original and the transfer task (Task A and Task B, respectively), is what defines the degree of transfer. Based on the schema theory approach of motor learning, studies investigating skill transfer have focused on the role of variable practice. This type of practice was aimed to promote a large variety in trial conditions, which was assumed to strengthen the motor program, or schemata. Empirical evidence has been found to support this notion (Schmidt, 1975; Schöllhorn, Mayer-Kress, Newell, & Michelbrink, 2009), as well as to dispute it (Sherwood & Lee, 2003; Van Rossum, 1990).

Whereas the definition of task similarity in schema theory has been debated, the dynamical systems account offers a defined concept of skill transfer. More specifically, the similarity of the tasks is defined in the task space such that successful skill transfer will take place if the relevant parameters of a task are the same (Braun et al., 2010; Ranganathan & Newell, 2013; Ranganathan, Wieser, Mosier, Mussa-Ivaldi, & Scheidt, 2014). Thus, if two tasks share movement parameters that define task success, it is more likely that transfer will occur than when these parameters are different.

The traditional line of reasoning surrounding individual differences resulted in a prolific line of research occupied with finding underlying abilities, investigating their relationship with complex skills, identifying methods to improve the abilities and with that performance and prediction of task success based on ability assessments (Ackerman, 1987; Adams, 1987; Fleishman, 1972). However, the theoretical advancements concerning the issues of individual

differences in motor learning have been limited. Besides the aforementioned genetic and environmental accounts, the variability in performance between individuals has traditionally been attributed to differences in a General Motor Ability (Ackerman, 1987; Brace, 1927). Although the idea is anecdotally appealing, especially considering the athletically gifted individuals that excel at several different sporting disciplines, scientific support of the position is lacking. Counter to this idea was that of the Specificity Hypothesis which suggested that abilities are entirely specific to a given task at hand and that being good at one task is in no way related to performance at another task, although they might appear similar (Lévesque, 1992).

The dynamical systems approach to motor control and learning offers a potential explanation to revitalize the study of individual differences in performance. The differences in constraints that are acting on the learning system will be different between individuals, resulting in differences in both the initial state (or, preferred dynamics) of the learning and differences in the pathway of exploration of the perceptual-motor workspace (Newell, 1986).

Individual Differences and Intrinsic Dynamics

Even though empirical evidence has suggested that changes in motor performance are highly dependent on the initial state of the learning (Kostrubiec et al., 2006), the issue of individual differences remains relatively unexplored in the study of motor learning. Both within- and between-individual differences in performance are relevant to the current study. The former relates to differences in behavior from the same individual in different contexts whereas the latter applies to different individuals demonstrating the same behavioral output while varying in their approach. Related to the latter is also the developmental issue of individual differences: humans

reach a similar developmental outcome in general movement patterns (walking, standing, etc.) through distinct developmental pathways (Thelen, 1995). As mentioned before, variables from the environment shape the possibilities and probabilities of behavioral responses. These variables can include gravity and desired walking speed, but could also be experimentally manipulated like the frequency in bimanual oscillation experiment (Kelso, 1981).

It follows that changes in physical fatigue or attentional focus for a given individual can result in trial-to-trial variations, with changes in muscular strength and experience leading to changes on a developmental timescale, even when task demands and environmental conditions are preserved. However, in many cases, both the task- and environmental constraints are dynamic (Davids, Button, & Bennett, 2008; Li, Van Den Bogert, Caldwell, Van Emmerik, & Hamill, 1999; Newell, 1986). Particularly in complex skills, for example, returning a serve in tennis, it can be argued that no execution of the stroke is the same as any of the preceding or subsequent strokes. Between trials, the environmental constraints on the system, like wind speed and direction may have changed, as well as the position of the opponent on the court. Similarly, it could be argued that returning a second serve, arriving at a lower speed, provides different task constraints than returning a first serve. Another example of changes in task demand could be the current score, as this could dictate the level of aggressiveness or conservativeness in the shot. In addition, the dynamics of the constraints of the individual are highly relevant for the task performance.

Firstly, there are changes in constraints within the individual. For example, during a tennis match, muscular fatigue will play an increased role as time goes on. Certain shots will be executed in a less powerful manner, or are eliminated as possible responses altogether. Similarly,

during a match, an individual might obtain knowledge about the strengths, weaknesses and playing preferences of their opponent, which can act as constraints on the individual.

Secondly, there are differences in individual constraints between individuals. Individual differences in performance have often been ignored in the motor learning and control literature, but play a fundamental role in understanding human behavior. Differences in constraints between individuals can exist at many levels of analysis, but are often separated in two main categories: structural and functional. Structural constraints relate to the more robust features of an individual like anthropometric features, such as height, limb length, muscle strength, body composition, etc. Although these features are not fixed, changes occur at a relatively slow rate, particularly compared to the functional constraints. The current set of skills of an individual is often considered to be part of their functional constraints.

The result of the combination of the aforementioned differences in constraints is what can be captured in intrinsic dynamics (Kovacs, Buchanan, & Shea, 2009; Thelen, Corbetta, Kamm, Spencer, & Schneider, 1993), as this represents the initial state of the learner and underlines the notion that all individuals start the skill acquisition process at a different point based on their previous experiences. The role of intrinsic dynamics has often been ignored in studies related to motor learning and skill acquisition in an attempt to focus on the effect of the experimental manipulation on behavioral output or performance. Similarly, in more applied settings such as rehabilitation and athletic environments, the differences in individual learners are often assumed to be negligible. From this standpoint, any pre-existing individual differences are confounding the effects of the intervention. In some cases, differences in intrinsic dynamics have been used to explain unexpected findings in learning studies (Estes, 1959; Skinner, 1990; Elsner & Hommel,

2001), or even the apparent lack of learning (Breland & Breland, 1961; Seligman, 1970; Garcia et al., 1974; Shettleworth, 1978; Timberlake & Lucas, 1989).

An Optimal Movement Pattern

Based on the individual differences in constraints and the ideas of exploratory learning, an important consideration arises that it is not imperative that a collective optimal movement pattern exists across all individuals for any given task. In fact, given the differences in individual constraints, ranging from differences in body morphology to natural movement tendencies, it is conceivable that the ‘ideal’ movement pattern is distinct for each individual on each task, even when environmental conditions are identical (Frank, Michelbrink, Beckmann, & Schöllhorn, 2008; Schöllhorn, 1999) . This provides an emphasis that challenges the common and traditional approach in practical skill learning realms, where coaches, instructors and therapists aim to find and strengthen an idealized movement state through repetitive drills or exercises. Rather, based on the constraints model, the emphasis should be on adaptive learning, where the coach should have a thorough understanding of the interaction between the intrinsic dynamics of the learner (*‘What can the individual already do?’*), the informational constraints and the task demands (*‘What should the individual be able to do?’*). Thus, the ability of the coach to evaluate the individual’s skill in relation to the task goal is of prime importance.

Generally, the focus of the motor learning literature as a whole, but specifically the feedback literature has been of a prescriptive nature. Knowledge of Results (KR) is traditionally one of the most used ways of conveying feedback to a learner, by providing information relative to the task success (Adams, 1971; Newell, 1974; Salmoni et al., 1984; Schmidt & Lee, 2011; Thorndike,

1931). However, given that KR does not provide meaningful information about specific changes in case the outcome was unsuccessful, many motor learning tasks involve Knowledge of Performance (KP) about the movement pattern through kinematic feedback (Ammons, 1956; Gentile, 1972; Schmidt & Lee, 2011; Wallace & Hagler, 1979; Weeks & Kordus, 1998; Young & Schmidt, 1992). However, there are numerous cases where neither kind of information is necessarily informative.

For example, goal-information as a reference of correctness is often readily available in sporting events (e.g. a basketball free-throw going in). Similarly, there are complex movement skills in which no explicit knowledge of the movement pattern is required in order to successfully satisfy the task demands (see juggling, Shannon, 1993). Certainly, there are exceptions in which the movement pattern is the task goal (e.g. in gymnastics), in which case the coach needs to convey information about the movement pattern in relation to the clearly defined rules as to what the movement should look like. Although it is relatively straightforward to deliver KR relative to goal performance, the issue of what information is provided during KP is less understood. Anecdotally, much of training practices rely on using reference KP based on the performance of the best performing subject, the so-called *champion model*. However, empirical evidence demonstrates that in redundant tasks, kinematic characteristics do not necessarily predict task performance, supporting the notion that there is not a unique optimal solution (Brison & Alain, 1996; Newell, 1996; Schöllhorn & Bauer, 1998; Verhoeven & Newell, 2016).

Previous work suggests that instructors should go beyond emphasizing a prescriptive movement pattern and instead facilitate the search for an optimal movement pattern by providing the appropriate constraints to the movement (Fowler & Turvey, 1978), such that the individual is able to explore the possible movement patterns and *discover* the appropriate pattern though a

self-guided process (Frank, Michelbrink, Beckmann, & Schöllhorn, 2008; Newell & Ranganathan, 2010).

Traditional coaching approaches fail to take into account the individual-centered approach outlined in the previous paragraphs and instead emphasize reproducing a pre-determined movement pattern based on what is considered *ideal*. This traditional approach stems from the idea that motor skills are represented in a cognitive structure (motor memory), where a repetition of a task strengthens the *memory trace* (Adams, 1971). Instead, by taking into consideration the idea that motor learning is an emergent property of the constraints, with intrinsic dynamics influencing task performance, the instructor can focus the attention on changing the constraints to the system in a way that learners are able to explore movement patterns independently.

In sum, one of the outstanding fundamental issues in motor learning is that of the individual differences in coordination and control of a complex task. During the skill acquisition process, learners practice a given task to find a stable pattern of relative joint motion. That said, it has been demonstrated that the differences between individuals at the start of an experimental practice period influences the pathway of learning (Kostrubiec et al., 2006, 2012; Kostrubiec & Zanone, 2002). However, these studies have used experimental paradigms that did not involve more than two degrees of freedom, limiting the potential of generalizing the understanding of the learning process.

In this study, we will investigate the effect of preferred dynamics on learning in performance in the context of a whole-body target-based throwing task. The skill of throwing is ubiquitous in sport, most notably in baseball (Fleisig, Chu, Weber, & Andrews, 2009; Fleisig et al., 2006) and basketball (Button, Macleod, Sanders, & Coleman, 2003; Oudejans, Van De Langenberg, & Hutter, 2002; Verhoeven & Newell, 2016). It has been used in a wide variety of studies of motor

development and learning, as it is a highly redundant task allowing for a wide range of individual differences in spatio-temporal patterns of the movement (Kernodle & Carlton, 1992; Langendorfer & Robertson, 2002; Robertson, Halverson, Langendorfer, & Williams, 1979; Schorer, Baker, Fath, & Jaitner, 2007). Depending on the requirements of context, the goal for the thrower is to throw the ball in varying combinations of speed and accuracy. This can be achieved by a sequence of joint motion that will result in the appropriate end-point velocity and direction.

From a developmental perspective, throwing has been used to study the stages (or *developmental steps*) of learning (Langendorfer & Robertson, 2002). Particularly, researchers have been interested to investigate at what age children start using certain body parts to throw (Robertson et al., 1979; Wild, 1938). The consensus from these studies is that throwing performance gradually improves throughout childhood, with effects of gender on performance. That said there have been few studies examining the changes in coordination modes of adults in a throwing-based task. A cross-sectional study of coordination patterns in different adult age-groups revealed that through adolescence, the performance increases and patterns become more advanced, but then regress into adulthood (Lorson, Stodden, Langendorfer, & Goodway, 2013).

CHAPTER 5

EXPERIMENTAL GOALS AND HYPOTHESES

This study was designed to investigate several important issues that bridge the gap between the theoretical accounts of motor learning and its practical applications. To this end, a new framework was outlined that integrates concepts from both motor learning and individual differences from a dynamical systems perspective. In this study, several predictions of the framework will be investigated, with the aim of challenging the traditional notions of skill learning. The general goal of the present study was to test the main hypothesis that the effectiveness of practice and training interventions is dependent on the preferred dynamics.

The first experiment addressed the issue of differences in preferred dynamics in a complex whole-body task. Individuals were asked to perform a task (throwing a ball at a target) under different target distance conditions. The participants were not given any instructions with regards to their throwing pattern, and they were informed that they could throw however they preferred. The task goal could be satisfied in different ways for different target conditions.

Experiment 1 tested the hypothesis that a task in which successful performance output can be achieved through a manifold of solutions will reveal a wide range of individual differences in those solutions.

A second hypothesis for this experiment was that, as the target conditions change, so do the imposed task constraints. As a result, we predict that changes in the movement pattern will result as a function of changing the target condition. In addition, we predict that these the

changes or transitions in the movement pattern occur at different conditions for different individuals.

The third hypothesis for Experiment 1 was that the observed preferred patterns in the throwing tasks are stable, in the sense that when the movement patterns are studied at an additional testing time, they reveal a similar pattern. To this end, a subset of individuals who participated in the initial probe were invited back for a second probe.

Experiment 2 tested the significance of the individual difference in preferred dynamics in a learning context. Individuals were asked to participate in a learning design that featured the same testing probe as in Experiment 1 in a pre- post- test design, with 3 days of practice in between. Whereas participants did not receive throwing-pattern instructions during the pre- and post- test, the movement patterns in the practice sessions were constrained by the experimental condition and were either congruent or incongruent with the individual's preferred pattern.

The hypothesis that was tested with this design was that different initial preferred states would result in different practice effectiveness, as measured by changes in task performance over time. Specifically, does practicing a movement pattern opposite to the observed preferred pattern result in a greater performance enhancement.

CHAPTER 6

EXPERIMENT 1 – INDIVIDUAL SOLUTIONS TO A REDUNDANT MOTOR PROBLEM

Introduction

Although motor skill acquisition has been a topic of interest for more than a century (Adams, 1987; Bernstein, 1967; Braun, Mehring, & Wolpert, 2010; Bryan & Harter, 1897; Schmidt, 1975; Skinner, 1938; Thorndike, 1931; Warren, 2006; Woodworth & Schlosberg, 1938), an active debate remains on what exactly is learned when an individual practices a skill.

Advancements on this, and related issues, are slowed by the complexity of the human movement system. Even at global levels of analysis, such as of the body segments, the control of human motion is intricate, yet well-controlled (Kauffman, 1996; Kelso & Engstrøm, 2006; Warren, 2006). Given that the complexity only increases when investigating at different levels (joints, muscles, neurons, etc.), it is understandable that a general theory of motor control is difficult to formulate (Tseng, Scholz, & Schöner, 2002).

Understanding motor learning is further complicated by the fact that learning is not directly observable. The processes that take place during skill acquisition have to be deduced from changes in behavior, performance, and through transfer tests. Traditionally, notions of skill learning have been built around mental faculties (Woodworth & Thorndike, 1901), abilities (Fleishman, 1972), schemata (Schmidt, 1975) and dynamical systems theory (Turvey, 1977).

One of the current positions of motor learning is that individuals learn the *task space* during practice (Newell, 1985; Turvey, 1977). More specifically, the idea is that, when faced with a novel task, individuals will explore a wide variety of potential movement patterns to find solutions to the movement problem at hand. In some cases, the task can be set up in a way that only one movement coordination pattern will satisfy the task criteria. In this case, the task space is constrained to a single solution and it is the goal of practice to find this solution. However, in many cases the task space consists of multiple solutions. In other words, a set of different movement patterns can lead to the same performance outcome.

It is suggested that in the process of exploring the relation between the movement possibilities and the performance (relative to the goal), individuals become aware of the movement variables that contribute to task success and those that do not. This line of thinking can, in some way, be found in many theories of skill learning (Braun et al., 2010; Jacobs & Michaels, 2007; Latash, 2010; Schmidt, 1975), and has led to analytical approaches based on this notion (Latash, Scholz, & Schöner, 2002; Müller & Sternad, 2004; Scholz & Schöner, 1999).

We argue that an underdeveloped position in this issue of learning is that of the individual differences in performance and behavior. Individuals approach a given task with a background that consists of skills, previous experiences and arguably more transient factors like motivation and mood that could influence not only task performance, but also the coordination of the solution to the task problem. Experiments considering these differences in initial states have been successful in providing empirical evidence that these tendencies have a strong effect on the pathway of skill acquisition (King, Ranganathan, & Newell, 2012; Kostrubiec et al., 2006, 2012; Kostrubiec & Zanone, 2002; Pacheco & Newell, 2015; Zanone & Kelso, 1997). The effect of individual differences on performance has been most commonly explored from the perspective

of transfer in learning, where investigators have been interested in finding the characteristics of practice that influence performance in a transfer test design (Adams, 1987; Newell, 1996).

Previous work has demonstrated that individual differences in strategic approaches to a redundant task influence performance on a subsequent related task (Pacheco & Newell, 2015).

That said, the experimental evidence for this has largely been limited to *simple* laboratory tasks that only involve the control of limited joint space degrees of freedom. The issue of individual differences becomes particularly interesting, however, for tasks where the task goal does not prescribe the movement pattern necessarily. These whole-body, complex tasks provide a manifold of solutions at different levels of the system-environment interaction. This manifold provides the possibility for behaviorally different outputs with the same performance output. Thus, it can be argued that even though all individuals are practicing the same task and learning the same coordination function, the differences in preferred dynamics or behavioral repertoires will lead to different coordination patterns while still maintaining the same performance outcome.

Nevertheless, many studies of motor learning (and to some extent experimental psychology in general) do not consider the effects initial differences between individuals on the experimental manipulation to be tested. In fact, pre-existing differences between participants have been suggested as a rationalization as to why the observed findings were not in line with expectations or hypotheses (Elsner & Hommel, 2001; Seligman, 1970). Furthermore, in more applied environments like athletic and rehabilitation settings, the practical approach of the (re-)learning often seems to disregard individual differences in favor of a one-size-fits-all approach (Molenaar & Newell, 2010; Newell & Verhoeven, 2016). However, it is worthwhile to explore the role that individual differences at the start of practice have on the learning process. This can

be done by establishing in what way the predispositions express themselves in the task at hand. By systematically varying a task parameter and observing changes in individual behavior a framework can be formed about the preferred solutions for each individual relative to the task and the potential phase transitions from one solution to the next.

In this experiment, we investigate individual differences in preferred task solutions by asking participants to throw a small ball towards a square target, placed on the ground at different target distances. Throwing has been a common task in studies of skill development and motor learning given its' complex and redundant nature (Kernodle & Carlton, 1992; Kudo, Tsutsui, Ishikura, Ito, & Yamamoto, 2000; Wagner, Pfusterschmied, Klous, von Duvillard, & Müller, 2012; Wild, 1938). In this particular task, individuals were asked to make throws using both dominant and non-dominant hands, in line with previous studies of performance and learning of target-based throwing (Kernodle & Carlton, 1992).

Individuals were given no instructions regarding the movement pattern such that both the redundancy of the whole-body task and the expected differences in behavioral repertoires of the participants would result in individual differences in solutions of the task problem. In other words, we expect that the *experience* of the individual will drive the selection of a movement pattern to throw the ball at the target. As a result, individual differences in preferred dynamics will express themselves as differences in movement patterns at different throwing distances for given individuals. We do not predict that the differences in movement patterns will be predictive of differences in performance, given that there is a manifold of solutions that satisfies the task criteria (Arutyunyan, Gurfinkel, & Mirskii, 1968). That said, we do expect to see a general pattern of performance changes with a change in target distance. More specifically, we anticipate that task performance will decrease as the target distance increases, reflecting a change in the

task constraints. Similarly, we anticipate that performance on the dominant-hand condition will be higher than that of the non-dominant hand as a result of increased overall use of the dominant hand (Bray, 1928; Kudo et al., 2000; Newell & van Emmerik, 1989; Stöckel & Weigelt, 2012; Verhoeven & Newell, 2016). Lastly, we predict that participants will demonstrate transitions in preferred movement patterns with changes in target conditions. As the constraints on the movement change, with changes in target distances, different preferred patterns will emerge. We anticipate the point at which these transitions occur will be different for different individuals, and might not occur in all individuals.

In addition, a subset of participants performed the task again at a later date, to investigate the similarity of task solutions within the individual at different time-points. This manipulation afforded a test of the hypothesis that the behavioral solutions remain relatively *consistent* over time and are only marginally influenced by transient effects.

Methods

Participants

22 right-handed participants (mean age: 24.2 years; 10 females) signed up to participate in this experiment. All subjects were recruited from the University of Georgia, Athens campus. Individuals with (minor) injuries were excluded from participation. Participants received a \$10 gift card as compensation for their participation. The University of Georgia Institutional Review Board approved the experimental procedures for the experiment. Written informed consent was obtained from all participants.

Apparatus

The experimental proceedings for each experiment took place at the Motor Behavior Laboratory at the Ramsey Student Center at the University of Georgia campus in Athens, GA. The movements of the individuals were recorded at 120 Hz through 8 VICON (Vicon Industries Ltd., Hampshire, United Kingdom) Bonita Optical motion capture cameras and analyzed through the VICON Nexus 2.0 software. 30 reflective markers were placed on the participant's body in line with the VICON Plug-in-Gait Marker Placement. The ball was equipped with 4 additional markers, to determine the release parameters and impact location relative to the target.

The target was placed horizontally on the floor (Figure 1) and was rectangular in shape, with each side measuring 140 cm. The center of the target was worth 7 points and measured 20 cm x 20 cm. From there, each rectangle increased in size and decreased in value (40 cm x 40 cm for 6 points, 60 cm x 60 cm for 5 points, etc.). The target location was recorded throughout the experiment using a VICON Bonita 720 C high-speed camera to monitor performance accuracy. Performance was manually scored by the experimenter, and later verified using video recordings of the high-speed camera.

Procedures

Upon arrival, anthropometric data were collected from the participant through measurements of body segments and reflective markers were applied to the body of the participant. After a brief calibration of the motion capture system, all participants were informed of the experimental proceedings.

At first, the maximum throwing distance of each participant was assessed. Each participant threw the ball 15 times with the dominant hand, with the instruction to throw as far as

they could. The mean distance of these trials (*Maximum Distance*; MD) served as a reference for the subsequent trials. This was repeated for the non-dominant hand, for a total of 30 maximum distance trials. During these trials, the target was not present. Because of the composition and the weight of the ball, it was unlikely that the maximum throwing distance would exceed the length of the testing facility (9.45 m). However, if the ball hit the wall, the maximum distance would be noted at 9.45 m. This was the case for 2 participants in the dominant-hand condition.

Subsequently, participants were asked to throw a ball over 5 different distances, relative to the maximum throwing distance of the individual. For the experimental conditions, the target was located at 10%, 30%, 50%, 70% or 90% of MD (see Figure 1). Each participant completed a total of 30 trials per condition, 15 with the dominant hand and 15 with the non-dominant hand, for a total of 150 trials. The order of the conditions was counterbalanced between participants to minimize the influence of previous blocks on performance. A 1-minute break was offered in between each experimental block of 15 trials.

For each trial, task performance was measured through the proximity of the ball landing spot to the center of the target. A trial received the maximum score of 7 when it landed in the middle of the target, and a score of 0 when it landed outside the target zone (see Figure 1). Trials were scored by the experimenter, and later verified using footage from the high-speed video camera. In case the ball hit the line in between two target scores, the highest number of points between the two was awarded. Participants received this performance score as feedback after every trial, as well as summary score after each practice block. Kinematic data of both the participant and the ball were recorded for each trial through the motion capture system. For data collection purposes, the participant initiated each trial after a *go* signal from the experimenter. A trial ended at the moment the ball landed at the target.

Participants were instructed to stand with their feet parallel and touching, with their arms relaxed to their sides at the start of each trial to ensure a similar starting position for each trial. Participants were only instructed to perform to the best of their abilities and were given no instructions related to the movement pattern, allowing for every participant to maximally utilize the large redundancy in movement patterns and release parameters that satisfy the task criteria. To maintain a good position relative to the motion capture equipment, the participant was instructed not to move outside of a 2 m x 2 m square marked on the floor.

8 participants of the original 22 came back for a second session, 4 to 6 weeks later, to test the similarities in movement patterns used in both sessions. The session consisted of the same experimental conditions and experimental order as their original session.

Data Analysis

Before exporting, all data were passed through a filter (4th order Butterworth low-pass filter with frequency of 10 Hz). Filtered data were exported from the Nexus software and imported into Matlab (v2008b, MathWorks, Inc., Natick, MA, USA). Trials with missing data were interpolated and only in cases where a temporary occlusion prevented analysis the trials would be removed. The total number of trials removed from the analysis was 46 (1.39 %).

The performance score was analyzed as a function of practice conditions and was contrasted between conditions using a Distance (5) x Hand (2) repeated-measures ANOVA. Additionally, the order effect of distance and starting hand was assessed through an ANOVA. An alpha level of .05 was used for all statistical tests. In the case of significant main effects or interactions post hoc pairwise multiple comparisons were performed with the Bonferroni correction procedure.

The kinematic data of the ball were reduced to the center of the ball, which was calculated as the three-dimensional midpoint of the 4 markers placed on the ball. The kinematic trajectory of the ball was used to compute the time-point of release as the frame at which the ball was more than 5 cm away from the marker placed on the throwing hand (in between the knuckles of the index- and middle finger). The ball was used to calculate the position and velocity of ball release.

The throwing style of the individual can be described in two ways; using the information from joint movements and that of the ball release parameters. Although using information about the joints is more accurate in describing the movement pattern, it is less directly related to task performance, as it requires knowledge of the exact timing of the ball-release relative to the joint positions and velocities. This is avoided when considering the release position and velocity parameters of the ball, which has a more direct relation with the landing spot of the ball, the ultimate task goal. Equations of projectile motions¹ were used to determine whether the performance output was largely influenced by the variation in position or variation in velocity of the ball. First, the standard deviation of ball position and ball velocity were calculated to get an idea of the estimated variation for each individual. Then, these estimates were inserted in equations of trajectory motion to analyze which component (velocity or position) more strongly influenced the landing position. This analysis revealed that release velocities were more influential, in line with previous findings (Pacheco & Newell, in preparation). Furthermore, although initial attempts at throwing pattern classifications considered the release position

¹ $X_l = X_r + V_x * t$, $Y_l = Y_r + V_y * t$, $Z_l = Z_r + V_z * t + (g * t^2)/2$ where x_r , y_r , and z_r represent the release position of the ball, v_x , v_y , and v_z are the release velocities and x_l , y_l , and z_l denote the landing location of the ball. Furthermore, g represents the gravitational constant (-9.8 m/s^2) and t the movement time. Given that the target is placed on the floor, Z_f is set at 0.

relative to the shoulder in the (e.g. higher than shoulder is overhand, etc.) several subjects carried out throws with an underhand style for which the release position of the ball was at shoulder height, complicating an accurate classification of overarm and underarm throwing. Hence, analyses of throwing style were carried out on the parameters of release velocity.

Based on the relative contribution of the directional velocity vectors of the ball at the release point, throws can be classified as underhand or overhand. Underhand throws have a higher relative contribution of the vertical velocity component compared to overhand throws that are predominantly x-dimension based (Figure 2). A threshold was designed to determine if a throw was overhand or underhand, such that if the z-component of the ball velocity was higher than 50% of the x-component, a throw was classified as underhand. A notable exception occurred in infrequent cases at the 10% distance where participants opted to vertically '*drop*' the ball, resulting in a velocity vector dominated by a (negative) z-component. These throws were excluded from the dichotomous classification. Lastly, the ratio of x- to z- velocity largely covaried with the release position of the ball, further supporting the decision to focus the analysis solely on the velocity components.

Classifications of throwing patterns (underhand versus overhand) were observationally verified by the experimenter in a random selection of 20% of the total trials. There was a 100% correspondence between the velocity-based classification and the observational classification. Furthermore, although the analysis of this experiment did not emphasize behavior at the joint-level, movement pattern classifications were further verified using a shoulder-elbow angle-angle plot (see Figure 3). Overhand patterns show predominantly elbow-based motions, whereas underhand patterns show a predominantly shoulder-based motion. These joint-based classifications also were consistent with the velocity-based classification on the selected trials.

All data analysis was performed at the individual level and not collapsed across individuals. For analytical purposes, the start of each trial was defined as the moment the *go* signal was given by the experimenter, with the end of the trial defined as the moment the ball was released. Throwing style was categorized as overhand or underhand, based on the decomposition of the ball velocity at the moment of release (see *Results* and Figure 2). Similarity between test and retest performance was assessed using a pairwise t-test on the cluster means of each condition.

Results

Performance Scores

The average shot score was 4.73 (SD: 0.72), with the lowest individual experimental average being 3.87 and the highest individual shot average 5.94. The lowest obtained (15-shot) block score was 9, and the highest was 105 (Figure 4).

The 5 (Distance) x 2 (Hand) repeated measures ANOVA revealed a strong effect of Distance on performance, ($F(4,18) = 138.44$, $p < 0.01$), as well as an effect of Hand ($F(1,21) = 28.72$, $p < 0.01$). A Distance x Hand interaction approached significance ($F(4,18) = 2.80$, $p = 0.06$). Post-hoc analysis of the Distance effect revealed that performance on each distance was significantly different ($p < 0.01$ for all comparisons), with a mean performance block score of 101.3, 89.0, 69.9, 54.4 and 40.1 for the five respective distances (10%, 30%, 50%, 70% and 90% of MD). Further analysis of the Hand effect revealed that the performance scores in the dominant hand trials were higher (73.44) compared to the non-dominant hand trials (68.45).

Throwing pattern – Release velocity

The throwing patterns were classified according to the velocity vectors (in x, y and z directions) of the ball at the moment of release. The overall velocity of the ball increased as a function of distance, regardless of throwing hand, as can be seen in Figure 5. Although the data displayed in Figure 5 are that of a single subject, this pattern is seen across all participants, as confirmed by a Distance (5) x Hand (2) ANOVA of the velocity, ($F(4,18) = 120.03$, $p < 0.01$). More specifically, when decomposing this total velocity vector, it becomes apparent that subjects manipulate the velocity of the ball in the x- and z- direction in response to changing target distances (Figure 6). A Distance (5) by Hand (2) repeated measures ANOVA of the velocity components confirms this observation. Main effects for Distance were found for X ($F(4,326) = 567.776$, $p < 0.01$), Y ($F(4,326) = 7.87$, $p < 0.01$) and Z directions ($F(4,326) = 110.61$, $p < 0.01$). Hand and Distance – Hand interaction effects were not observed.

An example of an individual release velocity profile can be seen in Figure 7. The figure is oriented to display the x-velocity on the x-axis and the z-velocity on the y-axis. Each dot represents one trial, with the different colors representing the different throwing distances. At the 10% throwing distance, all throws are made with an underhand pattern (trivial contribution of the z-component) and low variance. Now, focusing on the non-dominant throws (Figure 7B) and the trials at the 30% distance, the majority of throws were executed using an overhand pattern (the z-component was in the negative direction, indicating a downward throw), with the exception of two trials (circled in blue). For these trials, the individual opted to explore the underhand throwing pattern (with a large positive contribution of the z-component). Interestingly, this subject performed the same distance with an underhand pattern in the dominant hand throws (Figure 7A). The same observation can be made at the 50% distance, where three trials were

made with an underhand pattern (circled in purple), while the remaining trials were performed using an overhand pattern. This is an example of an individual who explores a different movement pattern during the block, but does not show a *switch* in movement pattern as the distance scales up.

An example of an individual who does show a pattern transition from one experimental condition to the next can be seen in Figure 8A. This particular individual shifts from a *drop* pattern at 10%, to an overhand pattern at 30% and an underhand pattern at 50% and beyond. Similarly, Figure 8D shows an individual with overhand throws in all conditions up to 90%, where a shift is observed to underhand throws. Of note, performance of these subjects was identical at 4.88 points per shot. Although as a group, throwing patterns shifted from predominantly underhand to overhand with increases in throwing distance (Figure 9A), this is not representative of the behavior at the individual level (Figure 9B), where each individual has a different preferred pattern at different conditions, even though the performance score is similar.

A Distance (5) x Hand (2) ANOVA revealed a significant effect of Distance ($F(4,18) = 7.45, p < 0.01$) on the overhand percentage, but not of hand ($p = 0.81$), nor was there an interaction effect of Distance and Hand ($p = 0.09$). A post-hoc analysis of the Distance effect revealed that this is fully driven by a significantly lower percentage of overhand throws in the 10% condition (1.5% of throws are overhand), compared to all other conditions.

Pattern-Performance Coupling

By definition, if the position of the release point in space stays constant, it is the release velocity of the ball (in x-, y- and z- directions) that determines the landing spot and thus trial performance. The velocity decomposition was then used to identify its role in predicting task

performance. Specifically, the standard deviation of the magnitude of the velocity vector in each direction was correlated with the block score for each individual. On average, the SD of the velocity showed a correlation of -0.66, -0.74 and -0.41 for X, Y and Z, respectively, suggesting that a better score is associated with a lower variability of the release velocity. Whereas the velocity and in the X and Z direction can show covariation as a result of compensatory effects, any deviation away from the middle of the target in the Y direction will directly lead to a reduction in performance. In addition, an ANOVA of performance and pattern reveal that there is no performance advantage for using overhand or underhand pattern in any of the throwing conditions, indicated by the absence of a main effect of Pattern ($p = 0.82$).

Test-Re-test Stability - Performance

Eight individuals who performed the throwing task came back for a second session of throwing performance, which consisted of the exact same task and task-order as they had experienced during the first session, to test for a learning effect.

Performance scores were entered in a Day (2) x Distance (5) x Hand (2) repeated measures ANOVA to test if the performance was comparable across the two testing probes. The ANOVA revealed a strong effect of Distance ($F(4,4) = 1563.55$, $p < 0.01$) and Hand ($F(1,7) = 11.34$, $p = 0.01$) on performance. The effects of Distance and Hand were in line with the previously observed effects. In addition, no effect of Day was found ($F(1,7) = 2.52$, $p = 0.16$). In other words, the average block performance on Day 2 (77.8) was not significantly improved compared to Day 1 (74.1). No significant interactions were observed.

Test-Re-test Stability – Throwing Pattern

For each condition, a cluster mean was calculated using a k-means clustering method and was contrasted with the same condition on the subsequent testing session. The similarity between the throwing patterns between the test and the re-test for each condition was assessed through a Day (2) x Distance (5) x Hand (2) repeated measures ANOVA (Figure 10). There was no effect of Day for X velocity ($p = 0.87$) and Z velocity ($p = 0.92$). In line with the findings previously discussed, an effect of Distance was observed for X velocity, ($F(4,18) = 95.59$, $p < 0.01$). For Y velocity, no main or interaction effects were observed.

Again, using the velocity as a classifier for overhand or underhand throws, a layout of the percentage of overhand throws was made for each individual and each distance (Figure 11). This reveals that the frequency of chosen patterns at a given distance is similar across two testing probes.

Discussion

The objective of this study was to investigate if a complex whole-body task would reveal individual differences in behavioral output, irrespective of differences in performance. More specifically, participants were asked to throw an object for precision at various distances and were not given any instruction regarding their movement pattern, leaving them free to solve the problem in their preferred way. Using a method based on release velocity decomposition, their throwing patterns were classified as *overhand* and *underhand*. It was anticipated that, given the redundancy of the task, the results would reveal differences in the selection of movement patterns for each individual.

Performance Scores

Given that the study did not have selection criteria relative to throwing-based experience, individual differences in performance were present. In the general sense, performance was better using the dominant hand compared to the non-dominant hand, and decreased as the target distance increased, which was in line with the expectations of the study and previous experimental findings on throwing (Kernodle & Carlton, 1992; Miller & Bartlett, 1993). The increasing difference in performance between the dominant and non-dominant hand with increased distance most likely reflects an effect of extended practice of the dominant hand. Whereas the dominant hand is able to manage the increased constraints induced by the increased target distance, the non-dominant hand presumably has a lower degree of prior practice in any range of tasks (Bray, 1928; Kudo et al., 2000; McDonald, van Emmerik, & Newell, 1989; Newell & van Emmerik, 1989; Stöckel & Weigelt, 2012; Verhoeven & Newell, 2016).

Throwing Patterns

Across all individuals, participants increased the total ball velocity at release with an increase in target distance. Although this appears a trivial observation, it is important to consider that all individuals respond to changes in the task constraints (e.g. further throwing distance requirement) by increasing throwing velocity. That said, the strategy with which individuals did so is not uniform across all participants, as revealed when the total velocity is decomposed in directional velocities (x, y and z).

Using this decomposition, throwing patterns were robustly classified as overhand and underhand, unveiling large individual differences in throwing strategies, even comparing

dominant- and non-dominant hand throws within a single subject. For example, Figure 3 suggests that whereas dominant hand throws at the 30% condition were exclusively performed using an underhand pattern, the non-dominant trials at the 30% condition were predominantly overhand. The ability to solve the task of throwing an object at a target in multiple ways becomes more evident when considering that subjects who have indistinguishable task performance (as measured through the task score) execute the task in a variety of ways, as demonstrated in Figure 9B. Taken together, this provides empirical support for the redundant complex task used in this study was successful at revealing individual differences in preferred solutions.

Given that the task- and environmental-constraints (Newell, 1986) for the individuals were identical, it can be inferred that the pre-existing tendencies and experiences drive individual differences in behavioral performance (King et al., 2012; Kostrubiec et al., 2012). Although it is unattainable to determine what specifically leads to these tendencies, it is undoubtedly a complex interaction of genetics and experience, resulting in differences in individual constraints specific to each task (Ackerman, 2014; Davids, Button, & Bennett, 2008; Newell, 1986). Whereas traditional investigations of individual differences worked towards identifying the underlying source of the differences (Ackerman, 1989; Fleishman, 1972), a dynamical systems based framework focuses on gaining knowledge of the preexisting repertoires for each individual and how they influence the task at hand.

Before the knowledge of preexisting behavioral repertoires can be applied, it is instrumental to assess whether the apparent experiment manifestations of the predispositions are truly that, or rather a reflection of more transient effects like mood or recency effects. If, for example, the individual is influenced by a game of basketball played earlier in the day, this could potentially have an effect on the observed behavioral performance in the task of this study.

However, for the subgroup of individuals that completed the task twice, performance was comparable, both considering the movement pattern and the performance output. Therefore, it can be argued that the observed differences in chosen movement patterns are a reflection of individual differences in preferred behavioral repertoires that are stable across testing probes.

This issue of relative stability between testing probes leads to the question of what happens to the initial preferred dynamics when an individual engages in practice at a given task. From the perspective that learning should be generalizable, it could be argued that expanding the behavioral repertoire to include as many movement patterns as possible is most advantageous. At the same time, especially in precision-based tasks, the stability of the movement pattern is often emphasized, suggesting that it could be most desirable to optimize one movement pattern. In addition, the acquisition of a second movement pattern might detract from the originally learned pattern (Kostrubiec & Zanone, 2002).

Future Research

From this viewpoint, it is possible to incorporate the findings of individual differences in preferred dynamics into the theories of skill learning. Given that motor skill acquisition can be seen as learning the underlying task structure for a given task, it is possible that the pre-dispositions of an individual limit the exploratory process that might be required for optimal performance. Particularly, in a task that has strict (physical) constraints on the possible solutions, as is the case in a precision-based throwing task, exploration of the task parameters is essential for successful task performance. This is where the instructions of a change agent (i.e. coach, therapist, experimenter) can play a significant role (Newell & Ranganathan, 2010). By providing instructions about the movement pattern, the change agent can set additional constraints to the

movement that compel the individual to go beyond the behavioral inclinations and explore the movement possibilities in the task space.

Future research should focus on exploring how instructional constraints shape the pathway of learning, and to what extent the initial differences in behavioral tendencies influence performance after prolonged practice. Regardless, rather than ignoring individual differences in performance, they can be harnessed as a powerful tool to not only understand what is learned with practice, but also to guide the learner to more optimal performance.

CHAPTER 7

EXPERIMENT 2 – HOW LEARNING IS GUIDED BY INDIVIDUAL DIFFERENCES IN BEHAVIORAL PREFERENCES

Introduction

Whereas we highly regard the differences between individuals in daily life, and particularly enjoy exceptional performance by athletes, musicians and academics, individual differences in behavior are often viewed as *noise* (Kanai & Rees, 2011; Seidler, Mulavara, Bloomberg, & Peters, 2015). Rather than utilizing the informational values that the individual differences hold, scientific conclusions are often based on a generalized statement of averaged data across all subjects. While this approach is reasonable if the behavior of all individuals is in line with the group-average, it becomes problematic when this is not the case (Molenaar & Newell, 2010). In fact, if a sub-set of individuals reveals a pattern that does not correspond to the observed group average, it can prove to be worthwhile to investigate what the source of this difference is.

A more individual approach to motor skill acquisition has been adopted by various lines of research over the past century. A prominent part of this literature was dedicated to finding *abilities* that substantiate performance (Ackerman, 1988; Ackerman, Beier, & Bowen, 2002; Fleishman, 1972). For example, if a given individual performs well in a test of solving mathematical equations and a test of long divisions, it could be said that this individual has a

high mathematical ability. From a motor learning perspective, this technique led to the construct of a General Motor Ability (Brace, 1927). Although from an anecdotal perspective, this is an appealing notion (consider for example high-school athletes proficient at more than one athletic discipline), empirical support has been lacking (Schmidt & Lee, 2011).

In fact, it has been suggested that the opposite is true, and that observed abilities are task-specific (Baker & Horton, 2004). It follows that rather than attempting to formulate the origins of individual differences, it could be more insightful to better understand the effects that pre-existing individual differences have on learning and performance. After all, if the aim is to create more optimal training and rehabilitation procedures customized for each individual, it is sufficient to get an idea of the current state of the individual at a given task as opposed to exploring the entire set of characteristics that may or may not contribute to performance.

The dynamical systems theory of motor control and learning provides an appealing framework to study the notion of individual differences in motor learning. Guided by theories of self-organization (Kelso, 1995; Kugler et al., 1980), it is suggested that movement coordination is an emergent process that is directed by informational properties. Rather than controlling all individual degrees of freedom (limbs, muscles, joint, etc.), the system is organized in functional units called *coordinative structures* (Kugler et al., 1980). However, although the movement patterns are held to emerge from the combinations of constraints on actions (Newell, 1986), this is not to say that only a single movement pattern can emerge. In fact, oftentimes multiple stable patterns of coordination can be spontaneously generated. These patterns are referred to as *attractors*, and are highly dynamic depending on the context.

One example of the changes to attractor dynamics is in the case of bimanual coordination (Kelso, 1984). In short, individuals were asked to move their index fingers to the rhythm of a

metronome. Whereas at low frequency rhythms, participants were able to do so in two manners (in-phase and anti-phase; *bistable*), this changed as the frequency was scaled up and the anti-phase mode became unstable, replacing it with the in-phase mode. This change in attractor layout of the stability of relative phase dynamics induced a *phase transition* and in the view developed here is key in understanding how individual differences might influence performance, as these phase transitions occur at different frequencies for different individuals.

Further investigation using this paradigm revealed an additional noteworthy element of individual differences. Whereas the majority of the participants were able to successfully generate two movement patterns (a relative phase of 0 and 180 degrees), a few subjects had an additional attractor around 90 degrees. A practice intervention designed to learn a new movement pattern revealed an interesting difference between these two sets of subjects: initially bistable subjects were able to create an additional attractor around the learned 90 degree pattern, whereas initially tristable subjects showed a shift from their pre-existing 90 degree pattern towards the learned 135 degree pattern. The results from this study supply two important notions: 1) it is informative to investigate which movement patterns are part of the current repertoire; tristable subjects already ‘knew’ the 90-degree pattern and 2) the initial state of the learner (bistable vs. tristable) determined the pathway of learning (Kostrubiec et al., 2006, 2012).

In this study, we investigate the effects of individual differences in natural tendencies of movement repertoires of motor learning in a throwing task that, unlike the bimanual coordination experimental protocol, requires the coordination and control of many joint-space degrees of freedom. Our previous study (Experiment 1) revealed that individuals show differences in preferred coordination patterns in a target-based throwing task, even when simply classifying the patterns as overhand or underhand. Given that individuals were not instructed to perform a

movement pattern a certain way, we presume that their pattern expressions reflect individual differences in behavioral preferences, regardless of where they originate. Although we did not directly assess the ability of individuals to generate different movement patterns, we did observe that certain individuals spontaneously explored different patterns in the same experimental condition. Based on this, we examine here to what extent the initial differences in this movement pattern influence the learning pathway. At the same time, we test if a paradigm of prolonged practice can influence preferred behavior of an individual.

To this end, individuals participated in a 5-day experiment in which their initial preferred dynamics were assessed on day 1 using the same paradigm as in Experiment 1 (pre-test) and then recruited for a practice intervention in which they practiced on a single experimental condition for three days. Based on the observed movement pattern on the pre-test, participants received additional instructional constraints to the movement during the practice sessions. Whereas some subjects were free to spontaneously select their preferred movement pattern (Control condition), others were instructed to perform in line with their predominant pattern in the pre-test (Congruent condition) or the pattern opposite to their preferred pattern (Incongruent condition).

Although the results of Experiment 1 revealed that the observed behavioral tendencies were similar across two testing probes for a sub-set of individuals, we test the prediction that the three-day practice intervention in this study will result in changes to these tendencies. We examined the hypothesis that although all individuals should show performance improvement on the task, the additional task constraints will affect individual performance differently. More specifically, it is anticipated that a practice period will have a strengthening effect on the pattern preference for participants in the Congruent performance, which will result in a lower number of trials outside of the preferred pattern in the post-test. For individuals in the Incongruent

condition, we hypothesize that the initially preferred pattern as demonstrated in the pre-test will not be the pattern used in the post-test. Rather, we expect participants to switch to the learned pattern in the post-test condition, even when given no specific movement pattern instructions.

Individuals who exclusively showed one movement pattern (e.g. overhand) will be more perturbed when asked to perform the opposite movement pattern in the incongruent condition. This perturbation will result in initially lower task performance scores, higher execution variability as well as a higher rate of movement exploration. Moreover, the higher movement exploration will have a positive effect on subsequent performance levels and thus that individuals that are most perturbed early in the practice period will show higher performance increases in the practice period compared to the other two groups.

Methods

Participants

33 right-handed participants (mean age: 24.8 years; 17 females) signed up to participate in this experiment. All subjects were recruited from the University of Georgia campus and provided informed consent by signing the consent form before participating. Participants received a \$50 gift card as compensation for their participation in all five sessions. One subject did not complete all 5 sessions and was subsequently removed from all analysis.

Apparatus

The equipment used in this experiment is identical to that in Experiment 1.

Procedures

The study spanned five days, in which participants completed a pre-test, three practice sessions and a post-test. Both the pre- and post-test consisted of the testing procedure explained in Experiment 1.

During the practice period, all participants completed trials on a target condition that was predetermined based on pilot data. The practice distance was chosen to be the 70% non-dominant hand condition for two reasons. Firstly, at this condition in Experiment 1 approximately half of the participants displayed an overhand throwing pattern and the other half displayed an underhand throwing pattern. Secondly, the performance drop-off from the 50% to the 70% condition was largest across all conditions, which suggests the greatest potential for performance improvement. For the same reason, non-dominant throws were chosen as the task over dominant-hand throws.

Participants were pseudo-randomly assigned to one of three groups: Congruent, Incongruent or Control. Participants in the congruent group were instructed to maintain the movement pattern they used in the pre-test session. For example, if a participant predominantly performed the task with an overhand throw at the experimental distance, the participant was instructed to continue throwing overhand throughout the practice period. The opposite held for participants in the incongruent condition. Participants in the control condition were not constrained by instructions and free to choose whichever movement pattern they prefer on any trial. Dichotomous classification (overhand vs. underhand) of the throwing pattern was determined using the velocity decomposition outlined in Experiment 1, and was observationally verified on 10% of the trials, matching the assessment in all cases.

A practice session consisted of 20 blocks of 10 trials, for a total of 200 trials. As in Experiment 1, the participant was instructed to throw the ball as accurately as possible to hit the target and get as high a score as possible. Performance scores were recorded and given as feedback after each trial, as well as after each block of 10 trials. In between blocks, the participant was offered a 1-min break. Each participant completed three practice sessions on three consecutive days to insure increases in performance. After the three-day practice period, participants returned to the testing facility to perform a post-test of the procedure from Day 1, with each participant completing 30 trials (15 dominant and 15 non-dominant) for each of the 5 trial conditions. Following this, movement coordination changes as a result of scaling the distance thrown will be contrasted to the initial observations from the pre-test.

Data Analysis

The processing of the performance data was identical to that in Experiment 1. An additional factor of Day was introduced to test for the effects of practice on PRE- to POST- test performance. The effect of Group (Congruent, Incongruent or Control) on PRE- to POST- test performance was tested using an ANCOVA, where the pre-test performance was included as covariate. Analysis of the throwing pattern was done according to the velocity decomposition, described earlier. Practice trials (Day 2 – Day 4) were organized in three Sets; Early, Middle and Late. Each set consists of 3 blocks (30 total trials).

The degree of exploratory behavior during practice was assessed using an autocorrelation analysis. Given that exploration can be seen as the search for different combinations of X and Z velocities, this structured search can be observed through the autocorrelation of the trials. The autocorrelation calculates the correlation of a time series (in this case, 30 trials with X and Z

velocities) with the same time series, but lagged. The autocorrelation score can be interpreted as follows: if the one-lag autocorrelation shows a highly negative correlation, it means that the subject is trying to actively correct for performance around a given point. For example, if a subject is trying to maintain an X velocity of 4, but consistently over- and under-shoots to 3 and 5, the one-lag autocorrelation will be highly negative. Conversely, if a subject is trying to actively explore the workspace and moving from an X velocity of 2 to 3, 4 and 5, the autocorrelation will be highly positive. Lastly, if a subject is maintaining a given end-point, the autocorrelation value will be close to zero. The autocorrelation was calculated from the first component from a PCA analysis of the X and Z components of ball-release variability that represents the structure of variance within each Set. We exclusively used absolute values of the one-lag autocorrelation for our analysis.

Results

Performance Score

The performance improvement after the training intervention was evaluated using a 2 (Day) x 5 (Distance) x 2 (Hand) repeated measures ANOVA (see Figure 12). Main effects were observed for Day ($F(1,30) = 45.67, p < 0.01$), Distance ($F(4,27) = 450.39, p < 0.01$) and Hand ($F(1,30) = 22.11, p < 0.01$) as well as interaction effects of Day x Distance ($F(4,27) = 8.65, p < 0.01$), Day x Hand ($F(1,30) = 10.67, p < 0.01$) and Day x Distance x Hand ($F(4,27) = 3.31, p = 0.02$).

Post-hoc analysis revealed that the effect of Day was the result of an overall performance increase after training. The mean block score before training (Day 1) was 73.69 and after practice (Day 5) was 79.70, which translates to a 6-point improvement per block, or a 0.4-point

improvement per shot. This suggests that the practice intervention generally led to a significant improvement in performance.

The effect of Distance was similar to what has been observed in the prior analyses of Experiment 1. The performance score decreased as distance increased, with a mean performance block score across the two scanning days of 101.66, 89.66, 78.37, 65.21 and 48.59 for the five respective distances (10%, 30%, 50%, 70% and 90% of MD). Further analysis of the Hand effect revealed that the performance scores in the dominant hand trials were higher (78.36) compared to the non-dominant hand trials (75.03, $p < 0.01$).

Analysis of the interaction effect of Day x Distance revealed that the performance improvement after practice was greater at further distances. Block score improvements after practice are 1.7, 1.8, 5.3, 9.8 and 11.4 for the respective distances (10%, 30%, 50%, 70% and 90% of MD). The interaction effect of Day x Hand revealed that the performance difference between the dominant and non-dominant hand was smaller after practice (1.72 per block) than during the pre-test (4.94 per block).

Lastly, the three-way interaction (Day x Distance x Hand) effect revealed the specific sources of performance improvement, expanding on previous observations. Specifically, the block performance differential between dominant and non-dominant hand was significantly reduced at the higher distances. Before practice, the dominant hand outperformed the non-dominant hand by 0.9, 3.7, 4.1, 9.4 and 6.6 points. After training, these differences were reduced to 1.4, 2.8, 2.8, 0.7 and 0.9 points.

An alternative way to interpret the performance data is through the analysis of absolute performance improvements after practice for each individual. For each condition, the difference between performance on Day 5 and Day 1 is taken. Main effect of Distance ($F(4,27) = 8.65$, $p <$

0.01) and Hand ($F(1,30) = 10.67, p < 0.01$), as well as an interaction effect of the both ($F(4,27) = 3.31, p = 0.02$) were observed. Post-hoc tests for the observed effects revealed that the amount of performance improvement between the pre- and post-test was larger as the target distance increased: 1.7, 1.8, 5.3, 9.8 and 11.4 for the respective distances. Similarly, performance improvements were higher in the (practiced) non-dominant hand (7.6) versus the dominant hand (4.4). Lastly, the interaction effect reveals that although performance improvements were observed across all conditions, they were largest in the non-dominant hand conditions of the 70% and 90% target conditions.

An ANCOVA was performed in order to analyze the effect of Group on pre- to post-test performance. The analysis revealed no significant effect of Group on performance improvement when taking into account the pre-test performance ($p = 0.22$)

From here, a Group (3) x Day (3) x Block (20) repeated-measures ANOVA was done to examine changes in the performance scores during the single-condition practice sessions (Day 2 through Day 4 – Figure 13). The results of this analysis confirmed a main effect of Day ($F(2,30) = 41.47, p < 0.01$) as well as Block ($F(19,13) = 10.84, p < 0.01$), but not of Group ($p = 0.36$). Furthermore, no interaction effects involving the Group factor were observed, suggesting that, at the group level, the assigned practice condition had no effect on performance changes during the practice sessions. Although no effects of Group assignments were found in either pre- to post-test performance improvement or practice session improvement, the main focus of this analysis is to emphasize the effect of initial individual differences in performance. The remaining sections reports changes in performance and behavior at the level of the individual.

Throwing Behavior

Based on the pre-test performance, the strength of each individual's behavioral preference was quantified by the ratio of trials the individual used the predominant pattern. For example, if an individual performed exclusively overhand during the 70% Non-Dominant trials in the pre-test, the pattern strength was set at 1. For an individual who performs underhand 8 times and overhand 7 times, the predominant pattern is the underhand throw, but the relative strength is 0.53, which is the minimum possible given the amount of trials in each pre-test condition. The range of relative strength across all subjects was 0.6 through 1 with a mean of 0.84 (SD: 0.12). A one-way ANOVA of the preference strength did not reveal a Group effect ($p = 0.56$), further supporting the equal distribution of individuals across groups.

To investigate the effect of the practice condition (Group) on changes to the overall movement pattern (overhand or underhand), we performed a one-way ANOVA on the absolute change in overhand percentage from the PRE- to the POST- test. If an individual shows a large change, this indicates that the preferred pattern in the 70% Non-Dominant condition has switched from overhand to underhand, or vice versa as a result of practice (Figure 14). Indeed, the ANOVA returned a significant difference ($F(2,30) = 50.81$; $p < 0.01$).

Further inspection of the results revealed that all but one subject in the Incongruent predominantly used the practiced condition in the post-test, rather than the preferred condition from the pre-test (see blue lines - Figure 14). That said, not all individuals used the new pattern exclusively, as 7 trials were performed using the initially preferred pattern (4.7%) when excluding the participant that did not switch. For subjects in the Congruent group, no pattern transitions were observed from PRE to POST (orange lines - Figure 14). However, the number of trials that individuals performed outside of their preferred pattern reduced from PRE (15) to

POST (2). No pattern changes were observed from the PRE- to POST- test in the Control condition, suggesting that no individual spontaneously switched.

Individuals in the Congruent group were asked to continue practice using their preferred pattern. However, within this group a range of pattern stability existed (0.6 through 1, mean: 0.80, SD: 0.11). For all individuals in this group, the level of stability during the pre-test performance was related to exploratory behavior in the first 30 trials of the practice blocks. Exploratory behavior, as quantified by the absolute values of the autocorrelation of the first component of the PCA on the velocity components, was higher for subjects with an initially less stable pattern, as revealed by a one-way ANCOVA with pattern stability as covariate ($F(1) = 10.36$, $p < 0.05$). Furthermore, although initial autocorrelation is determined by the pattern stability, this effect diminishes with time, and measures of autocorrelation converge for all subjects within the group (Figure 15A), suggesting that at the end of the practice period individuals randomly vary about a preferred combination X and Z velocity. This is confirmed through an ANOVA, revealing a main effect of Set ($p = 0.03$), with higher absolute autocorrelation scores in the first four sets compared to the last five.

The opposite pattern is observed for participants in the incongruent group. Instead of performing a pattern in agreement with their calculated preferred strength, individuals in this condition were asked to practice three days using a pattern that was opposite to their intrinsically preferred pattern. This resulted in the finding that a higher stability of the preferred pattern during the pre-test condition results in a higher exploratory strategy during the first trials of the practice session as marked by a higher absolute autocorrelation score in the first blocks of practice (Figure 15B). For the control group, no relation between initial stability and exploratory behavior was found.

The stability measure, block number and group membership were added into a stepwise linear regression to provide a prediction of the level of absolute autocorrelation. The regression outcome showed that block number and an interaction between stability and group predicted 78% of variance in the level of autocorrelation, or exploration. More specifically, the autocorrelation decreased with time, and the interaction between stability and group suggests that a higher initial stability has a positive effect on the initial autocorrelation score in the incongruent group, but not in the congruent group.

Exploration and Performance

The level of early exploration was not correlated to an overall increase in performance during practice ($p = 0.49$) nor to the specific increase in the 70% non-dominant condition from PRE- to POST-test ($p = 0.79$). However, there was a significant correlation between the absolute autocorrelation score of the first 30 practice trials and the overall performance improvement from the PRE- to the POST-test. Individuals with a higher exploration rate had a higher total PRE- to POST-improvement ($R^2 = 0.606$, $p = 0.04$ - Figure 16).

Discussion

In this experiment, we investigated the effects of initial differences in behavioral preferences on motor performance, and the interaction of these differences arising from different task instructions. More specifically, individuals with a wide range of behavioral tendencies were assigned to one of three conditions in a target-based throwing task. Whereas some individuals were free to perform the task without any constraints throughout practice, some individuals were

given additional instructions on their movement pattern, based on their initial preferences. The results showed that the initial level of preference stability plays a large role in the learning pathway, with individuals who are instructed to perform a movement pattern opposite to their strongly preferred pattern responding with a larger degree of exploration in subsequent practice sessions.

Performance Score

The performance results replicate previous findings in that an increase in distance resulted in a decrease in performance (Experiment 1; Kernodle & Carlton, 1992; Miller & Bartlett, 1993), and that the dominant hand outperformed the non-dominant hand (Experiment 1; Bray, 1928; McDonald, van Emmerik, & Newell, 1989; Newell & van Emmerik, 1989). Importantly, the change in performance score from PRE to POST reflects the effect of sustained practice, particularly on the 70% and 90% throwing conditions, where performance in the practiced non-dominant hand is now similar to that of the dominant hand. The increase in performance on the practiced condition from PRE- to POST-test corresponds to the average increase in performance during the practice trials, providing further support that these changes in performance are indeed practice induced. Whereas during the pre-test only three participants performed better than or equal to their dominant hand performance using their non-dominant hand at 70% throwing distance, now 18 of the subjects had higher scores in the dominant condition.

A potential influence in the PRE- to POST-test design is that of a warm-up effect. As can be seen in Figure 2, there is a significant effect of block on task performance, meaning that performance at the start of the practice session is lower than at the end. Given that the testing

probes in the PRE and POST test are only 15 trials per condition (the equivalent of 1.5 practice block), the results might be influenced by this warm-up effect, a process that has been shown to influence performance at the beginning of a practice session (Adams, 1952; Newell, Mayer-Kress, Hong, & Liu, 2009; Verhoeven & Newell, *in press*).

Given that the aim of the study was to investigate the effects of *individual* differences on learning, it is not surprising nor detrimental that no effects of Group were observed in the analysis of either the PRE to POST improvement nor the practice improvement. In fact, given the large variety of initial differences in behavior and performance for the individuals in each experimental condition it is to be expected that significance at the group level is hard to attain. As a consequence, the analysis of the individual movement patterns and their outcomes becomes more consequential.

Throwing Behavior

The stability of the preferred movement pattern of each individual was found to be highly relevant in predicting the pathway of learning (Pacheco & Newell, 2015). Although all individuals were able to improve their performance across practice blocks and from the pre- to the post-test condition, the manner in which they did so was directly influenced by their initial preferred movement pattern tendencies. More specifically, when an individual was asked to perform a movement pattern that was not part of their initial preferred repertoire (Incongruent condition) this led to high exploratory behavior in the subsequent practice blocks.

This is in line with the theoretical perspective on stability of movement patterns in motor learning (Haken et al., 1985; Kelso, 1995). Given that individuals were free to choose any movement pattern during the pre- and post-test, we hold that the spontaneously chosen pattern

represents the pattern that is perceived as most optimal by the individual (Kelso, 1984). From here it follows that, when instructed to perform a task that is incompatible with the originally chosen pattern, the need to explore the appropriate coordination between joint- and task-space arises. Individuals who show a lower initial stability and then are placed in the Incongruent condition have an initial advantage as presumably information about the coordination of the opposite pattern is more available compared to individuals who did not spontaneously generate the to-be-learned pattern. In this example, the individuals in the latter case will need to explore the essential variables of the task to a larger degree than others. The same holds for participants in the Congruent condition who show a lower stability of the preferred pattern. If, for example, an individual spontaneously throws overhand in 8 trials, and underhand in the other trials, there is no clearly preferred pattern for this individual. Therefore, the observation that these individuals have a higher degree of exploration is in line with our initial expectations.

Across all individuals, the degree of exploration diminished during practice (Figure 15), and all individuals predominantly executed the movement using an individualized preferred solution. The reduction of exploration is in agreement with previous findings that suggest that individuals become aware of the relevant task parameters with practice, and from there on try to stabilize performance around a given solution (Fowler & Turvey, 1978; Gel'fand & Tsetlin, 1962; McDonald, Oliver, & Newell, 1995; Newell & McDonald, 1992; Newell et al., 1989, Kelso, 1995; Schöner, Zanone, & Kelso, 1992; Zanone & Kelso, 1992), as indicated by an autocorrelation score approximating zero. This stabilization of behavior should be seen as equally important as that of initial exploration. Given that this is an accuracy-based task defined by a manifold of solutions, it is unlikely that performance increases can be achieved without a stabilization of behavior.

The results of this study did not reveal a direct relation between the degree of exploration during practice and performance increases during practice. Evidence was provided, however, that having a higher rate of exploration during the initial blocks of practice had a positive effect on performance improvement in the total PRE- to POST-test scores. In other words, individuals with a higher absolute autocorrelation in the EARLY block of the first practice day showed a higher total performance increase between the pre-test and post-test. Although this study was not directly designed to test the mechanisms of learning, this result suggests that a more active exploration of the task space, even in a single condition, has a positive effect on understanding the task constraints. Given that the target conditions other than the practice conditions are essentially scaled up (or down) from the practice condition, it could be said that the task dynamics are sufficiently similar across conditions such that an increase in understanding of one condition has a positive effect on the other conditions. This notion is supported by the finding that performance increases from PRE-to POST-test were greatest in the conditions that are presumably most similar to the practiced condition (e.g. 70% dominant, 90% dominant/non-dominant – Figure 12).

In this context, the role of exploration in learning has been debated (Braun et al., 2010; King et al., 2012; Pacheco & Newell, 2015). Based on the tenets of schema theory (Schmidt, 1975) and the subsequent variability of practice hypothesis, it was proposed that more variability in practice would result in better performance on tasks that the individual has not yet encountered. Our results seem in line with this proposition, as providing an additional instructional constraint to the movement (Congruent/Incongruent movement pattern) resulted in increased exploration. That said, the main point of this study was that this degree of exploration is determined, in part, by the individual differences in intrinsic dynamics. Thus, the induced

constraint (which is decided by the group assignment) is not sufficient to explain the effects observed in this study. Rather, it is necessary to incorporate the initial stability of the individual and its interaction with the induced constraints.

The focus of the study was to investigate the effects that individual differences have on practice pathways, but at the same time, the results from the study provide an important additional consideration. Namely, the prolonged practice influenced and, to a large degree, changed the preferred behavior of the individual. The fact that 9 of the 10 individuals in the incongruent group voluntarily selected the learned movement pattern rather than the initially preferred pattern is an indication that the behavioral preferences of individuals are dynamic and can be influenced with practice (Figure 14). Similarly, the 3 days of practice increased the stability of the preferred patterns in the Congruent group. This outlines the two-way interaction between initial differences in preferred behavior and practice pathways: individuals will learn differently based on their initial differences, which will result in new initial conditions for subsequent learning.

CHAPTER 8

GENERAL DISCUSSION

The aim of this study was to investigate the effect of preferred dynamics on performance and learning in the context of a target-based throwing task. To this end, two experiments were designed that tested specific hypotheses related to the influence of individual differences on task performance, and how these differences influenced the pathways of learning.

In the first experiment, individuals were asked to throw a ball at a target with high accuracy. Since no movement instructions were given, and the task can be successfully completed in a manifold of solutions, we observed a large range in movement patterns. Even when using a robust dichotomous classification of these movement patterns, individual differences in task solutions were observed in the same condition. With changes in the experimental conditions, either by altering the target distance and/or throwing hand, participants responded differently to these changes. The overview of responses for each individual creates a snapshot of their preferred patterns at any given condition. To test whether these snapshots are a reliable indication of pattern preference, individuals were asked to perform the task a second time, again without any instructional constraints in the movement. Comparison of the observed patterns to those the previous test reveal that the preferred patterns are highly reliable between two testing probes. This finding becomes particularly relevant considering that these preferences and their relative stability provide the background on which and subsequent learning takes place.

The second experiment was designed to test exactly that. By assigning individuals with a wide range of preferences and associated preference stabilities to three groups with different practice interventions, we were able to test the effect that initial preferences have on the learning pathway. From the results, it became apparent that the strength of the initial preference largely determines the learning pathway. More specifically, individuals who are asked to perform a movement pattern for which they do not have a strong spontaneous preference show stronger exploratory behavior during the practice sessions, which ultimately results in a better transfer performance to the non-practiced conditions.

Implications for Motor Learning

Individual differences in performance, let alone in learning, are rarely embraced in the field of motor behavior. Rather, in the traditional sense, any deviations from the general (group) pattern were often dismissed as noise and not given further consideration (Kanai & Rees, 2011). However, the finding that participants show individual differences in performance, even when the task- and environmental constraints are the same for each individual (Newell, 1986), means that the differences in individual constraints lead to differences in behavior in a redundant task. Although the constraints of individuals are, to a large degree, similar across all humans (e.g. body morphology, development over the lifespan), changes in knowledge, background and skillsets of individuals can result in differences in behavior.

The results of the study suggest that behavior is specific to the individual and that although the patterns at which individuals solve the motor problem, in this case, a target-based throwing task, are different, the task performance was not directly influenced by this. This finding challenges the idea of the *champion model* of learning (Latash & Anson, 1996; Newell &

Ranganathan, 2010). Rather than building the conditions of practice around channeling the learner towards a single optimal movement pattern, designing a practice intervention that stimulates exploratory behavior seems more effective. The findings from this study did not show an advantage for one movement pattern over the other, as overhand throws did not outperform underhand throws at any condition. Furthermore, the group instruction (Congruent or Incongruent) did also not directly influence the learning pathway. Rather, it was the interaction between the two that was relevant for changes in learning pathways. In other words, if the instruction combined with the backdrop of the individual stimulated exploratory behavior, this led to more successful task performance at the post-test level.

That said, the results from this study and previous work provide strong evidence that skill learning is best understood from the perspective of the behavioral repertoire of the individual. The dynamical systems approach provides an appealing framework to discuss these results, as the changes in (strength of) the attractor dynamics and their layout correspond to the changes observed in the throwing task (Kelso, 1984; Zanone & Kelso, 1992). The challenge remains to find effective ways to map out the repertoire relative to the task at hand.

In the less complex task of bimanual oscillation, the initial intrinsic dynamics of individuals are better understood. Naïve participants either display a bistable pattern, with attractors at the 0- and 180-degree phase relation, or a tristable pattern with an additional attractor at 90 degrees. As mentioned before, the initial layout of the individual has a significant impact on the subsequent learning pathway (Kostrubiec et al., 2006). Although this study did not directly assess the stability of the attractors, which can be seen as a limitation of the design, we believe that the spontaneous selection of a movement pattern is indicative of its stability. Similar observations were made in the earlier studies of bimanual coordination, where the preferred

frequency of oscillation was highly predictive of the transition frequency (Kelso, 1984). Even though the selection of an overhand or underhand movement pattern is arguably more actively guided by conscious control and decision-making processes than is the case in the example of bimanual oscillation, the spontaneous selection of one of the two patterns is indicative of the perceived relative stability of the patterns. In other words, subjects would not have chosen that pattern if they believed that it would be unsuccessful at the given task. This is further supported by the finding that subjects switch movement patterns between conditions in response to changes in task constraints and, moreover, switch patterns within a scanning condition, presumably because performance was deemed unsatisfactory.

In the dynamical systems framework, the process of learning can be described as the acquisition and stabilization of a new attractor, or movement pattern (Kelso, 2012). That said, the acquisition of a new movement pattern is often associated with high degrees of exploration (Fowler & Turvey, 1978), which is in contrast with increasing consistency, or stabilization (Zanone & Kelso, 1992). This contradiction provides an interesting challenge for change agents, as it is not possible to stimulate both simultaneously. As previously discussed, providing additional constraints to the movement acts as a stimulus for exploratory behavior (Ranganathan & Newell, 2013). However, what is noteworthy is that this exploratory behavior diminishes over practice. Thus, whereas exploratory behavior is triggered by a change in instructions, the stabilization process appears to be spontaneously set in motion by the individual. Thus, rather than correcting the movement based on a champion model template, coaches and therapists should allow individuals to explore the different solutions within the task space that result in the desired goal, as this seems to encourage the flexibility to perform well in other conditions.

The overall findings from this study provide support for a number of recommendations in line with the idea of *differential learning* (Schöllhorn, 1999). Given that many complex skill involve a requirement of repetitive performance, but rarely of repetitive behavior, the effectiveness of practice interventions focusing on recurring drills has been debated (Schöllhorn et al., 2006). Motivated by the findings that, even at extremely high levels of performance, a wide variety of individual movement patterns exist, several theorists have proposed the idea of differential learning. This approach moves away from the idea that the ‘average man’ exists and that all movement variability is noise.

Rather, variability within the individual can be seen as natural variations around the maintenance of a stable point, which is an essential feature of the dynamical systems view of motor control. Furthermore, the idea of variability between individuals can be captured well using a constraints model of motor performance and learning, where differences between individuals are the results of differences in individual constraints and their interaction with the task and the environment.

Implications for Individual Differences

The main focus of traditional research on individual difference has been to determine the impact of underlying abilities on the performance of a task (Fleishman, 1972), and, in some cases, to investigate if performance now can be predictive of future performance. Abilities, in many way parallel to that of individual constraints to movement (Newell, 1986), were thought to determine the proficiency in all skills. Given that studies on the topic failed to provide considerable support for the notion of motor abilities, the focus has moved closer to the idea of a wider variety of task-specific abilities.

Based on the idea that performance on a task requires a unique combination of abilities, it becomes improbable that these abilities can be mapped out successfully for each individual. Individual differences in performance arise as early on as the development phase in infants (Thelen et al., 1993), and are existent across many, if not all, movement tasks (Ackerman, 2007; Fleishman, 1972). The framework provided in this study is considerably more feasible, as it is not concerned with necessarily identifying the complex interaction of genetics and experiences that serve as the sources of individual differences and abilities (Simonton, 1999). Rather, it emphasizes a prospective approach oriented towards understanding how, given that there is likely no uniformity in experience across individuals, these differences might affect performance and learning.

Although it is possible that individual behavior and performance might converge over practice, the differences in individual behavior at the starting point of practice determines the pathway of change. Again, this has been demonstrated in examples of bimanual coordination (Kostrubiec et al., 2006), and search strategies in a speed-accuracy task (King et al., 2012; Pacheco & Newell, 2015). It has been suggested that these observed pre-disposed strategies are a way to further channel the constraints in a redundant task and limiting the number of possible solutions. In tasks like target-based throwing, the manifold of solutions is substantial, given the many combinations for position and velocity parameters that satisfy the task criteria. Therefore, exploring the task space based on intrinsic preferences might limit the area of the task space that the individual ‘needs’ to search through (King et al., 2012). This suggestion is substantiated by the finding that variability in the initial phase of practice is not associated with a random search through the task-space, but rather seems to reveal a structure of intentional search.

Thus, rather than individual differences in behavior and performance being merely a deviation from the general law of the assumed average, they could reflect a behaviorally meaningful advantage in managing the complexity of human movement in its interaction with complex tasks. Taking account of these individual differences from a constraint-led dynamical systems approach is a needed step for both the practical- and theoretical approach for (motor) learning.

Conclusion

In sum, we conclude that this study provides compelling evidence to consider the pathway of performance dynamics relative to the backdrop of individual differences. Given the task redundancy, there was no direct requirement for individuals to utilize the same solution for the required task goal, which leads to large individual differences in behavior. These differences in behavior are individual in the sense that they reflect pre-existing tendencies or preferences based on differences in experience and background. The main focus of the experiment was to investigate to what extent these pre-dispositions influence the task performance and learning pathways. Our results support the notion that the preference in task solution is highly individual, and that both in a robust classification (overhand- versus underhand throws) and a more detailed way (exact velocity decomposition and/or joint motion) individuals had a preferred solution in the task space.

The question that we raised here is whether these individual preferences influence the learning pathway. Indeed, we found that providing contrasting instructional constraints to the movement influences individuals differentially. More specifically, the stability of the initially preferred pattern relative to the to-be-learned pattern predicted the amount of exploration of the

individual in subsequent practice. Although these exploratory behaviors were not indicative of performance changes during practice, as all individuals converged to the same level of performance, higher initial exploration in the practice session resulted in a higher overall improvement from pre- to post-test performance. Not only do these results add to advancing the understanding of individual differences and its effect on performance learning, they also provide additional consideration for change agents to further investigate the relation between the individual differences in pre-dispositions and the desired state of the individual. Understanding the preferred movement patterns and their relative stability to the task-relevant repertoire holds the ability to guide the acquisition process and more optimally design the learning experience.

In closing, we would like to discuss a limitation of this study, which provides an opportunity for future studies. Although the robust classification of movement patterns was sufficient to answer the research question posed in this investigation, additional information on the details of the movement pattern would reinforce the findings. Within a movement category, such as overhand throwing, a large range of individual variations in movement patterns is observed, which might influence learning pathways as well. Furthermore, a kinematic analysis could be useful in providing more predictive measures of performance (Verhoeven & Newell, 2016). In this realm, potential measures that could be explored are the temporal coupling between joint motions, the coupling between the movement of the body and the ball release, and the synchronization between lower-body movements and upper body movements. Anecdotally, out of the individuals that used leg motion to support the throwing movement, half of the participants stepped out with their non-throwing leg and the other half with the throwing leg.

In addition, future work should emphasize the role of the task instruction in providing a context in which the learning is guided through an exploratory process. In this study, the

different experimental manipulations highlighted the need for the individual to explore or not, which provides a foundation for future studies to investigate the most optimal task instructions for successful exploratory behavior in the learner. Interactions between the duration of the exploratory phase and the retention and transfer of performance should be further evaluated, as well as the interaction between the initial skill level of the individual and the degree of exploration. If the stability measure used in this experiment is a reflection of the relative strength of the attractor, does it mean that a skilled performer has stronger attractors, or is expertise defined by a wide range of relative stable attractors?

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FIGURES

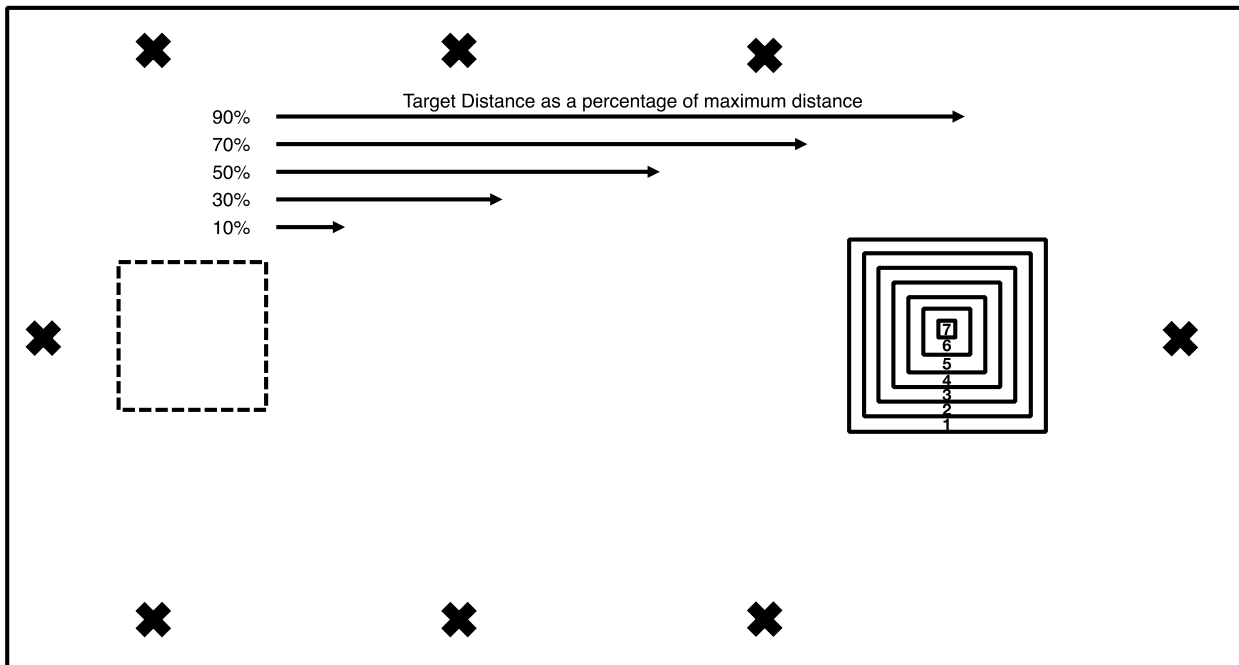


Figure 1 – Schematic representation of the experimental layout. Participants received the sole instruction not to cross the dotted line when they make their throw. Motion capture cameras (black crosses) recorded the movement of the participant. The target consisted of 7 squares of decreasing size, with the center square representing 7 points, etc. Missing the target resulted in 0 points.

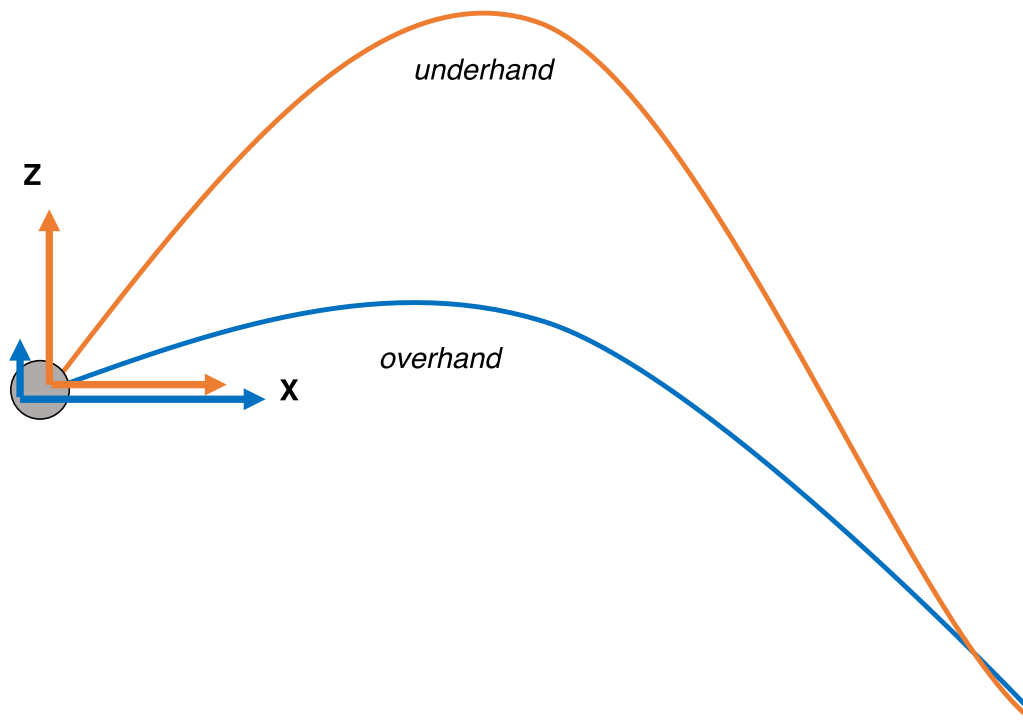


Figure 2 – Schematic illustration of differences in velocity decomposition between underhand- and overhand throwing patterns. For the clarity of the image, the decomposed velocity vectors have been separated slightly, however, this does not imply a difference in release position.

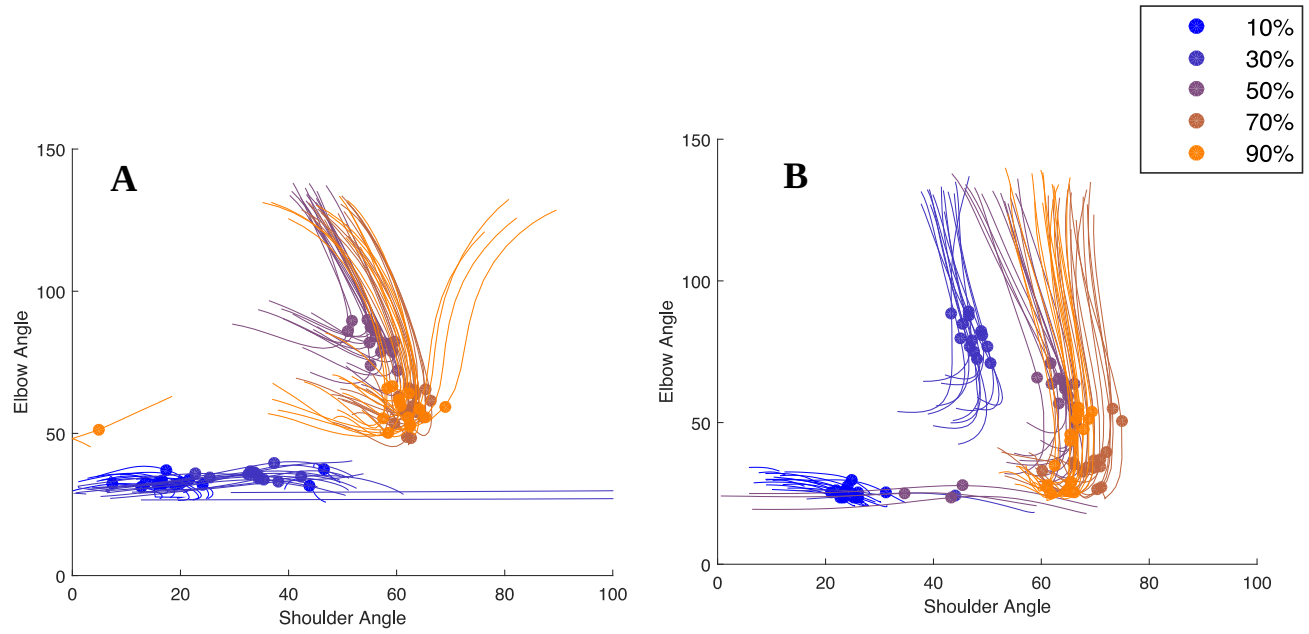


Figure 3 – Elbow-shoulder angle-angle plots from the throwing arm of a single subject in the dominant (A) and non-dominant (B) conditions for 20 ms before and 20 ms after the point at which the ball is released (filled circle).

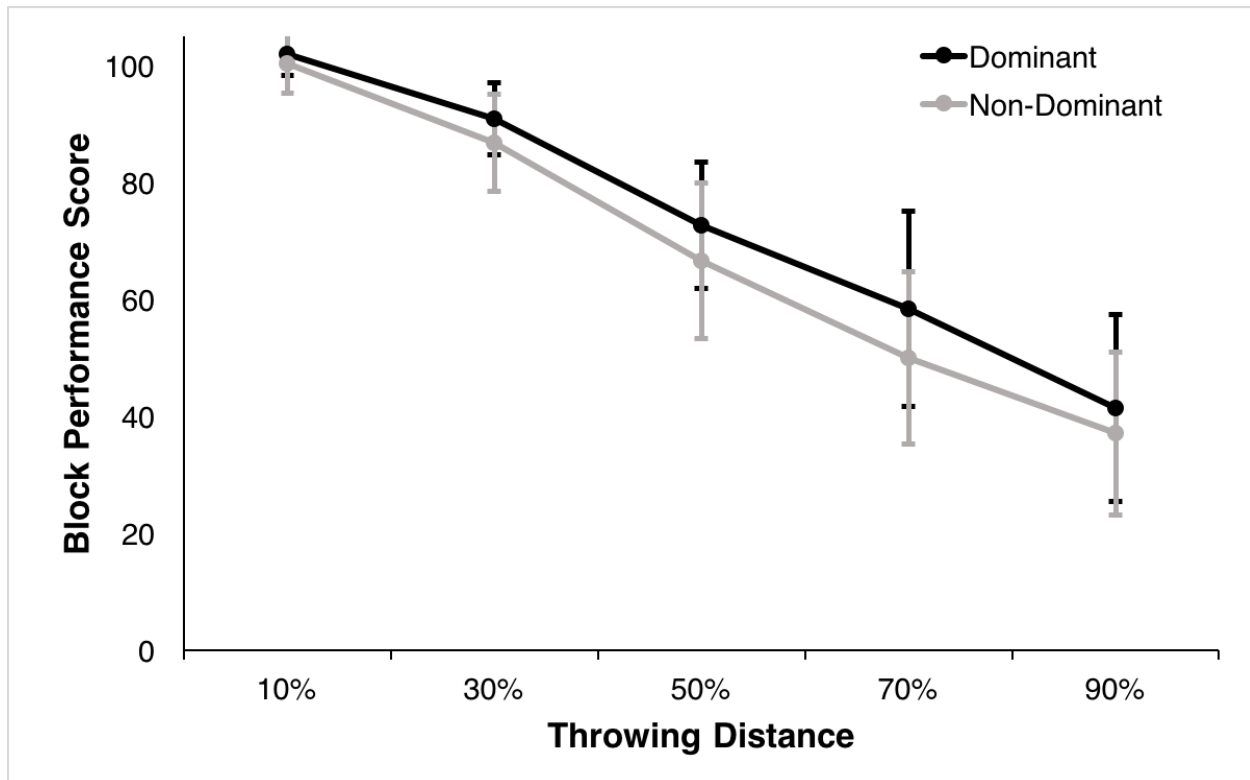


Figure 4 – Mean performance as a function of throwing distance and throwing hand. Each condition consisted of 15 trials, with a maximum possible block performance score of 105. Error bars represent the standard deviation of the mean.

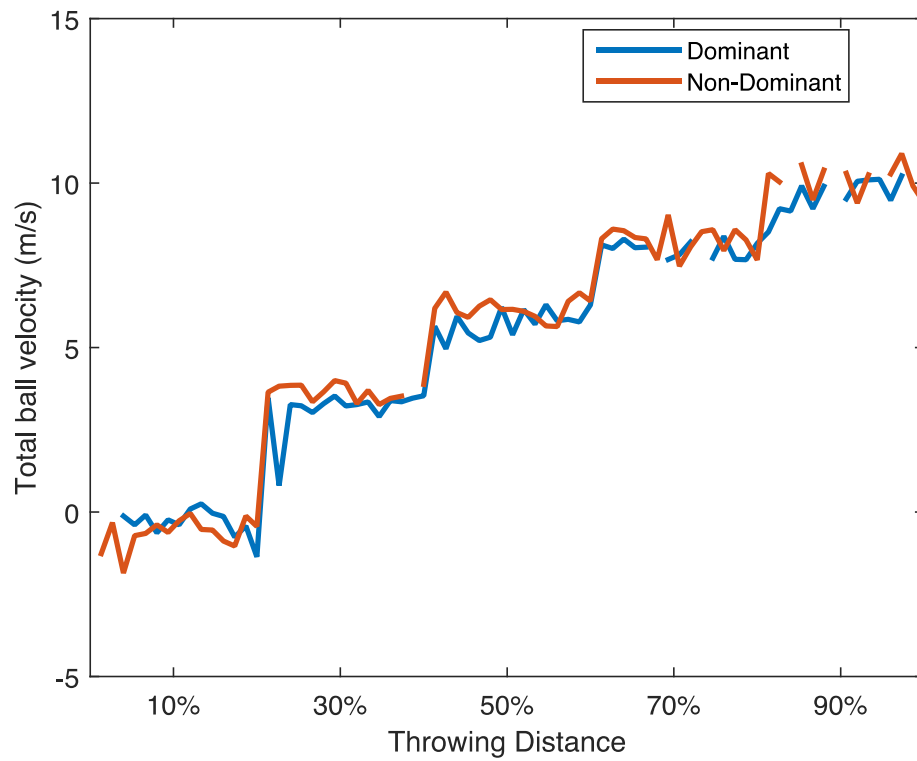


Figure 5 – Total ball velocity (sum of X, Y and Z directions) for each throwing condition for a representative individual.

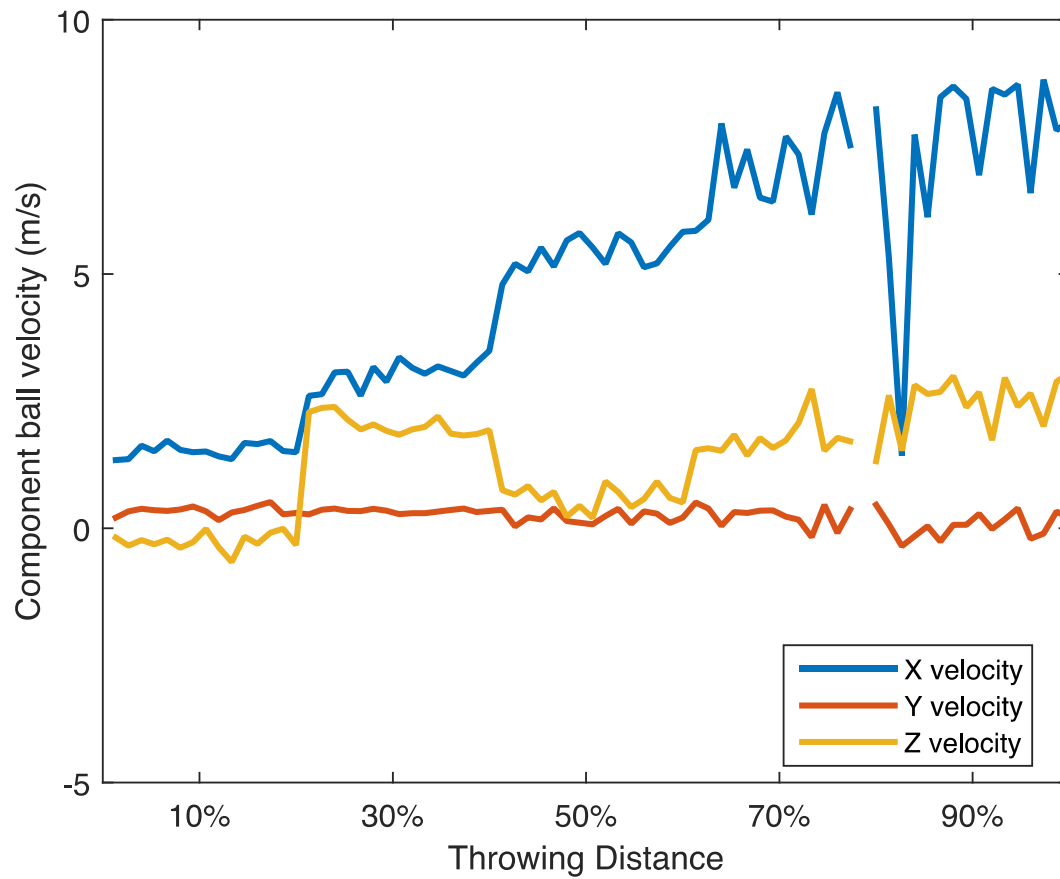


Figure 6– Decomposition of ball-velocity as a function of throwing distance for the dominant-hand throws for a single subject.

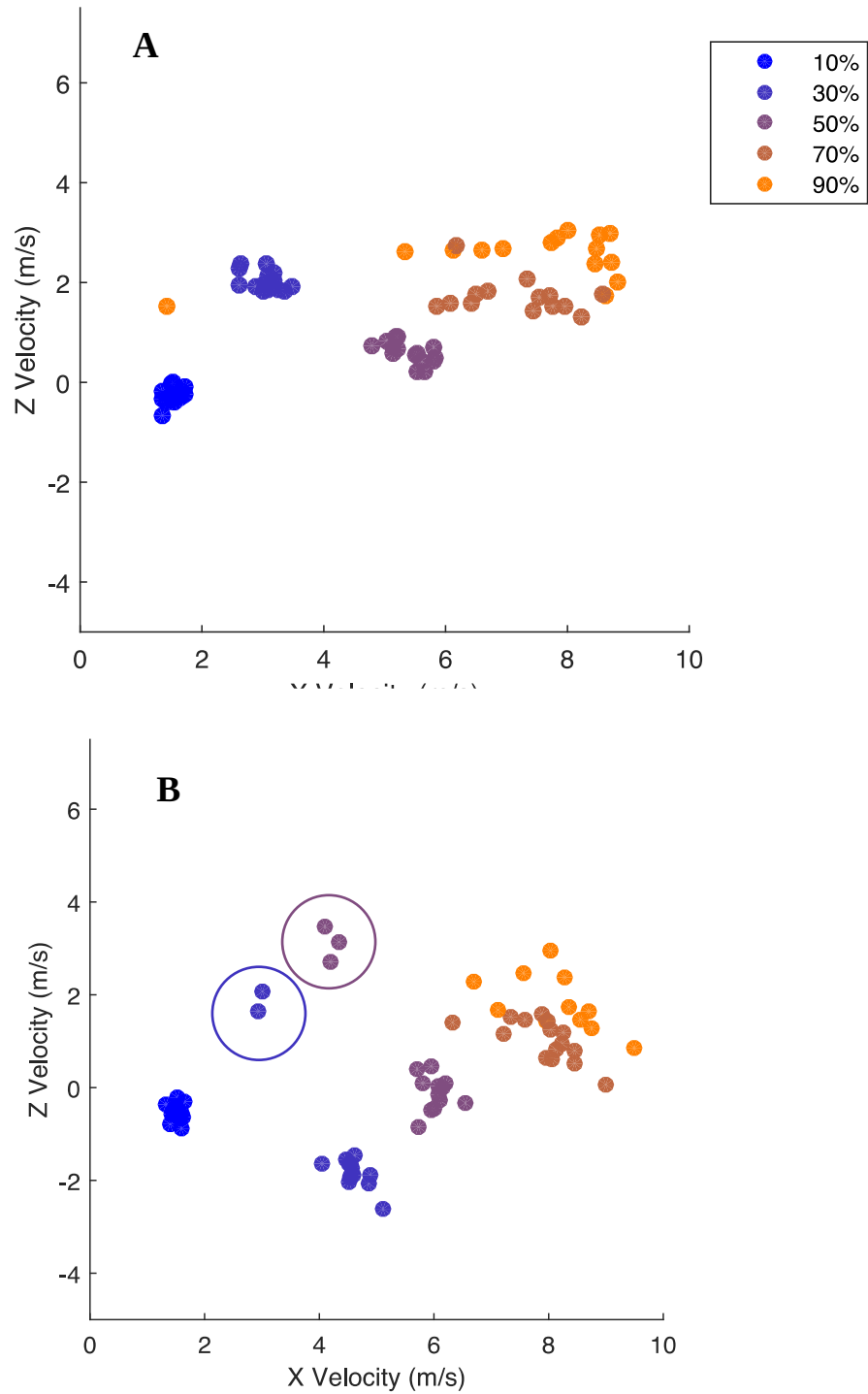


Figure 7 – Decomposition of the release velocity for a single subject in the dominant (**A**) and non-dominant (**B**) conditions. Each dot represents the combination of the X and Z ball release velocity for one trial. The color represents the different throwing distances.

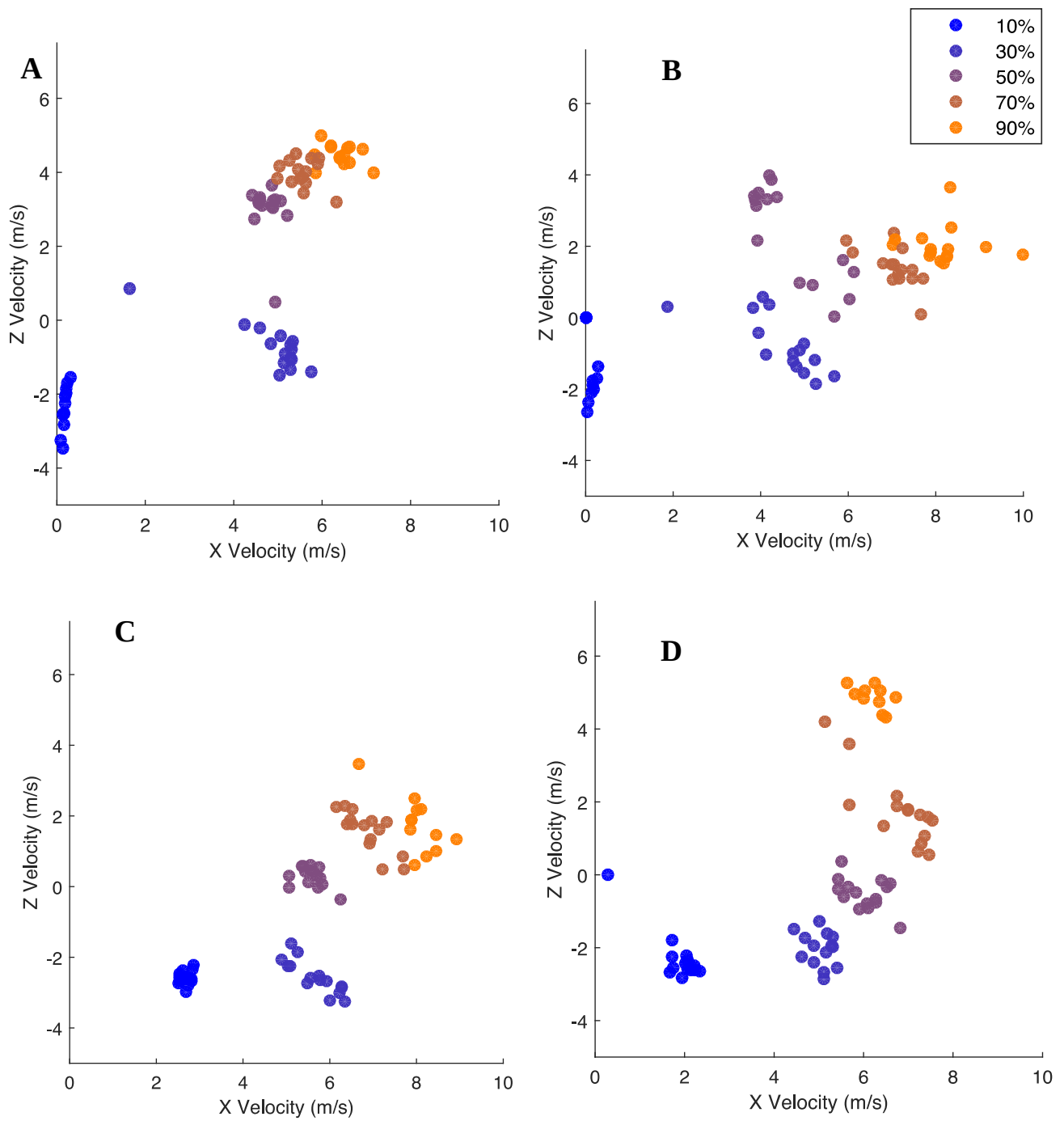


Figure 8 – Decomposition of the release velocity for two individuals. **A** and **B** represent the dominant and non-dominant trials for the first individual. **C** and **D** are the dominant and non-dominant trials for the second individual.

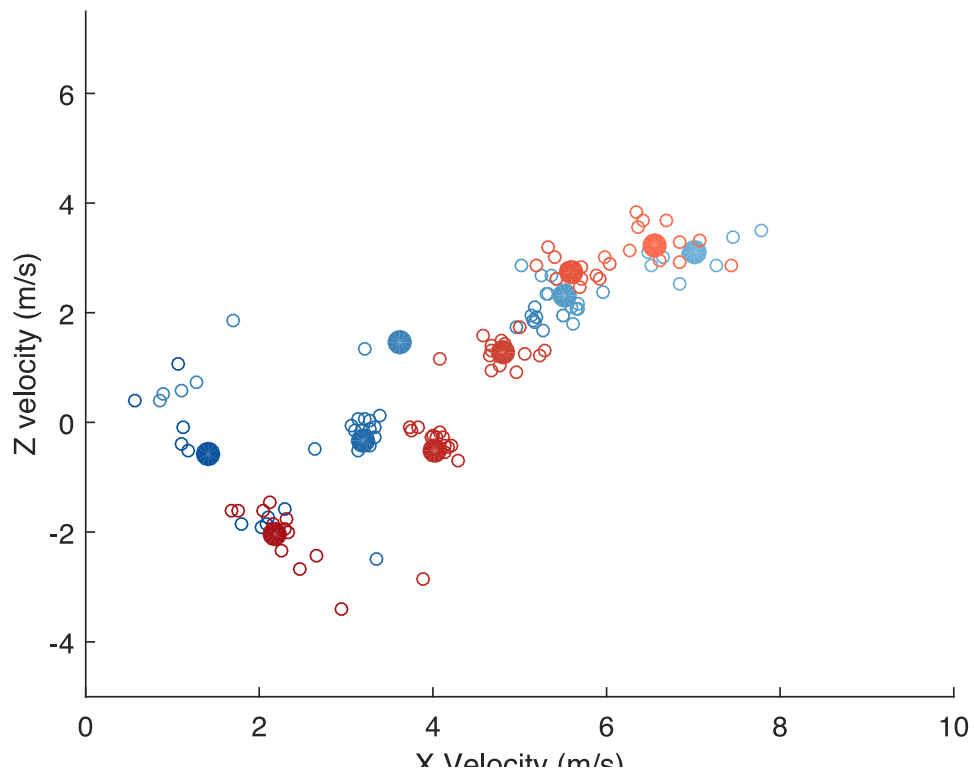


Figure 9– Representative example of the k-mean clustering procedure of throwing patterns. Each circle represents a single throw each of the dominant-hand condition for a single subject. The mean of the cluster is filled. Blue points represent Day 1 patterns and red points represent Day 2 patterns. The hue of the circle indicates the throwing distance, with the lighter dots being further throwing distances.

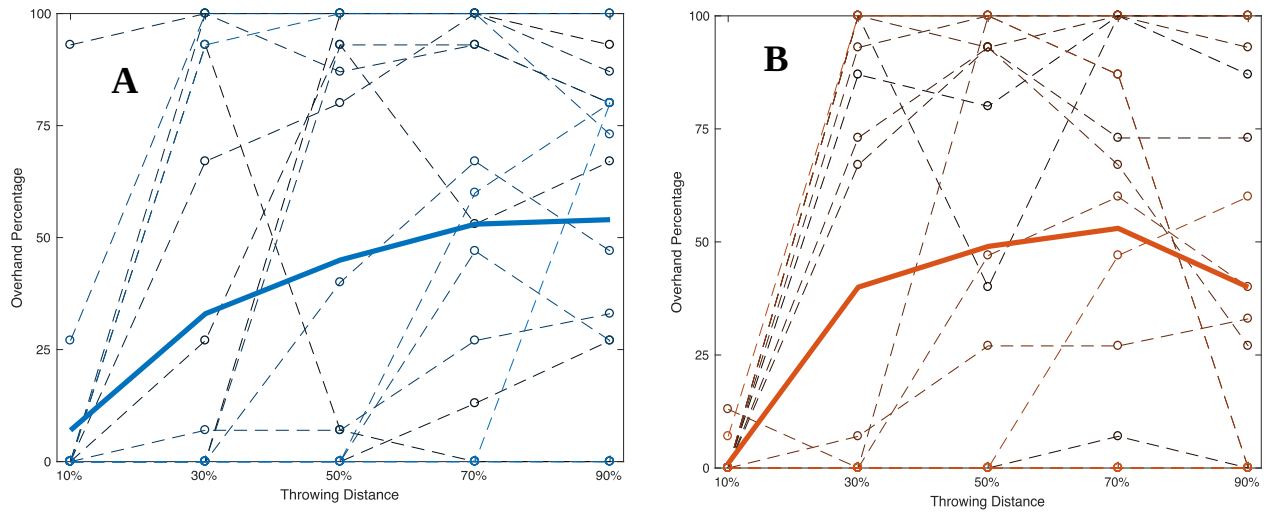


Figure 10 – **A** and **B** represent the plots of overhand percentage at each throwing distance for dominant and non-dominant, respectively. Each dotted line represents a single subject, with the colored line representing the group average.

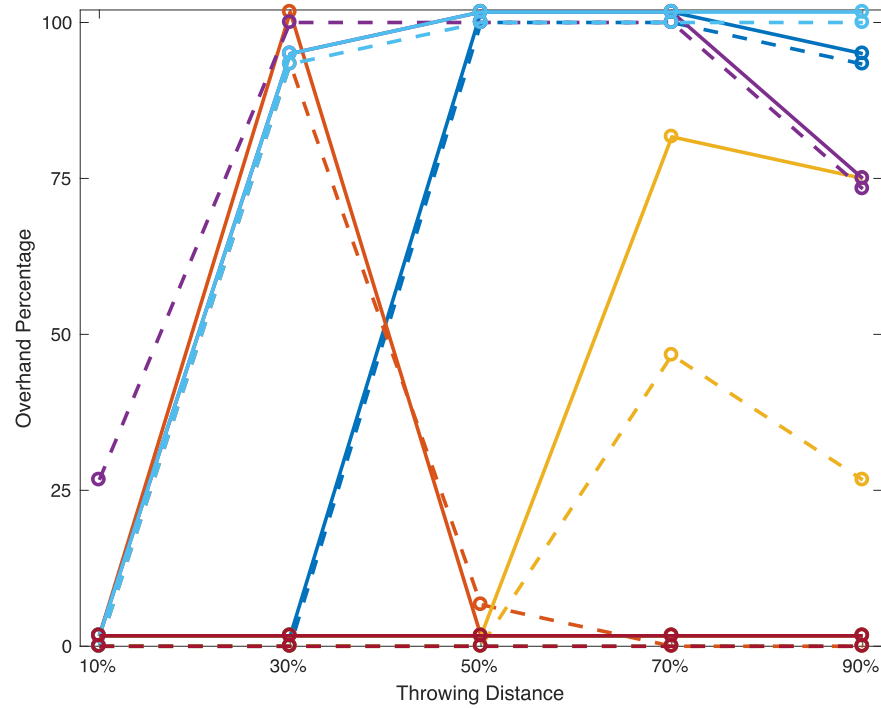


Figure 11– Layout of pattern preferences for 8 individuals who performed the throwing task twice. The dotted line represents the behavior on the first test whereas the solid line is that of the second test.

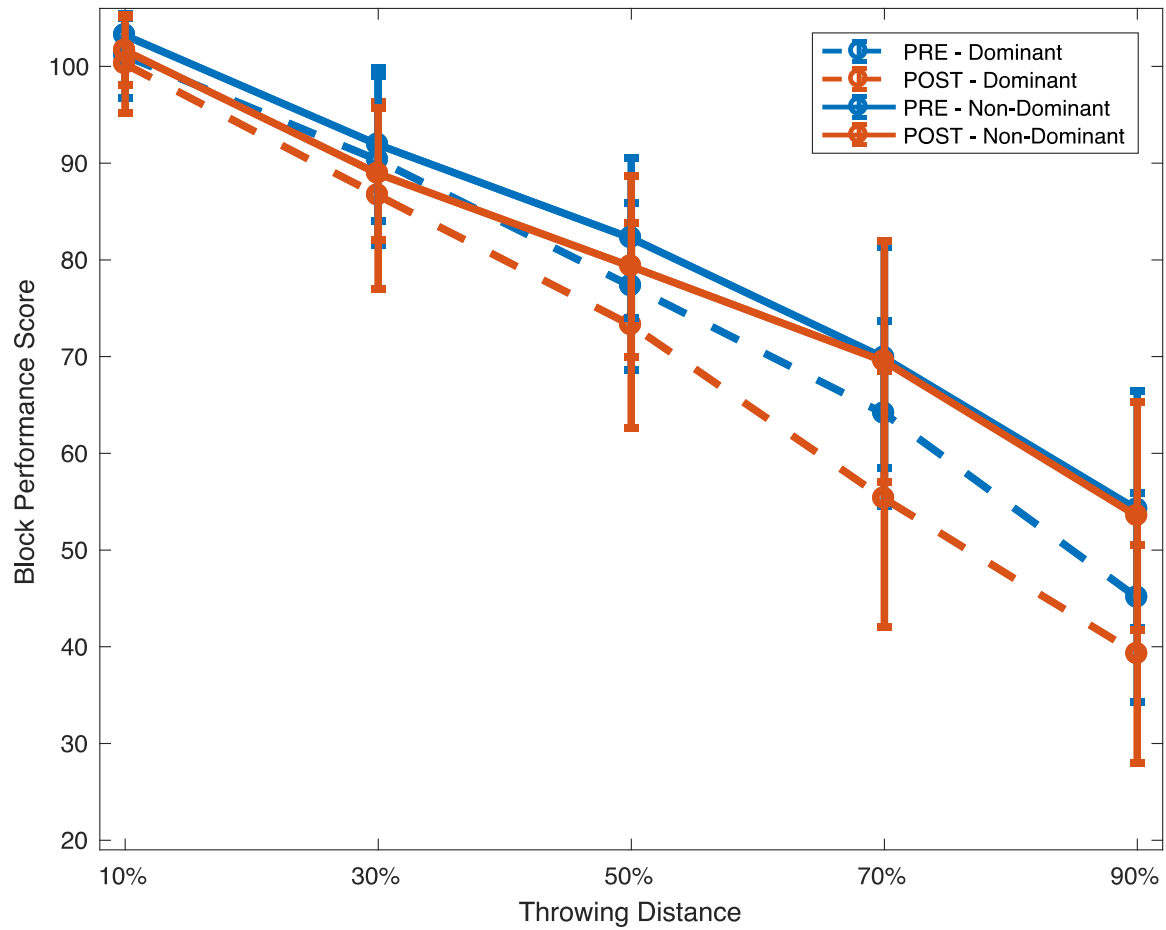


Figure 12– Task performance for the two different hand conditions as a function of throwing distance before the practice intervention (PRE) and after (POST). Each block consisted of 15 trials, with a maximum score of 7 per trial. Error bars indicate the standard deviation of the mean.

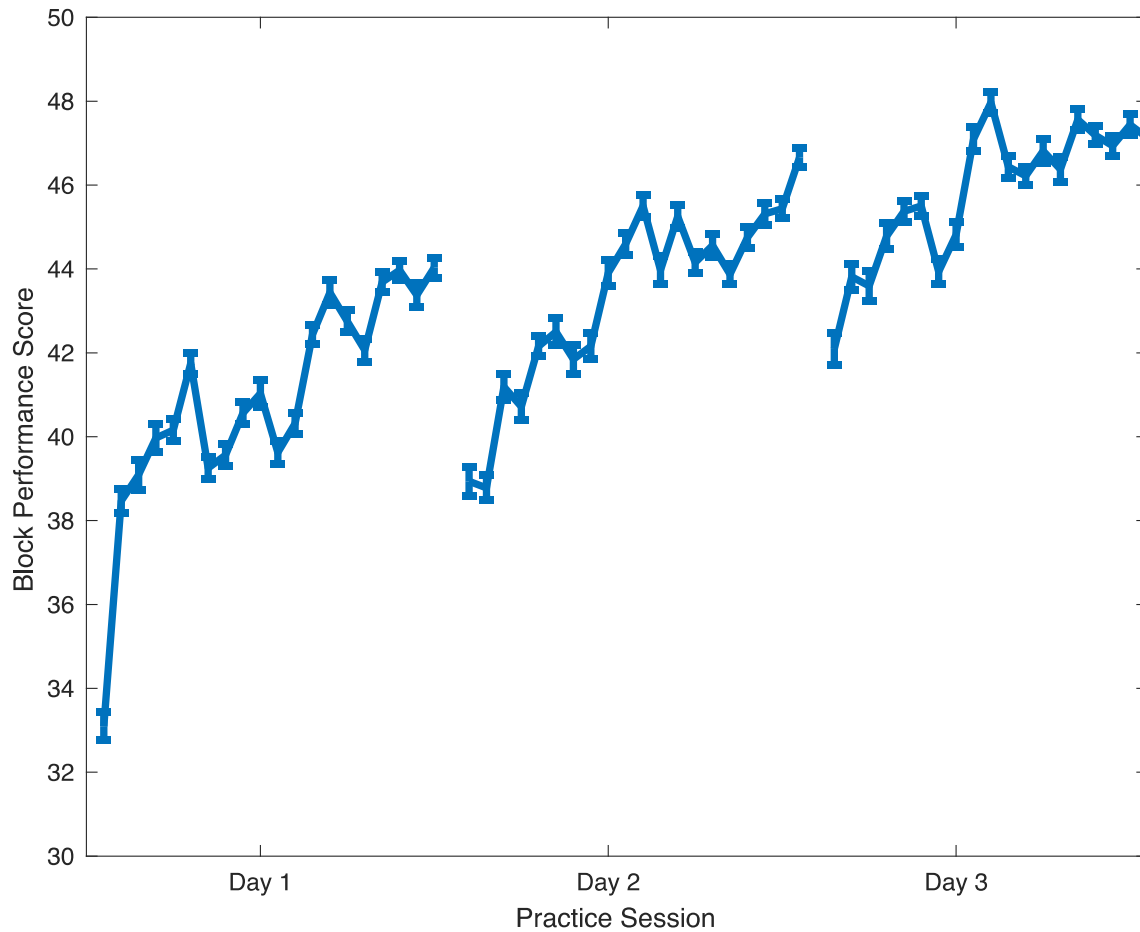


Figure 13 – Overall mean block performance across the three practice days. Each dot represents the performance average across all subjects in a single experimental block of 10 trials. The maximum score for a single block is 70 points. Error bars represent the standard error around the mean.

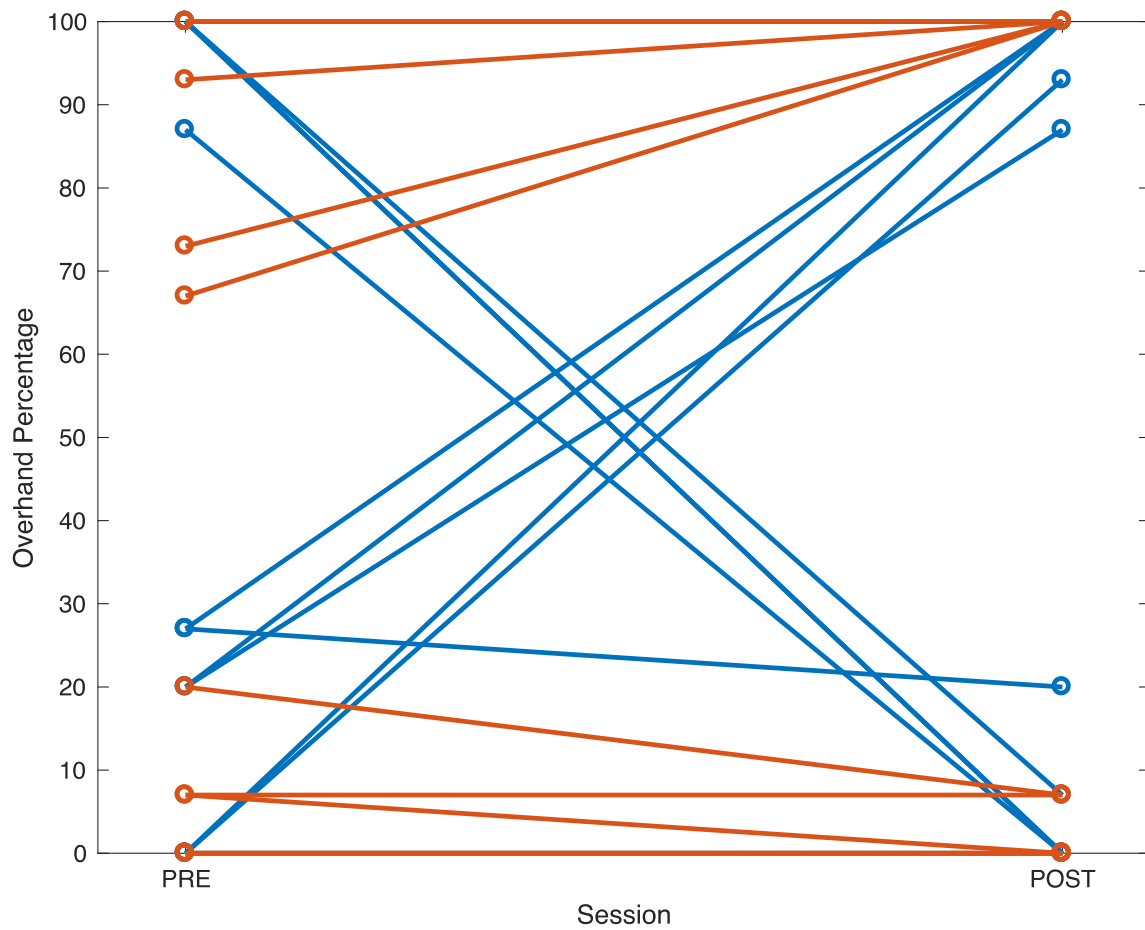


Figure 14 – Percent of throws made with an overhand pattern for each individual in the Congruent (orange lines) and Incongruent (blue lines) groups in the PRE and POST test condition.

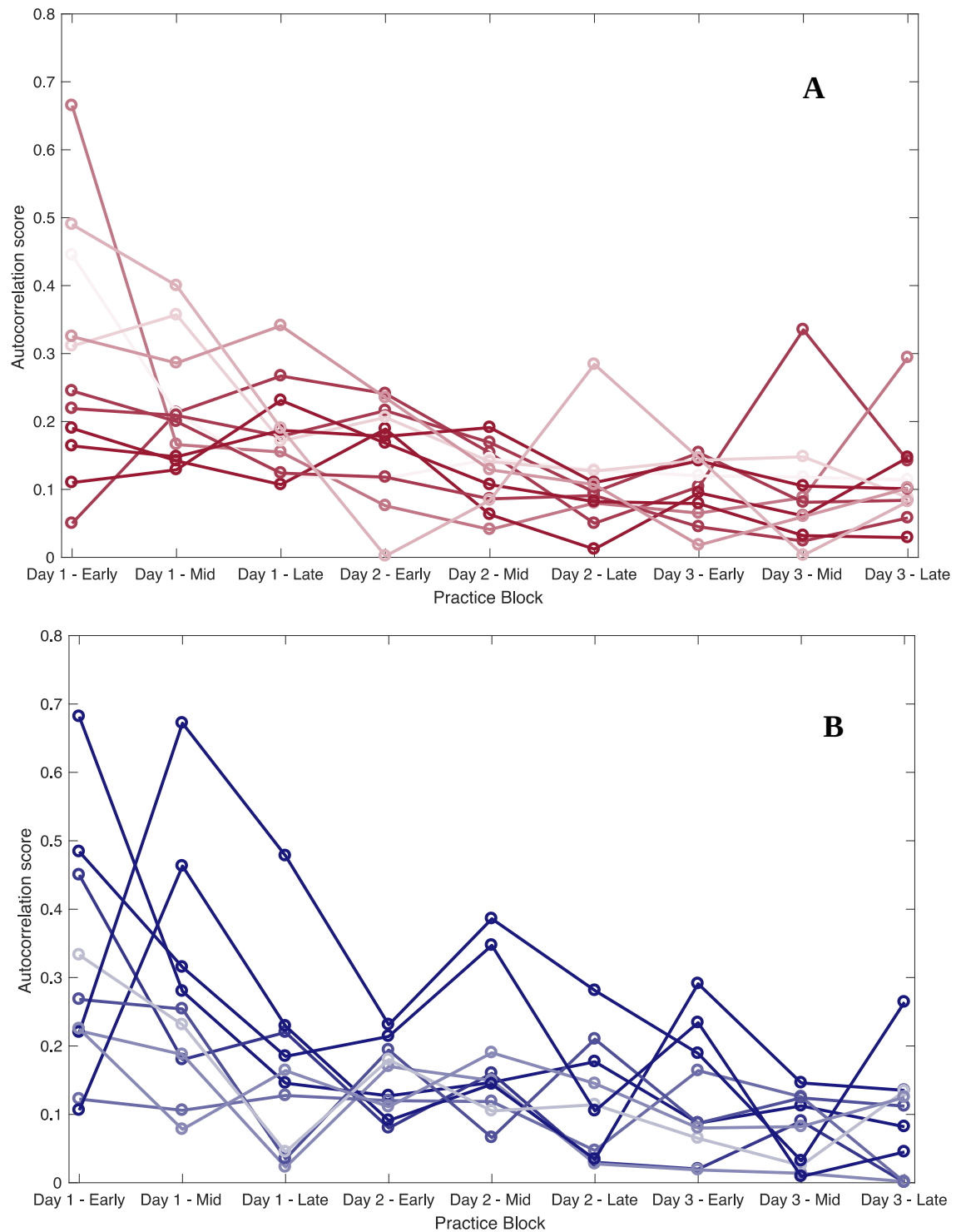


Figure 15 – Autocorrelation as a function of practice block. Each point represents the absolute autocorrelation value across a set of 30 trials (3 practice blocks). Each line represents an individual in the Congruent (**A**) or Incongruent (**B**) condition. The hue of the line is determined by the initial stability of the individual, with a darker hue indicating that this individual was more stable in their preferred pattern, as observed during the 70% Non-Dominant condition in the PRE-test.

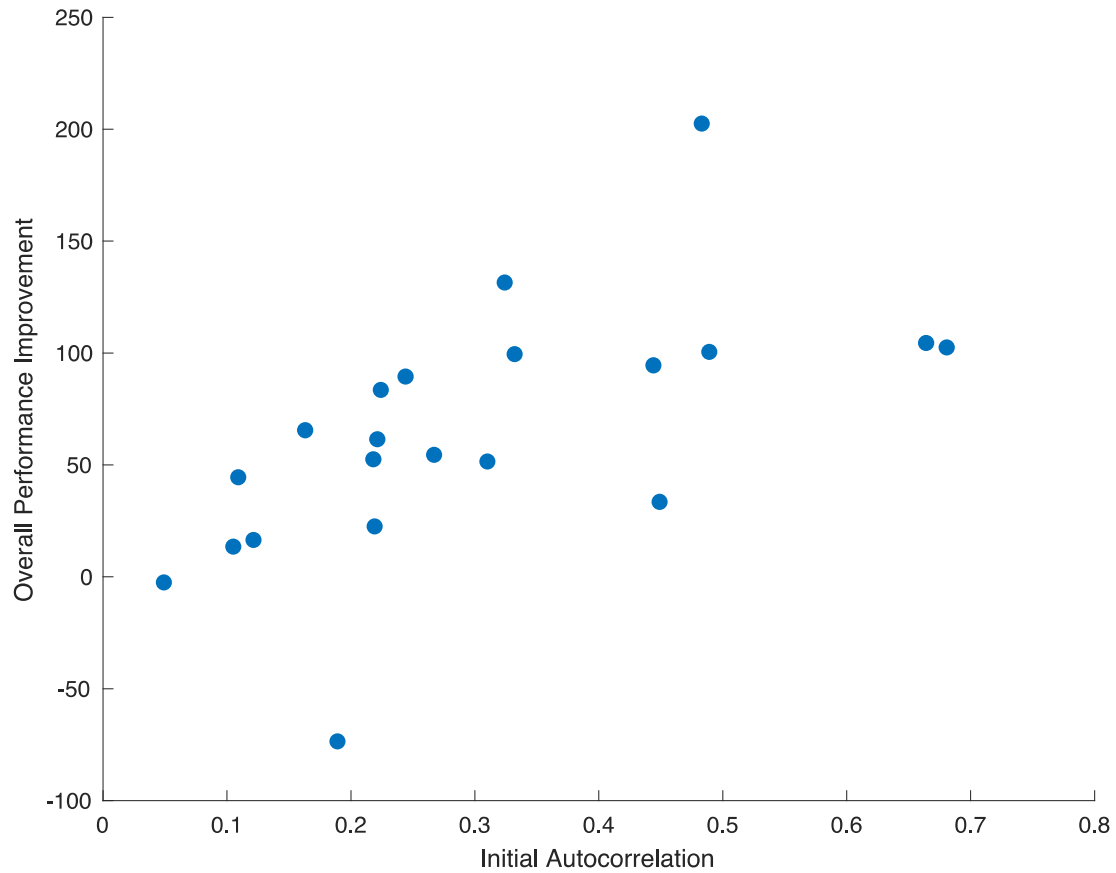


Figure 16 – Relation between the initial absolute autocorrelation score and the overall improvement between PRE- and POST- test across all target conditions. Every point represents an individual in the Congruent or Incongruent condition ($R^2 = 0.61$).