DOTTORATO DI RICERCA IN SCIENZE BIOMEDICHE

CICLO XXXII°

COORDINATORE Prof. Massimo Stefani

Motor Intelligence

The study of simple motor tasks as indicators for inter-individual differences

Implications for clinical practice and sport excellence

Settore Scientifico Disciplinare BIO/09 - M-EDF/02

Dottorando
Dott. Erez James Cohen

(firma)

Tutore
Prof. Diego Minciacchi

(firma)

Coordinatore
Prof. Massimo Stefani

(firma)

Anni 2016/2019

Table of Contents

Thesis Summary

This thesis aims to bridge between the theoretical concept of motor intelligence and its practice. Particularly, I seek to affront the problematic regarding to its quantification. As any transition between theory and practice, the theoretical framework must first be established. When it comes to Motor Intelligence specifically, though the theoretical groundwork had existed for a long time, the practicality of which had remained behind. This thesis begins by first examining the reasons for the discrepancy between theory and practice for motor intelligence, continuing by a proposal for a practical approach based on the successful implementation of the concepts of intelligence (Chapter 1).

The approach presented here is made on two fronts; the first front consists of the identification of suitable tasks for quantification of various aspects of motor control (Chapters 2-4). Specifically, Chapter 2 examines the potential of drawing and tracing tasks as tools for assessment of fine motor control, tested on a large number of subjects with specific attention to individual differences and the implications of these tasks to motor control. The results evidence that there is no correlation in terms of precision between the two tasks and that this lack of correlation is task dependent and not shape dependent. This allows for a classification of subjects, based on their level of tasks precision, as either drawers or tracers. Results obtained from the study suggest that for an accurate evaluation of fine motor control, both tasks should be used integrating their results. Chapter 3, extends the findings in Chapter 2 to elementary children, investigating the development of components of fine motor control using a tracing and a drawing task. The study demonstrates that, while tracing capacity improves greatly with age, drawing capacity improves only slightly. This trend may be due to possible involvement of attention as well as maturation patterns of the nervous system. The tasks, by being simple, economic and rapid, may represent a good instrument for motor control quantification during development, especially for population screening of eventual delays in maturation of motor control. Chapter 4, assesses the sensitivity of a tracing task following specific interventions, examining how the manipulation of objects, specifically fidget spinner, may influence fine motor control using a spiral tracing task. Results suggest that while fidget spinners do improve precision in tracing, it does not appear to be due to any inherent characteristic of the spinners themselves, as Sham group also demonstrated improvements.

The second front consists of the creation of instruments and methodological approaches that could be used for quantification (Chapters 5-7). Chapter 5 introduces a novel quantification method for 3D analysis of movement using a single camera, with a specific attention to the widespread implementation of movement analysis. Chapter 6, introduces a novel approach for the quantification of motor adaptation, using a simple continuous task which seeks to facilitate testing, and consequently used also in clinical settings. The adequacy of the task was evaluated by examining for aftereffects and generalizations (considered as indicators for motor adaptation). Results affirm the suitability of the task for examining adaptation, specifically, long-lasting after effects and generalization both for size and shift were found. Chapter 7 introduces a novel quantification approach during motor learning which is aimed to evidence individual differences in strategy selection during learning. This execution-centric approach is able to predict behavior during learning, regardless of outcome.

Finally, Chapter 8 closes this thesis by discussing the approach presented here in a general context along with some concluding remarks and possible future directions.

1 Introduction

Abstract. The study of human movement for a long time was predominated with the formulation of general theories and models of motor control, leaving individual differences as part of an inevitable, though expected, error variance. This state of mind goes in contrast with the widely accepted notion that differences, for various attributes and abilities, are not only present between individuals but also are crucial for a comprehensive understanding of the mechanisms and processes underlying movement. However, the complexity entailed in adequately constructing a study aimed to examine individual differences (regarding what aspects should be considered, their reliability and significance) represents a strong deterrent for the entire field. Though current research is more inclined toward the study of individual differences, it still falls short from its objective. This is partially due to faulty planning of studies as well as difficulties related to the interpretation of findings. The end result is a plethora of articles that merely evidence the existence of differences, whereas the nature and usefulness of this knowledge remains dubious. In this chapter I will cover the general approach of studying differences in the field of motor control with an emphasis on the study of individual differences. I will continue by discussing the potential of quantification and characterization of individual differences in a wider perspective of intelligence, and conclude by presenting the possible application of this concept in the field of motor control as the study of Motor Intelligence.

Intelligence, in general, is considered to be a certain measure for individual differences. Therefore, any discussion regarding intelligence or types of intelligence should begin with some review of quantification individual difference. Specifically, in the context of this thesis, which regards a relatively novel concept of "Motor Intelligence", it is imperative to first begin with reviewing the common approaches used to evidence and quantify differences in the field of motor control. I will therefore begin by first discussing the study of group differences in motor control, followed by an examination of the approaches used to quantify individual differences. These aspects will later be used along with existing notions of intelligence to provide the groundworks for "Motor Intelligence" and the possible translation of this concept into practice.

Before beginning the discussion about the study of differences, it is important to consider that the various aspects of motor control cannot be measured directly, only estimated from motor output, hence our knowledge of motor control is derived from behavioral observations. Therefore, it should be emphasized that motor control theories are constructs: models that attempt to elucidate control principles based on a certain neuroanatomical consensus (Schwartz, 2016). According to this classical view, the motor system is composed by specific structures and follows a certain hierarchy: with the sensorimotor and premotor cortexes, basal ganglia, and the cerebellum as higher centers for movement elaboration followed by the descending pathways and peripheral nerves to reach the target muscles (Squire et al., 2013); Though there is no doubt that the above mentioned structures are cardinal structures for movement elaboration and production, a problem arises when components of motor control models are assigned to structures of the nervous system.

This problematic stems from a certain dogma in neuroscience, which surmises function from anatomical connectivity: physical structures are assigned specific functional roles and are interconnected in putative circuits in an attempt to define causal sequences of interaction (Frisch, 2014; Genon et al., 2018). Though an assignation approach facilitates the formulation of models and theories, it is unlikely that biological systems, and in particular a vastly inter-connected system such as the nervous system, would follow these rules. In fact, the distinctions between classic motor structures have been blurred by neuronal responses sensitive to somesthetic input, including skin indentation, muscle stretch, and joint displacement, to the motor cortex (Schwartz, 2016). Moreover, the involvement of motor structures in numerous processes renders even more difficult this distinction, e.g., (Lametti and Watkins, 2016).

The biological constructs and their behavioral repercussions are certainly of interests and of importance when it comes to movement, however, when the concepts being studied become less defined and more abstract, attribution of processes to physical areas of the brain becomes rather redundant. In fact, studies of motor learning have demonstrated a plethora of areas participating, however their specific role and contribution of each area to the process is less defined and varies depending on the context (Hardwick et al., 2013). Therefore, although the understanding of neural basis of movement is undoubtedly important, it goes beyond the scope of thesis, which is mostly focused on the quantification of motor output.

1.1 Group differences in motor control

The study of group differences is an attractive direction for research. Since differences between groups are usually evident *a priori*, when attempting to evidence differences for aspects related to movement it is almost guaranteed to yield clear and coherent results. In fact, there are numerous papers highlighting the differences in movement and motor control related to different age groups (Zoia et al., 2006), different health conditions (Hsu et al., 2019), different sexes (Moreno-Briseño et al., 2010), different cultures (Bardid et al., 2015), different socioeconomic statuses (Klein et al., 2016), the list is immense.

The beauty of this approach, is that the objective is very clear. The two populations being studied clearly possess some differences, now we just have to investigate whether or not these differences also extend to what we wish to investigate, for example, male female differences in motor learning (Moreno-Briseño et al., 2010). However, in most cases it is abundantly clear that differences are present (or to be expected), for example, children compared to adults have a completely different body composition and maturation of the nervous system, factors known to influence motor control even in a relatively homogeneous population (Söğüt et al., 2019). Therefore, it is quite a banality determining that differences also ensue for motor control when comparing two populations that are defined by their differences for these factors. Moreover, also in cases where the differences are less evident between the two groups in question, since the objective of the study is clear (i.e., evidencing difference), then simply by examining numerous parameters, the likelihood of finding a difference for one of them is very high. A suitable example is that of a study examining motor learning strategies in basketball players and their implications for anterior cruciate ligament injury prevention (Benjaminse et al., 2017). This study compared 3 groups, a visual instructions group, verbal instruction group and a control group. Though the data in examination included a complete full body kinematic and kinetic analysis, the reported results were essentially limited only to ground reaction force and knee flexion moments.

These types of studies, while reporting results that are statistically significant, are devoid from scientific rigor and usually produce results that are rather useless and, at times, even misleading (Head et al., 2015). Though there may be occasions in which resorting to random search of significance between groups could be of value, however, this is a rather lazy approach that guarantees to yield results with a certain scientific contribution that is discrete at best. The end result of which is an explosion of information with slight content and very limited usefulness.

1.2 Individual differences in motor control

Individual differences in movement research were for a long time considered as an inconvenience, masking the desired output of group data (Kirkcaldy, 1985). The importance of individual differences was always widely acknowledged, after all, in some sense it is the foundation of our perception of reality. However, even though it seems obvious that two individuals are different, the study of what renders them different is by far much more complex. In fact, instead of discussing individual differences as a concrete concept, the preferred terminology considers inter-individual variability rather than differences e.g., (Raffalt et al., 2016). Though it may seem that the two may represent synonyms of the same idea, the conceptual difference between them is immense. While differences are concrete and determined, variability considers a certain spread, referring not to whether or not two things are different, but rather to *how much* similar or different two things are (Urdan, 2017). Under this respect, a measure of inter-individual variability is more a measure of the sample homogeneity than actual difference and, as such, could be considered as an extension to group studies.

The objective of studying individual differences is quite the contrary, taking the small differences and amplifying them to caricature-like proportions. This concept was already realized in animation much earlier than in movement research (Thomas and Johnston, 1995). According to this view, it is the small, sometimes invisible, differences that are most characteristic. Small traits are magnified to be rendered as evident as possible; otherwise, it becomes difficult to differentiate one person (or character) from another. In fact, the first assumption that must be made when attempting to study individual differences is that different individuals are different. Following that we can search for the best way to demonstrate/evidence those differences.

1.2.1 The three R's of individual differences

1.2.1.1 Ranking

It would go without saying that the moment we affirm that differences exist between individuals we implicitly assume that individuals could be ranked accordingly. The simplest example for this is considering physical traits such as height. Some individuals are short and some are tall, and regardless of the population we take under consideration, we can always rank them from shortest to tallest. This is the first fundamental requisite for investigating individual differences.

When we wish to apply it to motor control, we examine a performance for a certain task, again, our starting point is assuming that some individuals would perform better in this task and some worse. Therefore, ranking in this case could be made from worst to best, a commonly used approach in competitive sport (Motegi and Masuda, 2012; Reid et al., 2014). This may be applied not only to task success, but also to any parameter aspect of the performance we wish to consider. For example, we could examine execution speed and thus rank individuals from slowest to fastest, or strength thereby ranking from weakest to strongest, and so forth. No matter what aspect we wish to examine, we should be able to rank individuals accordingly. This implies that any parameter under question must be, first, quantifiable, and second, continuous. Boolean data, for example, while being very useful for division, are obviously not adequate for ranking.

Surprisingly, studies oriented toward investigating individual differences in motor control demonstrate a certain abstinence from the term "ranking" e.g., (Stark-Inbar et al., 2017). It seems that when it comes to human factors in non-competitive settings, there is a preference to use "reach-around" terms, which imply that a certain ranking had taking place, but is not fully considered as such. Therefore, it is more likely to find terms such as "below average" or "low-scoring" instead (Chorba et al., 2010; Sayers et al., 2016). Surely any parameter under investigation, given an adequate number of samples, would eventually result in a Gaussian distribution; therefore, when discussing population results, it may be more useful utilizing a terminology that references the mean of the population (e.g., below average). Still, whether personal preference drive toward the use of one terminology over another, conceptually the process remain the same.

1.2.1.2 Repeating

Even if a ranking is obtained for a certain parameter, it still does not mean that it is valid. Since our focus is on evidencing actual differences, we cannot accept any ranking until we examine whether or not it is consistent. Here enters the concept of repeatability, the successive measurements of the same measure carried out under the same conditions (Plesser, 2017). Since a ranking by a single measure may be influenced by various factor, obtaining the same ranking after repetition increases our confidence in the ranking e.g., (Mok et al., 2016). For example, if we test performance in a certain task, some individuals may have not fully understood the task and consequently underperformed, then the re-testing helps to eliminate that. Especially when done on several occasions.

Furthermore, the more objective our quantification is, the more reliable our ranking would be. Rater evaluation for example, usually used for quantifying qualitative aspects of performance, cannot guarantee a repeatability of results and may also present personal biases (Gingerich et al., 2011). Therefore, we should always strive for an objective quantification.

1.2.1.3 Reasoning

Once something is found to be repeatable it does not necessarily mean that it is of scientific value. When we consider individual differences, evidencing them is not enough (we assume that they will always be present), but understanding their meaning and their importance in the context of previous knowledge is imperative (Bavdekar, 2015). With a carefully planned study this is usually not an issue, since we already seek to address a very specific question. However, in studies in which differences were evidenced by means of collecting large amounts of data, it is often difficult to account for the differences we report e.g., (Benjaminse et al., 2017). Without a clear idea of how a certain difference contribute to the general understanding, an entire study can become trivial.

1.2.2 Difficulties in the study of individual differences

Even though the general approach for studying individual differences is relatively straight forward. It appears that still there is a preference to avoid this argument at all cost. The main issue, once taking out of the equation notable group differences, is what are we left with? Meaning, what are the aspects of movement that are of value to study, and how to study them in a way that evidence differences between individuals.

1.2.2.1 The output measure

Perhaps the most difficult question when constructing a study aimed toward evidencing differences is what is the output measure that we should consider (Barak and Duncan, 2006; Shishov et al., 2017). While we may have a general idea of what we wish to examine (e.g., motor learning, speed-accuracy tradeoff etc.), when we begin to review the parameters that may be examined, it is hard to determine which would be the most valuable scientifically and would also prove to be suitable for evidencing individual differences. Even when we do find a parameter which we deem suitable, since often times we cannot be completely sure whether the results would be repeatable, we risk conducting a study which would not yield results.

On larger datasets, for example when conducting a kinematic movement analysis, the problem becomes even more pronounced. As mentioned earlier, the likelihood of finding a certain parameter which would satisfy the requisites of studying individual differences is high. However, the significance of this parameter may not be of value. Still, as these types of studies consider an immense amount of data, the amount of time and resources dedicated may increases until the entire idea would be abandoned or would resort to methodology aimed to evidence significance (Head et al., 2015).

Another issue that may increase the difficulty of identifying an output measure is the complexity of the task being studied. The more complex the task is, the more aspects could be considered and the more difficult it becomes to determine which measure should be compared. In fact, while it is obvious just by sheer observation that most movements are subject to great individual differences, most movements cannot be studied and controlled in experimental settings. Therefore, we try to simplify and reduce general concepts to their acceptable minimum. The problem with the simplification approach is that results derived from simplified approaches do not necessarily generalize to complex ones (Wulf and Shea, 2002). Consequently, over simplification may mask either the original movement completely, or the differences between individuals for the original movement.

The biggest deterrent for the study of individual differences after all is, again, that the second you start investigating individual differences you are bombarded with an infinite amount of data. Therefore, we must decide on one measure in order to make sense of things.

1.2.2.2 Reliability and significance

To determine the reliability of a study, or more specifically, of a certain difference found, we must demonstrate its repeatability (see 1.2.1). Naturally, retesting and reproducing results does not come without a cost, and therefore, it already represents a difficulty. However, even once something is found to be repeatable we must view and discuss its importance in the context of previous knowledge. This at times is not necessarily immediate and may require a follow-up study to put it in context.

1.2.2.3 Sample size

In order for a concept to be effectively applicable to the general population, our study's sample must be sufficiently large (Faber and Fonseca, 2014). Since often when investigating individual differences there is a sense of uncertainty (related to the choice of the output measure, or repeatability as well as there are numerous parameters to consider), most studies focused on individual differences usually recruit a small number of subjects. This way, while characterization of the differences within the sample may be quite evident, generalizing the results to a larger population is not admissible (Faber and Fonseca, 2014). The recruitment of more subjects for a study presents its own difficulties, regardless of the scientific dilemma that we are facing. Consequently, more complex studies prefer small sample size, simple studies may have larger sample size.

1.3 Potential of studying individual differences

Up until now we have discussed the general approach to the study of individual differences and its limitations. However, it is perhaps more important to understand what is the usefulness of this knowledge. Why do we need to quantify objectively these differences? And how can we use these differences in a wider context? In an attempt to answer these questions, we will deviate from movement research to the field of psychology, in which for a long time individual differences were examined, characterized and implemented with success, and their study was proven to be beneficial. Specifically, we will examine the case of intelligence and intelligence quotient and discuss the possible translation of this concept to movement studies.

1.3.1 Intelligence and Intelligence Quotient

1.3.1.1 Intelligence

The concept of intelligence has existed for a long time, though a consensus regarding its definition remains debatable, it is largely agreed that intelligence refers to certain cognitive abilities which are different between individuals (Legg and Hutter, 2007). The term, though debatable, has been the basis of the field of differential psychology, a field dedicated to the study of individual differences (Deary, 2012). Throughout the history of intelligence research (over a hundred years already) two objectives were evident, the first of which is that evidencing individual differences for cognitive abilities has important implications, the second, a direct consequence of the former, is that there is a need to adequately quantify intelligence in order to apply this concept to practice. This is rendered evident by the numerous efforts and proposals made and debated regarding the quantification of intelligence (Boake, 2002; Gottfredson and Saklofske, 2009). Perhaps the most influential work was that of Charles Spearman (Spearman, 1904) who, by discovering a general factor common to many different mental abilities, has provided the bases for the field of differential psychology and laid the foundation for models of intelligence testing (Deary, 2012).

1.3.1.2 Quantification of intelligence

Perhaps the greatest difficulty in differential psychology to date is the quantification of intelligence. Specifically, since the definition of intelligence was left open to interpretation, understanding what to examine exactly depended on what we wished to evidence. Initial attempts for quantification of intelligence were concerned with the assessment of extreme cases. Notably, in the 1800's the French physicians Jean Esquirol and Edouard Seguin investigated intelligence in individuals with intellectual disabilities whereas the British scientist, Francis Galton, focused on the ability of men of genius (Kaufman and Harrison, 2008). Though initial tests consisted of the examination of use of language, it was already evident that performance in non-verbal tasks was also important. Specifically, Galton employed an approach based on sensory discrimination and sensory-motor coordination integrated with anthropometric measures (Galton, 1885). It was only later that Alfred Binet shifted the focus of intelligence testing to higher mental processes, creating a series of test aimed to quantify aspects such as memory, comprehension, imagination and moral sentiments (Binet and Simon, 1904). These tests were later referred to as the Binet-Simon Scale in 1905, and were used to assess children for mental retardation. In 1916 a revision of the Binet-Simon Scale by Lewis Terman (Stanford-Binet Scale) first introduced the term Intelligence Quotient (IQ), considered the mental age divided by the chronological age multiplied by 100 (Terman, 1916).

The Binet scale, though widely accepted at that time, had a few evident shortcomings. Most notable of which were the use of primarily verbal tasks and the use of a single global score for intelligence. During World War I, the great need to rapidly classify new recruits lead to the formulation of a series of tests based on the Binet-Simon scale along with performance tests (Boake, 2002). Subsets of these were later used by David Wechsler, and were introduced in 1939 as the Wechsler-Bellevue Scale (Wechsler, 1939) which, differently from the Binet scale, included both verbal and nonverbal tasks as well as the calculation of 3 scores: verbal IQ, performance IQ, and full-scale IQ. Since then, several revisions were made to the Wechsler scale, which is still widely in use to date.

Though this short review of intelligence testing is certainly lacking, for a more thorough review of the subject refer to (Boake, 2002; Deary, 2012; Gottfredson and Saklofske, 2009; Kaufman and Harrison, 2008), what is evident from this brief discussion is the fact that quantification of intelligence rises from certain practical needs. In fact, the use of intelligence testing specifically in schools is considered to be more objective than teacher evaluations, which is why they became widely accepted in education (Vane and Motta, 1984). Moreover, diagnostic criteria for intellectual disabilities is practically defined by results in standardized intelligence testing (American Psychiatric Association, 2013).

1.3.2 Multiple intelligences.

1.3.2.1 Theory

For a long time intelligence was considered a single entity, following the view of Spearman (Spearman, 1904). It is now, however, widely accepted that there are different types of intelligences. Currently there are three theories dominating the view of a plurality of intelligences: the CHC theory (i.e., Cattell, Horn and Carroll), the multiple intelligences theory, and the triarchic theory. Regardless of the theory taken in consideration, there is an agreement that current IQ models are not sufficient to cover all aspects related to intelligence.

The CHC theory is considered perhaps as the most comprehensive theory related to distinction of cognitive abilities. The theory represents the integrated works of Cattell, Horn and Carroll (Carroll, 1993; Cattell, 1941; Horn, 1968). The basic idea of CHC theory is that there are three strata of intelligence that are hierarchically related to each other. Stratum I includes narrow abilities, Stratum II, broad abilities, and Stratum III, general ability (Sternberg, 2012). According to this view, the abilities encapsulated within Stratum I relate to specific, measurable, abilities of the categories (or broad abilities) included in Stratum II. For example, reading comprehension is a narrow ability in Stratum I, which is one of the measurable abilities under the category of reading and writing (one of the broad abilities in Stratum II). The categories are all considered as part of the general ability (i.e., Stratum III). Therefore, we could consider this view as somewhat of an extension of Spearman's model of a general intelligence.

The multiple intelligences theory was proposed by Howard Gardner under the premise that there is no "general intelligence" broadly construed, but rather that it is multiple (Gardner, 2006). Gardner suggested the existence of eight different types of intelligences, all relatively independent from one another. These intelligences include: linguistic, mathematical, spatial intelligence, musical intelligence, bodily-kinesthetic intelligence, naturalist intelligence, interpersonal intelligence and intrapersonal intelligence.

The triarchic theory, proposed by Robert Sternberg argues that intelligence comprises three sets of skills: creative, analytical, and practical (Sternberg, 1985). Where creative skills are those concerned with the generation of novel ideas. Analytical skills seek to assure that the ideas are good ones. Finally, practical skills are concerned with the implementation of the ideas and persuasion of others of their value. The triarchic theory therefore considers that the different types of intelligences are somewhat interconnected, as opposed to Gardner's view of completely independent intelligences.

1.3.2.2 Practice

Though the above mentioned theories of multiple intelligences have gained a fair amount of attention, their implementation was less than optimal. When specifically investigating the proposed theories, the CHC theory proved to be the most supported one in terms of empirical findings (Flanagan and Dixon, 2014). However, since the CHC theory is rather complex and includes a large number of items, it is mostly represents the theoretical grounds from which subsets are used for other tests (Keith and Reynolds, 2010). As for the multiple intelligence theory, attempts have been made for testing the various types of intelligences, however, in this cases (considering the ample difference between the types of intelligence) the proposed tests fall short by limiting themselves to either questionnaires or certain tasks which are not consolidated e.g., (Almeida et al., 2011; Singh et al., 2017). Also in this case, it is hard to create a univocal model for testing that can adequately address all of the proposed types in a single test. As for the triarchic model, due to its vague definitions and its focus on day-to-day situational problem solving, there are only a few studies that have examined parts of it not under the form of a test though (Sternberg and Grigorenko, 2001). Therefore, it still represents more a theoretical than a practical concept.

1.4 Motor Intelligence

Independently of one's preferences toward a certain theory of intelligence, it is relatively clear that each of them consider a certain motor component of intelligence. In fact, the notion of a "movement based" intelligence was already noted in the 1800's (Galton, 1885). According to the modern theories, this component may be explicitly considered, as in Gardner's theory (i.e., bodily-kinesthetic intelligence), or more implicitly considered, as in Sternberg's theory (i.e., practical intelligence). Also, items related to psychomotor functions were added to revisions of the CHC theory (McGrew, 2005). Still, even though the notion of movement related intelligence predates even the consolidation of intelligence testing, the term "Motor intelligence" was coined relatively recently (Berendsen et al., 2002).

The value and the importance of movement ability quantification are noted in clinical practice, sports science, as well as in education. It is therefore somewhat perplexing that with all the attention related to the study of movement, there is still no consensus regarding its evaluation and assessment. Though there are tests aimed toward the quantification of movement in specific fields, such as professional athletes and children (Bruininks and Bruininks, 2005; Folio and Fewell, 2000; Henderson et al., 2007; McKeown et al., 2014; Piper et al., 1992; Russell et al., 2013). The majority of items included in these tests are subject to rater evaluation, which renders them not objective as well as logistically difficult for a wide-spread implementation. In clinical practice, the evaluation of movement is not standardized and is reliant completely on the examiner's own perception (Brazis et al., 2007).

It is for these reasons exactly that the debate regarding motor intelligence was initiated (Berendsen et al., 2002). However, as the discussion related to motor intelligence was initiated, it already encountered a strong opposition (Olsson, 2002). Some of the argumentation against a model of motor intelligence relate more to the practical issue of constructing a new model of intelligence that entails a long process of demonstrating that the new intelligence meets traditional standards for intelligence. However, as for intelligence testing in general, where there is a need there are also solutions. If we consider that intelligence testing already has a history of over 200, the "long process" referred to by Olsson is a false deterrent.

A second argument raised was regarding the definition proposed by Berendsen and colleagues "the capacity to understand, perceive and solve functional problems in various environments by motor behavior in a flexible, dynamic, efficient and productive way" (Berendsen et al., 2002). The emphasis given to perceiving, understanding and solving problems does not seem to be particularly motor-centered, and would be assessed just as well with existing intelligence tests (Olsson, 2002). Though the definition proposed is indeed lacking, within the field of intelligence to date there is still no agreement regarding the definition of intelligence in general (Legg and Hutter, 2007). Therefore, a revision of the definition may be introduced, giving more emphasis on movement than on perception. Lastly, and perhaps most substantial objection, whereas much is known about the taxonomy and predictive validity of human intelligence differences, there has been relatively little progress in understanding their nature (Deary, 2001). Consequently, the introduction of a new concept of intelligence, with its own taxonomy, without understanding of the reason for differences, does not contribute to our current understanding, and belittles the entire concept in general.

Recently, Hands and colleagues, have also brought forth a discussion in an attempt to resuscitate the old concept of "General Motor Ability" (Hands et al., 2018). This, similar to the Spearman's model for intelligence (Spearman, 1904), hypothesizes a single general ability for motor control. The authors discuss the issues with current assessment tools for motor capacity, and provide argumentations supporting a global motor ability derived mostly from analysis models and other theoretical works. However, their proposal falls short from conception, as the discussion of existing theoretical concepts without a practical framework to accompany them is destined to be abandoned, the same as as the original theoretical models that preceded it e.g., (Brace, 1930; McCloy, 1934; Spearman and Jones, 1950).

It is certainly a daunting task to characterize possible individual differences in motor control, and in general. However, the study of motor intelligence should stem from the study of individual differences and their characterization, not from the formulation of theories and taxonomy.

1.4.1 Approach to motor intelligence

Given the existing knowledge of human movement, along with the approach for studying individual differences in motor control (see 1.2 Individual differences), the transformation of theory to practice is largely facilitated. Similar to IQ, we assume that a certain motor intelligence quotient would not consist of a single measurement but of multiple measurements, based on certain taxonomy. In terms of motor control, several taxonomic classifications for motor abilities already exist (Fleishman, 1964; Gentile, 1972; Schmidt and Lee, 2005). For simplicity purposes, I will consider a one-dimension classification system that differentiates skills depending on the sizes of the primary muscle groups required to produce an action i.e., gross motor skills vs. fine motor skills (Magill, 2004).

Considering the contexts of potential implementation of a motor intelligence test (e.g., clinical practice, schools, sport settings), certain prerequisites must be taken into account. The first of which, as mentioned earlier, is that quantification must be objective. The second, the approach must be logistically simple and flexible, so as to allow for testing in different environments. Lastly, simple tasks are preferable, as complex tasks are not only problematic in terms of analysis but also may cause *a priori* biases due to differences educational background or specific training.

The approach presented here is made on two fronts; the first front consists of the identification of suitable tasks for quantification of various aspects of motor control (Chapters 2-4). Specifically, Chapter 2 examines the potential of drawing and tracing tasks as tools for assessment of fine motor control, tested on a large number of subjects with specific attention to individual differences and the implications of these tasks to motor control. Chapter 3, extends the findings in Chapter 2 to elementary children, investigating the development of components of fine motor control. Chapter 4, examines the sensitivity of a tracing task following specific interventions.

The second front consists of the creation of instruments and methodological approaches that could be used for quantification (Chapters 5-7). Specifically, Chapter 5 introduces a novel quantification method for 3D analysis of movement using a single camera, with a specific attention to the widespread implementation of movement analysis. Chapter 6, introduces a novel approach for the quantification of motor learning, using a simple task that seeks to facilitate testing, and consequently be used also in clinical settings. Finally, Chapter 7 introduces a novel quantification approach during motor learning which is aimed to evidence individual differences in strategy selection during learning.

Though certainly the work presented in this thesis is partial at best, when considering a vast argument such as “Motor Intelligence”, I do believe that it may help to create a certain framework which could potentially be extended to a more complete approach. Therefore, with this work I hope to make an initial step toward a translational shift of a concept that, to date, remains mostly theoretical.

2 Precision in drawing and tracing tasks: different measures for different aspects of fine motor control

Abstract. Drawing and tracing tasks, by being relatively easy to execute and evaluate, have been incorporated in many paradigms used to study motor control. While these tasks are helpful when examining various aspects relative to the performance, the relationship in proficiency between these tasks was not evaluated to our knowledge. Seeing that drawing is thought to be an internally cued and tracing an externally cued task, differences in performances are to be expected. In this study, a quantitative evaluation of the precision of circle drawing and tracing, and spiral tracing was made on 150 healthy subjects. Our results show that, while precision is correlated when repeating drawing circles, tracing spirals, or tracing circles as well as between tracing spirals and tracing circles; there is no correlation when subjects performed drawing circles and tracing spirals or between drawing and tracing of circles. These results suggest that this lack of correlation is task dependent and not shape dependent. We suggest that the evaluation of fine motor control should include both a tracing and a drawing task, taking in consideration the precision in each task. We believe that this approach could help not only to evaluate fine motor control more accurately, but also to identify subjects who are more reliant on either internal or external cueing and to what extent.

2.1 Introduction

Tracing and drawing tasks represent attractive tools for the evaluation of various aspects relative to motor control. As such, many paradigms designed to study motor control have incorporated them as part of their assessment. Most of these paradigms use simple shapes as their employment may be both easily executed and measured, while still providing valuable information of upper limb functioning as well as motor control (Smits et al., 2018). Specifically, the precision of performance in spiral tracing tasks has been incorporated as part of the neurologic examination for the evaluation of fine motor control (Cohen et al., 2018b; Hoogendam et al., 2014; Miralles et al., 2006; San Luciano et al., 2016). On the other hand, circle drawing is widely incorporated in timing-based tasks in which the smooth and continuous motion of circle drawing has been used to compare discrete and continuous motor tasks for timing control (Repp and Steinman, 2010; Robertson et al., 1999; Spencer et al., 2003; Studenka et al., 2012). In this case, the drawn circles are not evaluated for precision, but for timing consistency between repetitive drawings of the shape. There are also examples in which the precision of the drawn circle was evaluated. It was shown that the area and roundness of the circles correlated with stroke severity and were suggested to represent outcome measures for stroke rehabilitation (Krabben et al., 2011). Also, precision in circle drawing was used to evaluate speed-accuracy tradeoff when temporal constraints are introduced (Gatouillat et al., 2017) as well as motor equivalence (i.e., the similarity of movements produced by different sets of motor commands, utilizing different muscle groups; Portnoy et al., 2015).

Surprisingly, even though drawing and tracing tasks are widely used to evaluate fine motor control (Mergl et al., 1999; Smits et al., 2018; Sülzenbrück et al., 2011, 2010; Vuillermot et al., 2009), very few studies have investigated the relationship between drawing and tracing. Worth noting are the works of Gowen and Miall, in which the researchers have analyzed eye-hand interactions for both tracing and drawing of simple shapes; they have reported a tighter eye-hand coupling for the tracing task than the drawing task as well as more frequent pursuit eye movements for tracing than for drawing (Gowen and Miall, 2006). Following that, the researchers have further shown that different cerebral areas are

---

Cohen EJ, Bravi R, Bagni MA, Minciacchi D (2018) Precision in drawing and tracing tasks: Different measures for different aspects of fine motor control. Hum Mov Sci. 61:177-188. doi: 10.1016/j.humov.2018.08.004.

activated when drawing was compared to tracing, suggesting the former to be a more cognitive task than the latter (Gowen and Miall, 2007). This is to be expected when also considering that tracing is an externally cued task and drawing is internally cued (Flanders et al., 2006; Sailer et al., 2000; Thut et al., 2000; van Donkelaar and Staub, 2000). In fact, it was shown that externally and internally cued performances may differ. Differences in performance were found when auditory synchronization (externally cued), measured as synchronized wrist oscillations to an auditory stimulus, was compared with auditory imagery (internally cued), measured as wrist oscillations synchronized to the recall of an auditory stimulus, with the auditory synchronization task being more precise than auditory imagery (Bravi et al., 2015, 2014). Specifically, based on autocorrelations of the performances, the auditory imagery task seemed to employ more emergent-based timing whereas the auditory synchronization task a more event-based timing. Also, it was suggested that internally and externally cued tasks may be used evaluate different aspects relative to motor control. This was shown in some auditory-motor paradigms involving finger tapping in which the synchronization phase (externally cued) was suggested as an estimator for anticipatory mechanisms (Repp, 2011; Repp and Moseley, 2012), whereas the continuation phase (internally cued) as an estimator for drift (Collier and Ogden, 2004). These observations not only reinforce the hypothesis that differences in performance for tracing and drawing tasks are to be expected, but also that the two tasks may be used to evaluate different aspects relative to fine motor control.

To our knowledge there is no study that evaluates whether the proficiency in one task correlates to the other. It was shown that substantial difference in precision may exist among individuals in certain types of tasks (Madison, 2004). Also, investigations of precision in an angle reproduction test, for which the results remain relatively constant for repetitions distant in time, have revealed that healthy subjects may be categorized according to their level of precision (Callaghan et al., 2002; Perlau et al., 1995). Therefore, it appears that for certain types of tasks, when not subject to specific training, differences in precision may exist between individuals with some individuals being inherently more or less precise. It is possible to hypothesize that differences in precision among individuals may ensue also for both tracing and drawing tasks. It is also possible that, considering the differences between the tasks, no correlation in terms of performance precision would be found.

In this study, we seek to evaluate whether the precision in drawing and tracing tasks is constant among subjects. If indeed the two tasks evaluate fine motor control, it would be expected that, in the population, precise individuals in one task would also be precise in the other. We consider the two most widely used tasks in literature, spiral tracing and circle drawing. We first assume that subjects may be ranked according to their level of precision in performing either task. Therefore, the initial step consisted in evaluating whether this ranking is persistent (i.e., repeatable) for each task. Following that, in order to compare the tasks, we consider the differences between them, mainly different task and different shape. Therefore, we have fragmented the comparison into two: task comparison for the same shape (i.e., circle drawing compared to circle tracing) and shape comparison for the same task (i.e., circle tracing compared to spiral tracing). Following that we have evaluated the case of a different shape and a different task (i.e., circle drawing and spiral tracing).

Our hypothesis is that tracing, by being a different task compared to drawing, should not correlate with drawing, in terms of precision in the population. We expect that while subjects may be ranked according to their level of precision for both tracing and drawing, and that this ranking will remain relatively constant for all tasks regardless of shape, the precision in drawing compared to tracing among subjects would not correlate, again, regardless of shape. If our results go in line with our hypothesis, it should be possible to classify subjects as either drawers or tracers and to use this classification to accurately evaluate fine motor control.

2.2 Materials and Methods

2.2.1 Participants

One hundred and fifty healthy adults were recruited for this study (age: 23.1±2.6 years; 61 males). All participants were right handed (81.7±17.5; laterality score from the Edinburgh Handedness Inventory; Oldfield, 1971). Participants were naive to the task and the purpose of the study, and free of documented visual, motor, and neurological impairments. All subjects reported to have a corrected-to-normal visual acuity. All subjects reported to not have any previous experience in using a graphic pen tablet. The participants were university students who volunteered for the study. Participants were not paid for their participation. The study protocol was approved by the Institutional Ethics Committee (Comitato Etico Area Vasta Centro AOUCareggi, Florence, Italy) and all procedures conformed to the code of ethics of the Declaration of Helsinki. All participants gave written informed consent.

2.2.2 Set up

The set up in this study is the same as the one used in Cohen et al., 2018 and is briefly summarized. The participants executed both tracings and drawings, projected on a monitor, while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen (Figure 2.1). All tasks were performed using graphic pen tablet (Wacom Intuos® CTH-690AK, Tokyo, Japan; active area: 216 x 135 mm).

Each participant was tested individually. Participants were randomly assigned to one of six groups (Figure 2.1) composed of 25 participants each: Drawn Circles (Group 1; males=9), Traced Spirals (Group 2; males=9), Traced Circles (Group 3; males=13), Drawn Circles vs Traced Circles (Group 4; males=10), Traced Circles vs Traced Spirals (Group 5; males=10), or Drawn Circles vs Traced Spirals (Group 6; males=10).

2.2.3 Task

For all tasks we have specified to trace or draw the circles and trace the spirals as precisely as possible with no regard to the speed of execution. Before starting the task, each subject was asked whether the instructions were understood. Specifically, for the circle drawing task, instructions stated "draw a circle as precise as you can, meaning a circle having a constant radius", if instructions were not understood, it was further specified to "draw a circle as round as you can".

For Group 1, participants were asked to draw a circle counterclockwise starting at 12 o'clock. After a minute from conclusion, participants were asked to draw a circle again counterclockwise starting at 12 o'clock. No information was given regarding the dimensions of the circles. For Group 2, participants were asked to trace a spiral beginning from the center and going outward. After a minute the task was repeated. The spiral templates were designed for a medial to lateral performance of the dominant hand (i.e., counterclockwise for the right hand). For Group 3, participants were asked to trace a circle counterclockwise starting at 12 o'clock. After a minute from conclusion, participants were asked to trace a circle again counterclockwise starting at 12 o'clock.

As Groups 4, 5 and 6 represent only different combinations of the tasks in the first three groups, the indications for performance of the specific tasks were identical to those in Groups 1, 2, and 3. Depending on the first task in Groups 4, 5 and 6, after a minute the participants were asked to perform the other task assigned to that group (Figure 2.1). The order of either first task or second task was randomized so as to obtain an equal number of participants who started with either the former or the latter. The minute interval between trials was chosen seeing that it is considered to be well beyond the capacity of working memory (Siegel, 2002).

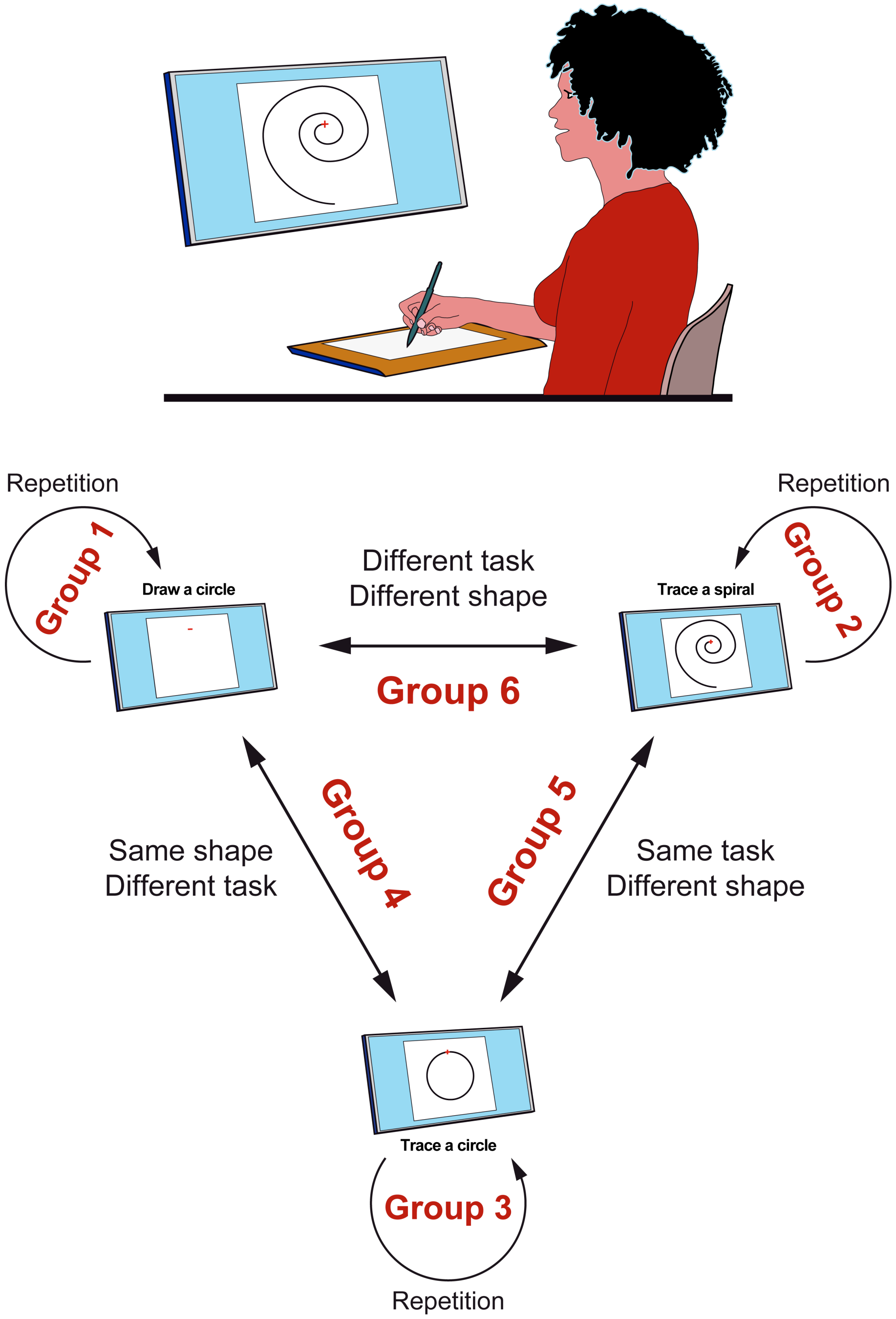


Figure 2.1. Setup and Experimental design. The upper panel illustrates the working setup used in the experimental session. The graphic pen tablet was placed in front of the screen, and the participants were asked to execute either the drawing or the tracing task, while seated, without the support of either wrist, arm, or elbow, in such a way that the only contact was made through the pen on the tablet. The lower panel illustrates the experimental design. Participants (n=150) were randomly assigned to one of the six groups, each consisting of 25 subjects: Drawn Circles (Group 1), Traced Spirals (Group 2), Traced Circles (Group 3), Drawn Circles vs Traced Circles (i.e., same shape; Group 4), Traced Circles vs Traced Spirals (i.e., same task; Group 5), Drawn Circles vs Traced Spirals (i.e., different shape and different task; Group 6). Each participant performed 2 trials with a 1-minute interval between them. The trials were different according to the experimental group and consisted of: for Group 1 – draw a circle and repeat; for Group 2 – trace a spiral and repeat; for Group 3 – trace a circle and repeat; Group 4 – draw a circle and trace a circle, randomized order; for Group 5 – trace a circle and trace a spiral, randomized order; for Group 6 – draw a circle and trace a spiral, randomized order.

To exclude performance differences between genders, the results of both tracings and drawings were compared by using an unpaired two sample t-test. The comparison was made on the results of Groups 1, 2 and 3 (repetition groups) in which the measurements could be directly compared. The t-test did not reveal any significant differences between genders within groups for both the first and second tracings/drawings. Therefore, the results for each group were pooled together, regardless of gender.

2.2.4 Analysis

Using Matlab, we have developed an algorithm to measure the accuracy of the drawn circles. The algorithm consisted of first finding the centroid of the drawn shape. This was achieved by taking the mean value of all *x* and *y* coordinates, the result of which would provide a reference center, from which the actual center could be calculated. From the reference center, points were organized according to their angle and were then reduced to 360 points, having one point per angle. This was done in order to reduce the sensitivity to the way the shape was drawn (e.g., parts drawn slower will result in more points). After the point reduction, the mean value of all x and y coordinates were calculated on the remaining point, and the result was considered as the center of the circle. Following that, the distance of each point (prior to the reduction) of the drawing from the center was calculated (Figure 2.2). These distances were considered as the radii for the drawn circle, the mean value of which would result as the radius of the corresponding perfect circle. Seeing that no indication was provided regarding the size of the circle, the coefficient of variation (CV; i.e., standard deviation/mean) of the radii was considered as a measure of the precision of the drawn circle, bearing in mind that for a perfect circle the variability will be zero. The same algorithm was used also for CV analysis of the traced circles.

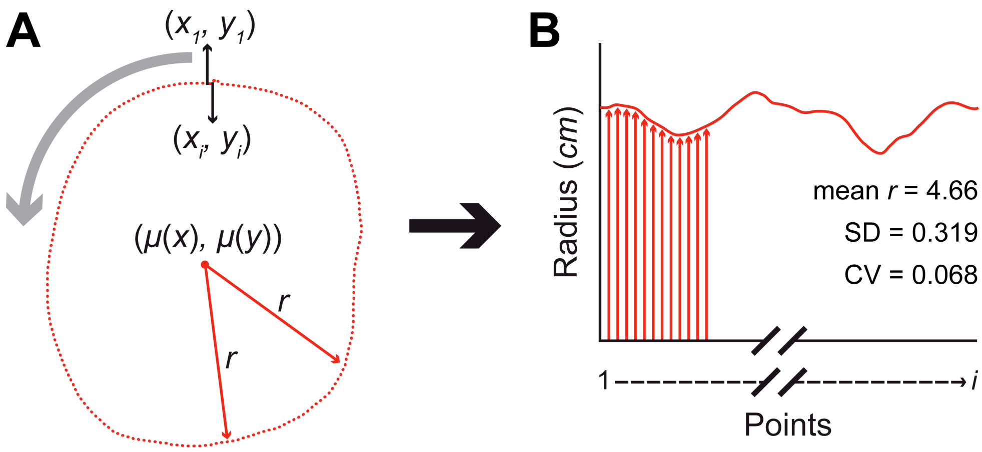


Figure 2.2. Drawn circles analysis. An example of the calculation of the precision of a drawn circle. **A.** A drawn circle represented as points starting at point 1 (with the coordinates x1, y1) and going counterclockwise to the end point (with the coordinates xi, yi). The mean (μ(x)) and mean (μ(y)) values were considered as the centroid of the drawn circle, and the radius of each data point on the drawing (r) was calculated as the point's distance from the centroid. **B.** The measured radii of the consecutive points, from which the CV of the radii was calculated for each drawing. CV of the radii in this example was found to be 0.068. SD = standard deviation.

For spiral and circle tracing analysis the algorithm consists of serial angle-based calculation of the traced spiral or circle deviations from the template (Cohen et al., 2018b). Points of the tracing (n = 6,643 per traced spiral and n=2,984 per traced circle, normalized to the size of the template) were organized both according to their distance from the spiral center as well as according to the angle; for circles, the points were organized only according to the angle. Seeing that for the spiral there is no constant measurement (e.g., radius), the CV could not be used as a measure of accuracy in this case. For each point the residual difference (RD) between the tracing and the template was measured, considering the template as the expected value. Since we are interested only in deviations from the template, RDs were considered as absolute values. For each tracing (spirals and circles) the mean RD was calculated (Figure 2.3).

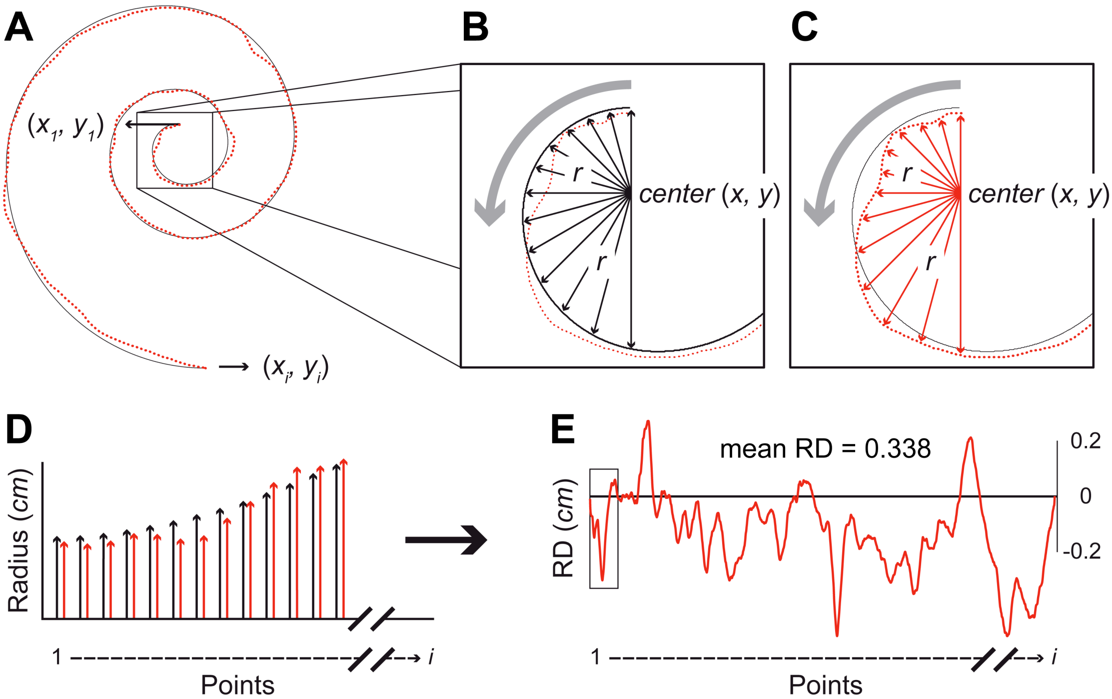


Figure 2.3. Spiral tracing analysis. An example of the calculation of the precision of a traced spiral. A. Both the spiral template (in black) and one example of tracing (in red points) are illustrated. B, C. The distance from the spiral center (i.e., r, radius of the spiral; center with the coordinates x, y) was calculated for each point of the template (B) and of the tracing (C) from the template's center. D. RDs were calculated as differences between the radius of each point of the template (black) and the radius of the corresponding data point of the tracing (red). E. The red graph indicates the RDs of the example of tracing with respect to the template (black line). The small box represents the example illustrated on B, C, and D. The mean RD in this example was found to be 0.388 cm.

2.2.5 Statistics

In order to evaluate whether a correlation exists between performances in terms of precision, the Pearson correlation coefficient was used on CVs for circle drawing and tracings and on mean RDs for the spiral and circle tracings. Specifically, the Pearson correlation coefficient was calculated for Group 1 using CVs of the drawn circles; for Group 2 using mean RDs of the traced spirals; for Group 3 using both CVs and mean RDs (independently and in combination) of the traced circles; for Group 4 using CVs of the drawn and traced circles; for Group 5 using mean RDs of the traced spirals and circles, and CVs of traced circles; for Group 6, using CVs of the drawn circles and mean RDs of the traced spirals.

2.2.6 Classification approach

A support vector machine (SVM) algorithm was used for classification of the subjects in two groups (drawers and tracers). The SVM algorithm finds an optimal separating line in the data, with a maximum margin, to separate the two groups. SVM models are simple to implement and have the added advantage that the data sets do not need to present a particular class of distributions, moreover, they are also flexible and allow to expand the model by adding more parameters if needed (Noble, 2006).

As the training data for the SVM model, a randomly generated dataset was created containing hypothesized cases of ideal and univocal drawers and tracers. This was done by considering normalized data in which maximum precision for a task is considered as 0 and minimum precision as 1. Following that, a series of virtual subjects (n=1,000) was randomly generated (i.e., training data), who are proficient in one specific task but not in the other (where proficiency is considered as values between 0 and 0.2, non-proficiency as values between 0.8 and 1). In this study a linear kernel function was used for data fitting, which was cross validated 10-fold. In addition, the posterior probability was calculated for each subject, expressing the data as statistical probability of effectively belonging to one group or the other (values range from -1 to 1). The model tested on normalized data from group 4 and 6.

2.3 Results

Subjects were ranked in descending order in terms of precision (i.e., increase in CV for Drawn Circles; increase of mean RD for Traced Spirals) of the first performance. The Pearson coefficient revealed a significant correlation between the first and second drawing of circles for Group 1 (i.e., Drawn Circles), with an R-value of 0.96 and p-value <0.001 (Figure 2.4). The same trend was shown for Group 2 (i.e., Traced Spirals), with an R-value of 0.97 and p-value <0.001 (Figure 2.4).

Group 3 (i.e., Traced Circles) also demonstrated the same trend as Groups 1 and 2 (Figure 2.4). The Pearson coefficient in this case was calculated in several ways. First, the CVs of the first and second tracings were compared, resulting in an R-value of 0.97 and p-value <0.001. Second the mean RDs of the first and second tracings were compared, resulting in an R-value of 0.96 and p-value <0.001. Then the CVs of the first tracings was compared with the mean RDs of the second tracings, resulting in an R-value of 0.95 and p-value <0.001. Finally, the mean RDs of the first tracings was compared to the CVs of the second tracings, resulting in an R-value of 0.97 and p-value <0.001. Finally, the correlation between CVs and mean RDs for the first tracings and the CVs and mean RDs of the second tracings were calculated, both resulting in an R-value of 0.99 and p-value <0.001.

For Group 4 (i.e., Drawn Circles vs Traced Circles), subjects were ranked in descending order, in terms of precision of the drawn circles. In this case, no correlation was found between the performances with R-value of 0.106 and p-value >0.05 (specifically, 0.61; Figure 2.5).

For Group 5 (i.e., Traced Circles vs Traced Spirals), subjects were ranked in descending order in terms of of precision the traced spirals (i.e., increase in mean RD). When comparing the CVs with the mean RDs of the traced circles a very high correlation was found, with an R-value of 0.99 with a p-value <0.001. A significant correlation also was found between the traced circles and traced spirals when comparing mean RDs of the two, with an R-value of 0.91 and p-value <0.001. An even higher correlation was found when comparing the CVs of the traced circles with the mean RDs of the traced spirals, with an R-value of 0.95 and p-value <0.001 (Figure 2.6).

For Group 6 (i.e., Drawn Circles vs Traced Spirals), subjects were ranked in descending order, in terms of precision of the traced spirals. In this case, similarly to Group 4, no correlation was found between the performances with R-value of 0.26 and p-value > 0.05 (specifically, 0.21; Figure 2.7).

The SVM model separated the data from Group 4 and Group 6 into two groups, drawers and tracers (Figure 2.8), along with the posterior probability for each subject, expressing the data as statistical probability of effectively belonging to one group or the other (values range from -1 to 1) (Figure 2.9). It is possible to notice that while some subjects could be considered as ideal tracers or ideal drawers, there are also subjects that have an equal probability of belonging to either group.

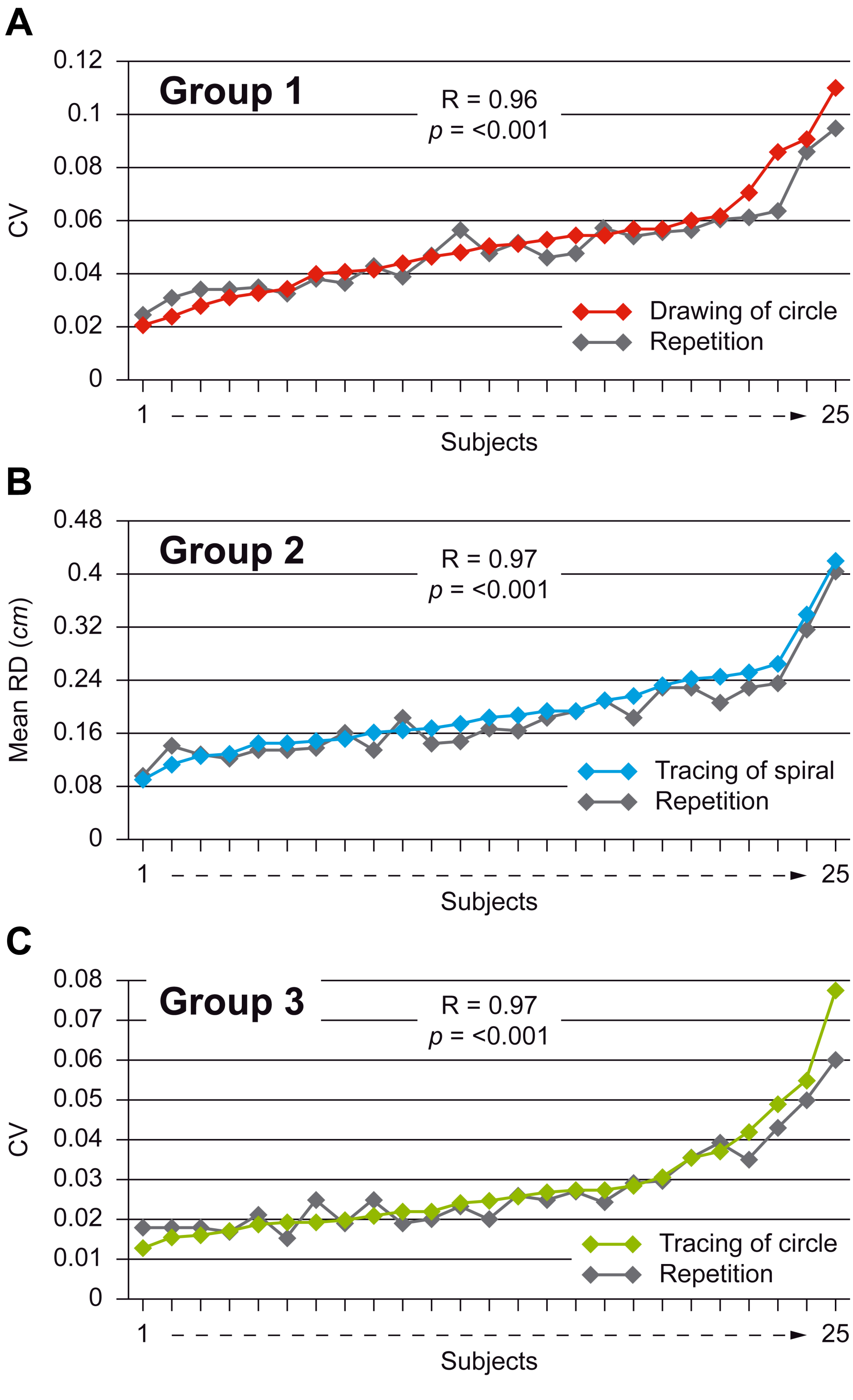


Figure 2.4. Results Groups 1-3. A. The results for Group 1 (i.e., Drawn Circles) for the first (red) and second (grey) drawing are shown. Subjects (n = 25) are ranked in descending order in terms of precision (i.e., increase in CV) of the first drawing. It is possible to see a high correlation between the two drawings, meaning that those who were precise in the first were also precise in the second. B. The results for Group 2 (i.e., Traced Spirals) for the first (blue) and second (grey) tracing are shown. Subjects (n = 25) are ranked in descending order in terms of precision (i.e., increase in mean RD) of the first tracing. It is possible to see a high correlation between the two tracings, meaning that those who were precise in the first were also precise in the second. C. The results for Group 3 (i.e., Traced Circles) for the first (green) and second (grey) tracing are shown. Subjects (n = 25) are ranked in descending order in terms of precision (i.e., increase in CV) of the first tracing. It is possible to see a high correlation between the two tracings, meaning that those who were precise in the first were also precise in the second.

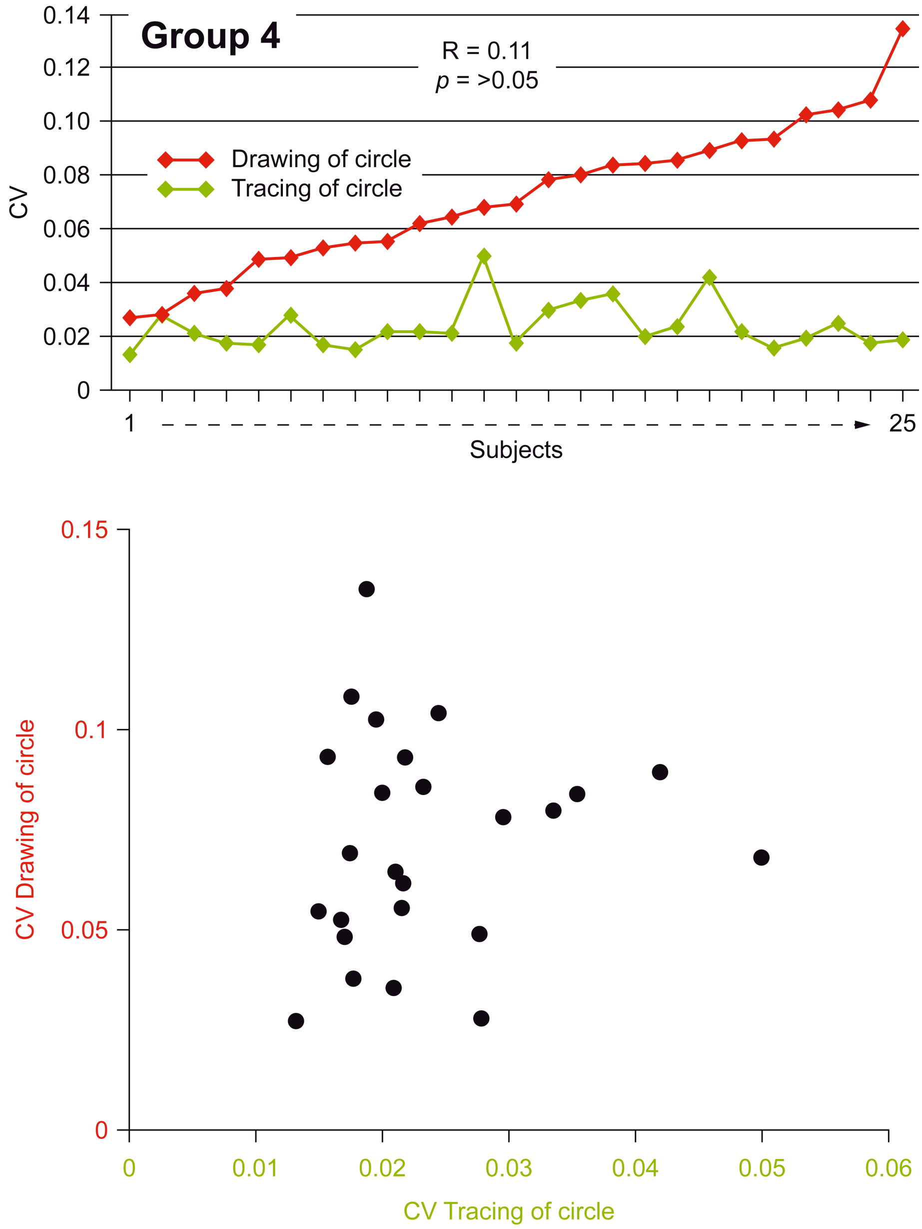
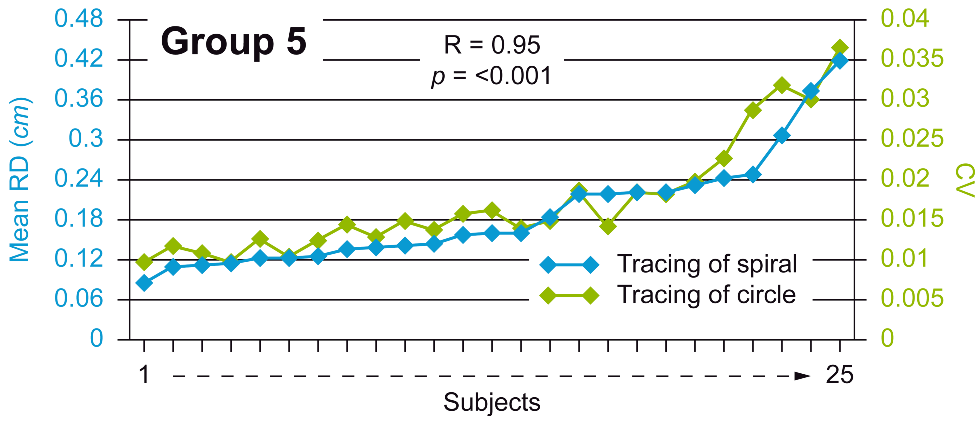


Figure 2.5. Results Group 4. A. Results for Group 4 (i.e., Drawn Circles vs Traced Circles; n = 25). Subjects are ranked in descending order in terms of precision (i.e., increase in CV) of the drawn circles (red). Corresponding CV values of the traced circles (green) are reported. It is possible to see that there is no correlation (R-value of 0.11 and p-value > 0.05) between the precision in drawing and in tracing circles. B. Scatter plot of the results for Drawn Circles and Traced Circles, each dot represents a subject.



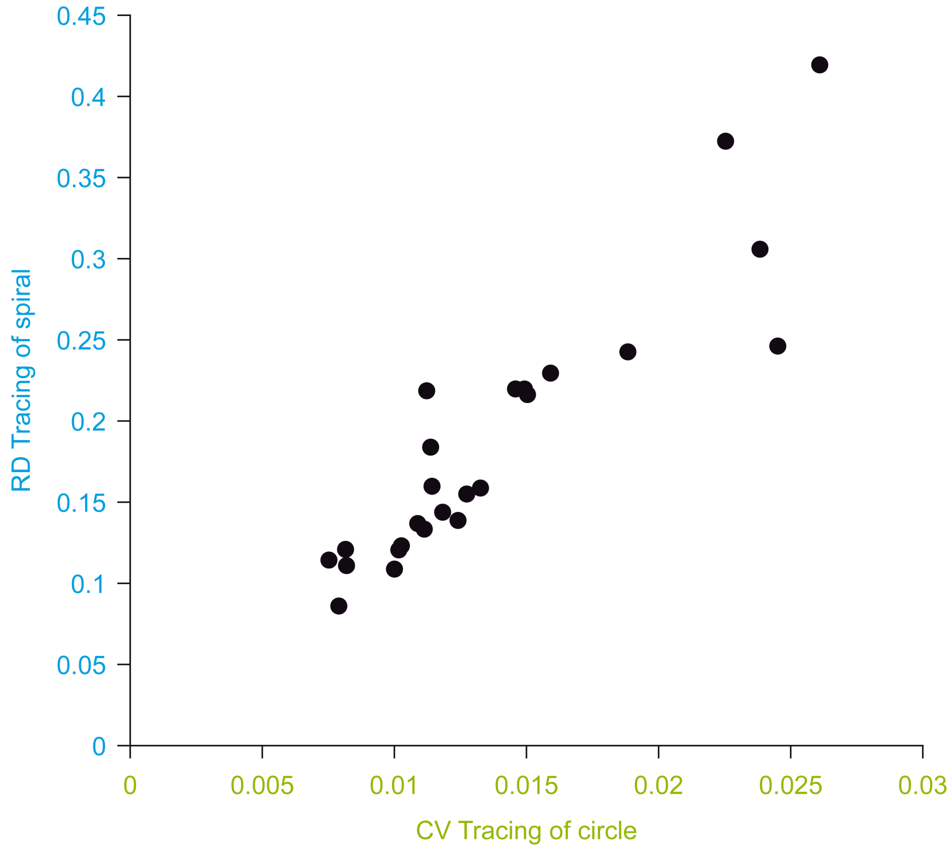
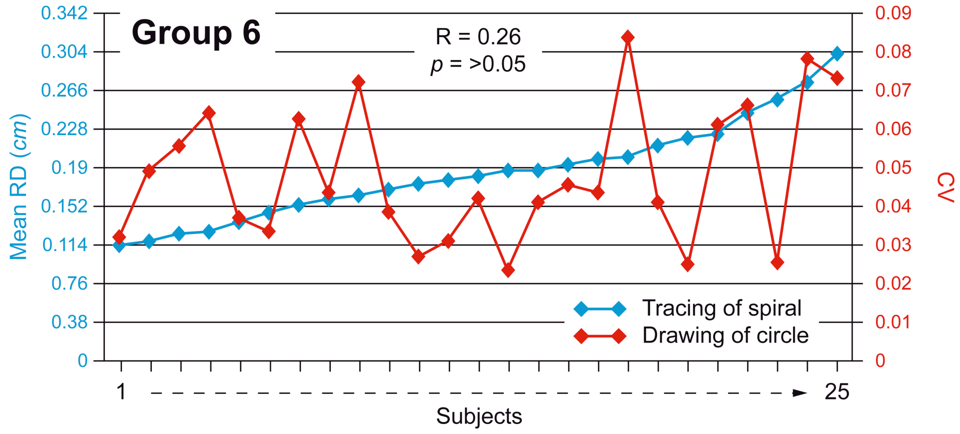


Figure 2.6. Results Group 5. A. The results for Group 5 (i.e., Traced Circles vs Traced Spirals) are shown. Subjects (n = 25) are ranked in descending order in terms of precision (i.e., increase in mean RD) of the traced spiral (blue). On the right side corresponding CV values of the traced circles (green) are illustrated. It is possible to see a high correlation between the two tracings, meaning that those who were precise in tracing a spiral were also precise in tracing a circle. B. Scatter plot of the results for Traced Circles and Traced Circles, each dot represents a subject.



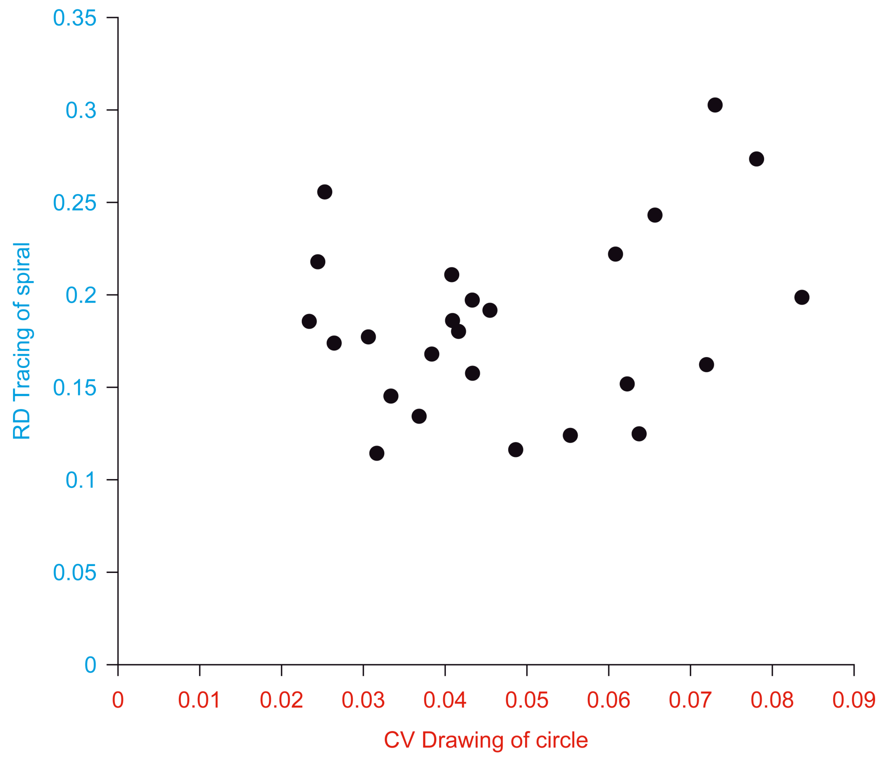


Figure 2.7. Results Group 6. A. Results for Group 6 (i.e., Drawn Circles vs Traced Spirals; n = 25). Subjects are ranked in descending order in terms of precision (i.e., increase in mean RD) of the traced spirals (blue). On the right side are reported corresponding CV values of the drawn circles (red). It is possible to see that there is no correlation (R-value of 0.26 and p-value > 0.05) between the precision in tracing spirals and drawing circles. B. Scatter plot of the results for Traced Spirals and Drawn Circles, each dot represents a subject.

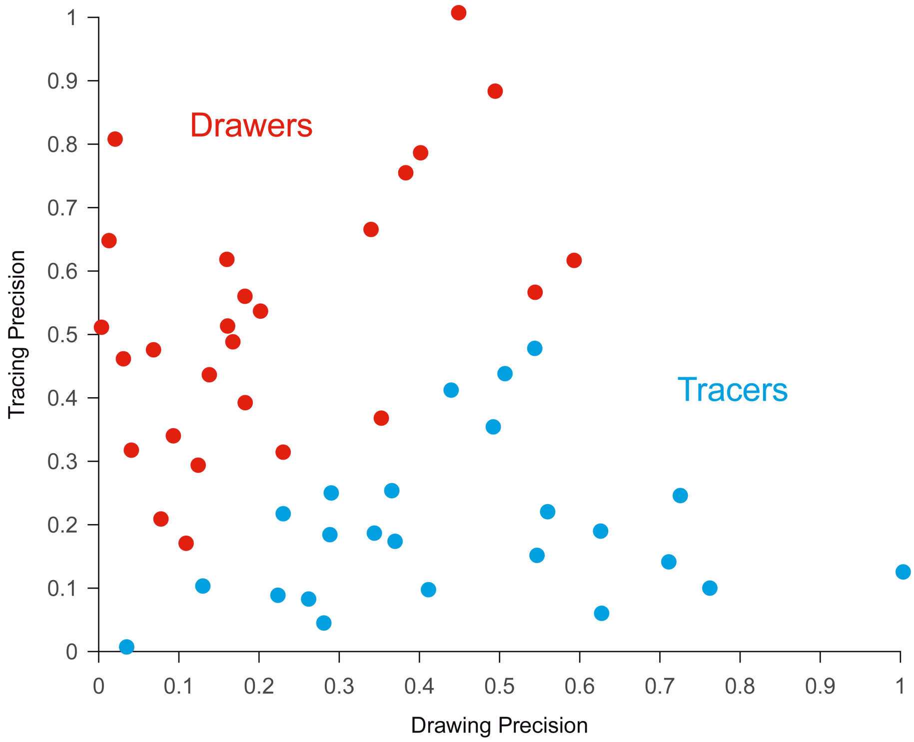


Figure 2.8. SVM Classification. The figure shows a scatter plot of pooled results from Group 4 (Drawn Circles vs Traced Circles) and Group 6 (Drawn Circles vs Traced Spirals). Results for each group were normalized considering the maximum precision for each task as 0 and minimum precision as 1. The SVM classification divided the results into two mutually exclusive groups, tracers (in blue) and drawers (in red).

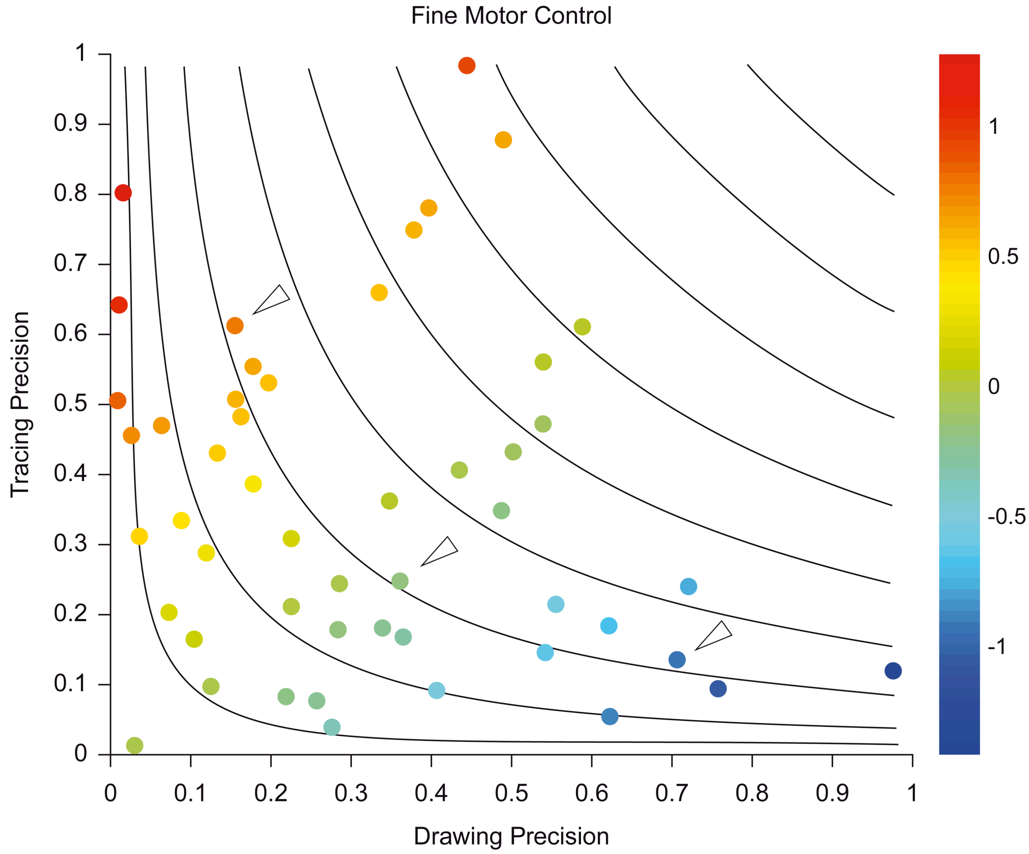


Figure 2.9. Posterior Probability and Fine Motor Control Quantification. The figure shows a scatter plot of pooled and results from Group 4 (Drawn Circles vs Traced Circles) and Group 6 (Drawn Circles vs Traced Spirals). Each dot represents a subject, and the color of the dot represents the posterior probability of that subject as being either a tracer or a drawer (color gradient on the right side; values ranging from -1 to 1). As fine motor control in a task is also dependent on the subject's propensity towards external or internal cueing (tracing or drawing), when quantifying fine motor control, these factors should be taken into consideration. This is illustrated by the curved lines in the figure which delimitate similar subjects, in terms of fine motor control, by considering the product of the precision in the two tasks. Therefore, a good tracer having 0.1 precision in the tracing task and 0.9 in the drawing task, would be equivalent to a good drawer (0.1 in drawing and 0.9 in tracing), which would also be equivalent to a non-tracer non-drawer with 0.3 and 0.3, as 0.1 x 0.9 is equal to 0.3 x 0.3. In the figure the arrowheads indicate three similar cases. The orange subject is a good drawer (0.15 drawing precision * 0.61 tracing precision = 0.0915 effective fine motor control), the green subject is neither a drawer nor a tracer (0.36 drawing precision * 0.25 tracing precision = 0.09 effective fine motor control), and the blue subject is a good tracer (0.7 drawing precision * 0.13 tracing precision = 0.091 effective fine motor control).

2.4 Discussion

From this study it is possible to see that spiral tracing, circle tracing, and circle drawing provide reliable results for motor precision (measured as CVs for circles and as mean RDs for spirals and circle tracing). This is made evident by the constant relationship between tasks repetitions (high correlations between repetitions for Group 1, Group 2, and Group 3; Figure 2.4). The results also indicate that subjects who are precise in one task remain precise in said task, at least beyond the capacity of working memory (Siegel, 2002). This trend is to be expected considering that differences in precision were shown to occur for different tasks among individuals (Callaghan et al., 2002; Madison, 2004; Perlau et al., 1995).

Furthermore, it is also evident by the results that drawing and tracing are, as expected, in fact different, as shown by the lack of correlation between tasks in Group 4 and in Group 6 (Drawn Circles vs Traced Circles and Drawn Circles vs Traced Spirals, respectively; Figures 2.5 and 2.7). Specifically, when we consider the lack of correlation in Group 4 (i.e., same shape and different task) with the high correlation in Group 5 (i.e., same task and different shape), it seems the the lack of correlation in Group 6 (i.e., different shape and different task) is effectively task dependent rather than shape dependent. Moreover, while the comparison between drawn circles and traced circles (i.e., comparison between tasks for the same shape) did not reveal any correlation, it is still possible that the use of the same shape in the two tasks may be considered as repetition; as such, it could be subject to repetition priming or learning effect between trials (Patel et al., 2017; Siniscalchi et al., 2016). Also, as no indications were made regarding the drawn circles' size, the use of a circle template for the tracing task could cause a visual conditioning of the subjects when drawing the circles (Renaux et al., 2017). Taking these factors into consideration, it is possible that the correlation between the two tasks may be even lower than that reported here.

These results raise some interesting questions as both drawing and tracing tasks are used for evaluation of fine motor control (Cohen et al., 2018b; Mergl et al., 1999; Smits et al., 2018; Sülzenbrück et al., 2011, 2010; Vuillermot et al., 2009), however, their usage appears not to be interchangeable. Though this may suggest that using solely one of the tasks for evaluation of fine motor control may produce inconsistent results, it is still not sufficient in explaining what do these tasks effectively evaluate as well as what could be inferred from performance differences in the two tasks.

In an attempt to respond to these questions, we begin by noticing that, when examining the results of this study (specifically those of Group 4 and 6), there are certain individuals who appear to be better drawers than tracers and vice-versa. Let us simplify the situation by first considering a population consisting of either drawers or tracers, which are mutually exclusive. Let us further assume that for each of these groups, precision in the specific task in which they are proficient in, is a good estimator for fine motor control.

Considering all that is known regarding these tasks in literature, the main difference between the tasks is the presence or absence of a template, or in other words the cueing (internal or external; (Flanders et al., 2006; Gowen and Miall, 2007, 2006; Sailer et al., 2000; Thut et al., 2000; van Donkelaar and Staub, 2000). Applying this notion to the proposed population of drawers and tracers, we can deduce that drawers are more reliant on internal cueing whereas tracers are more reliant on external cueing. In addition, it was previously shown that drawing tasks also employ different neural areas than tracing tasks; in particular, a greater activation in the cerebellar crus I, pre-supplementary motor cortex, dorsal premotor cortex (Gowen and Miall, 2007). Conversely, the striate and extrastriate areas, as well as the anterior intraparietal sulcus were shown to be more active during the tracing task (Gowen and Miall, 2007). Therefore, it would not be entirely incorrect to assume that dissimilarities in brain activity could account for the differences between drawers and tracers.

At this point, the task in which the subjects are less proficient in, could not serve as a quantifier for fine motor control, as our *a priori* knowledge suggests that the performance in said task does not evaluate the full potential of the subject (which we know is either a drawer or a tracer); moreover, the performance in the less proficient task is not correlated with the performance in the other task. Therefore, the less proficient task must evaluate a different aspect, which could very well be the reliance or functioning of the weaker cueing modality. For example, precision in a drawing task for a tracer would quantify his reliance on internal cueing. As the reliance on the weaker cueing modality is already known to employ activation of different cerebral areas, the performance in less proficient task could also be considered as a measure of the functionality of these areas.

If we apply this concept to the data in this study, we first assume that certain individuals in the population are drawers and others are tracers, and classify the population of groups 4 and 6 in these terms. However, it is clear that such a net distinction is inaccurate, as not all of our cases were ideal drawers and tracers. To overcome this, we may examine the results of the posterior probability, which expresses the statistical probability of a subject as effectively belonging to one group or the other.

When observing the data in this way (Figure 2.9), it is clear that the there are some subjects who could be considered as ideal drawers or ideal tracers, neither drawers or tracers, as well as intermediate cases. This sort of dispersion does not only have a descriptive purpose, as we have already discussed, there are some practical implications. In fact, more than the sole evaluation of fine motor control, the two tasks give also information regarding the reliance on external or internal cueing. Therefore, as fine motor control in a task is also dependent on the subject's propensity towards external or internal cueing, evaluation of effective fine motor control must consider these factors. As such, a more accurate way of quantifying fine motor control would be by using the product of the precision in the tracing and drawing task. An example for this is shown in Figure 2.9.

Some issues regarding this study should be mentioned. The first is the comparison between the measurements of Group 6 (Drawn Circles vs Traced Spirals), in which two different types of values are used (i.e., mean RDs and CVs). However, seeing that these values are used only to represent indicators of task precision, and considering the high correlation between the two types of values for the traced circles (i.e., mean RDs vs CVs in Group 3 and in Group 5), the use of them by extension to compare the correlation between precision of traced spirals (measured as mean RDs) and of drawn circles (measured as CVs), is justified. Also, various combinations were used to compare CVs and mean RDs in Group 3 (see Results), all of them revealing very high correlations. Even though the measurements are not equal, the differences in terms of correlation due to the use of different measurements did not go beyond 4% (found between CVs of Traced Circles and RDs of Traced Spirals in Group 5, see Results). Therefore, the use of different measurements is not expected to affect the data in this study as the correlations found were all sufficiently strong.

Another issue is the exclusion of the spiral drawing task. Quantitative evaluation of spiral drawing presents several limitations. Considering the complexity and the different ways that exist to draw a spiral, it would not be possible to test the precision of the drawn spirals across subjects as it is very unlikely that the same shape would be drawn. While precise instructs could help reduce this variability, they are also not as readily understandable as those for circle drawing, rendering the spiral drawing task much more complex than the other conditions. The only paper to our knowledge that has quantitatively compared precision of drawn spirals is that of Longstaff and Heath, 2006. However, in that study, a spiral was presented to the subject before the trial, and furthermore, subjects performed a training period in order to obtain relatively comparable drawings before comparing the results to an ideal spiral. The addition of these constraints, while rendering possible the comparison of drawn spirals, does not go in line with our experimental paradigm, which seeks to avoid learning of the task. On the other hand, the elimination of these constraints results in a variability between shapes that would render the comparison meaningless. Moreover, other papers who addressed spiral "drawing" quantitatively, have effectively evaluated a spiral tracing task (Hoogendam et al., 2014; Miralles et al., 2006; San Luciano et al., 2016). Therefore, in adhering with the current literature we have limited our study to spiral tracing. Also, the original premise of the study was to evaluate the differences between spiral tracing and circle drawing. By fragmenting it to comparisons for shape and for task, and by considering the previous studies comparing tracing and drawing as well as externally and internally cued tasks (Bravi et al., 2015, 2014; Collier and Ogden, 2004; Gowen and Miall, 2007; Repp, 2011; Repp and Moseley, 2012) it is licit to generalize our results to other shapes, in accordance with models of analytic generalization and case-case transfer (Firestone, 1993). As such, we may infer that spiral drawing would be equivalent to circle drawing, considering that our results suggest that ranking in terms of precision is task dependent and not shape dependent.

It should be also noted that this study was concentrated only on differences in terms of precision between the tasks. In light of the results, we believe that some differences in the strategy employed for each task (e.g., speed-accuracy trade-off, pen pressure during execution, posture, etc.) may also exist. Though it would be interesting to examine the differences between the subjects and groups from a biomechanics point of view, it goes beyond the scope of the present study.

2.5 Conclusions

In this study we have shown that there is no correlation between precision in a drawing task compared to a tracing task. Further, we have demonstrated that the lack of correlation between the two is effectively task dependent and not shape dependent. We argue that evaluating fine motor control by using a single task may produce inconsistent results. To overcome this limitation, we suggest that the evaluation of fine motor control should include both a tracing and a drawing task, taking in consideration the precision in each task separately and in combination. This study also demonstrates that there is no difference in precision between tracing of circles and of spirals. Therefore, for a widespread implementation, we suggest that fine motor control evaluation would be better tested by using circle drawing and circle tracing tasks. In both tasks it is possible to use the same measurement (i.e., CV), which is already independent of other factors (such as size of circle, and number of points etc.). This way, results from different studies could be more readily compared. We believe that the approach presented here could help not only evaluate fine motor control more accurately, but also identify subjects who are more reliant on either internal or external cueing and to what extent. Using this knowledge, it would be possible to tailor specific strategies in both clinical and professional settings, dependent on subjects reliance on a specific modality of cueing, to improve fine motor control.

3 Development of Fine Motor Control Components in Elementary School Children: Assessment Using Precision in Drawing and Tracing Tasks

Abstract. Fine motor control is fundamental for our interaction with the world. As such, adequately quantifying fine motor control is imperative for the understanding of both the individual level of mastery as well as development of motor behavior. Recently, we have shown that using different tasks to evaluate fine motor control may produce different results, suggesting that measures for fine motor control are multiple and carry different significance. Specifically, the drawing tasks may be indicative for internal cueing reliance, whereas tracing tasks for external cueing. To better understand how subject develop a certain preference for cueing, we have evaluated fine motor control by measuring precision in both a circle tracing and a circle drawing task on 265 typically developing children ages 6-11. Our results first, confirm that the lack of correlation between performances in tracing and drawing task also exists during development. Furthermore, we display that the most significant improvement during this period of development is that of tracing, whereas drawing improved only moderately. Specifically for tracing, most significant differences were found between the 2nd and 3rd grades, followed by between the 4th and 5th grades. Results for tracing appear to be in line with previous developmental patterns described for handwriting. Furthermore, in light of the differences between drawing and tracing we discuss the potential role of attentional focus as well as cognitive development as possible influencing factor that may account for the different developmental patterns found in this study. We conclude that using a drawing and tracing task for fine motor control evaluation, by being rapid, economic and simple, may be a valuable tool for monitoring development in elementary school children.

3.1 Introduction

During development, the nervous system is under a continuous modification and maturation, as such the adequate quantification of various functional components is imperative. For motor control specifically, many motor proficiency evaluation tests were introduced (Beery and Beery, 2010; Bruininks and Bruininks, 2005; Folio and Fewell, 2000; Henderson et al., 2007; Piper et al., 1992; Russell et al., 2013). Out of these test, only the Bruininks-Oseretsky Test of Motor Proficiency (BOT-2; Bruininks and Bruininks 2005) and the Movement Assessment Battery for Children (Movement ABC-2; Henderson et al. 2007) are specifically oriented toward typically developing children of scholastic ages. While these tests examine both fine and gross motor skills, their administration is quite lengthy (20-40 min for the Movement ABC-2 and 45-60 min for BOT-2; Matheis and Estabillo, 2018). Furthermore, these are all commercial tools and, as such, do not come without a cost, consequently, a wide spread implementation is quite cumbersome.

Cohen EJ, Bravi R, Minciacchi D (2019) Development of Fine Motor Control Components in Elementary School Children: Assessment Using Precision in Drawing and Tracing Tasks. Under Review

A commonly used approach for the examination of fine motor control is represented by the employment of drawing and tracing tasks (Cohen et al., 2018b; Gatouillat et al., 2017; Smits et al., 2018; Sülzenbrück et al., 2011; Vuillermot et al., 2009). These tasks, due to their simplicity do not require any prior preparation and are administered relatively quick. However, as recently evidenced, while both tasks are considered as estimators for fine motor control, there is no correlation between the two (Cohen et al., 2018a). In an attempt to explain the differences, the authors have suggested that subjects may have a different level on reliance on external or internal cueing with some subjects favoring the former or the latter.

It should be noted that during development, drawing and tracing tasks can be considered as skills under development and, therefore, may indeed be controlled differently compared with adults. In fact, adult handwriting, by being subject to years of practice and repetition, becomes automatic requiring minimal attentional control (Tucha et al., 2008). Children's handwriting on the other hand, not only is not automated but is also subject to immense changes, most significant occurring between ages 7 and 10 years, transitioning from visual feedback based control to stable motor representations (Palmis et al., 2017; Rueckriegel et al., 2008). Though handwriting is considered to be a more elaborate task than drawing of simple shapes (Rueckriegel et al., 2008), it does provide insight to potential differences in motor control during these stages of development. Not surprisingly, correlations were found between drawing and handwriting proficiency in children (Bonoti et al., 2005). Therefore, it is possible that during development individuals cueing reliance may be different than that reported in adult performances.

In this study we have investigated the use of drawing and tracing tasks to evaluate development of fine motor control in elementary school children. Specifically, we examine the precision in a circle drawing task compared to a circle tracing task. We assume that, similarly to adult subjects, no correlation would be found between the proficiency in drawing and in tracing. Furthermore, considering the gradual maturation of the nervous system during development, we expect to find a gradual improvement for both tracing and drawing across ages. Finally, we examine the eventual differences that may be present between tracing and drawing proficiency across ages.

3.2 Materials and Methods

3.2.1 Participants

265 elementary school students, ages 6-11 (138 males), were recruited for this study. 1st grade (n=73; 38 males, 35 females; 10 left handed), 2nd grade (n=45; 24 males, 21 females; 4 left handed), 3rd grade (n=64; 35 males, 29 females; 8 left handed), 4th grade (n=35; 20 males 15 females; 5 left handed), 5th grade (n=48; 21 males, 27 females; 3 left handed). Participants were naive to the task and the purpose of the study, and free of documented visual, motor, and neurological impairments. All subjects reported to have a corrected-to-normal visual acuity. All subjects reported to not have any previous experience in using a graphic pen tablet. The study protocol was approved by the Institutional Ethics Committee (Comitato Etico Area Vasta Centro AOUCareggi, Florence, Italy). Prior to the start of the experimental procedures, the parents/guardians of each child provided informed consent for their child to participate. The director of the school also signed an agreement that formally allowed the children to be tested in the school. The study protocol and all procedures conformed to the code of ethics of the Declaration of Helsinki.

3.2.2 Set up and Task

The set up in this study is very similar as the one used in Cohen and colleagues (2018a) and is here briefly summarized. The participants executed both tracings and drawings, projected on a monitor, while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen (Figure 3.1). All tasks were performed using graphic pen tablet (Wacom Intuos® CTH-690AK, Tokyo, Japan; active area: 216 × 135 mm). Each participant was tested individually.

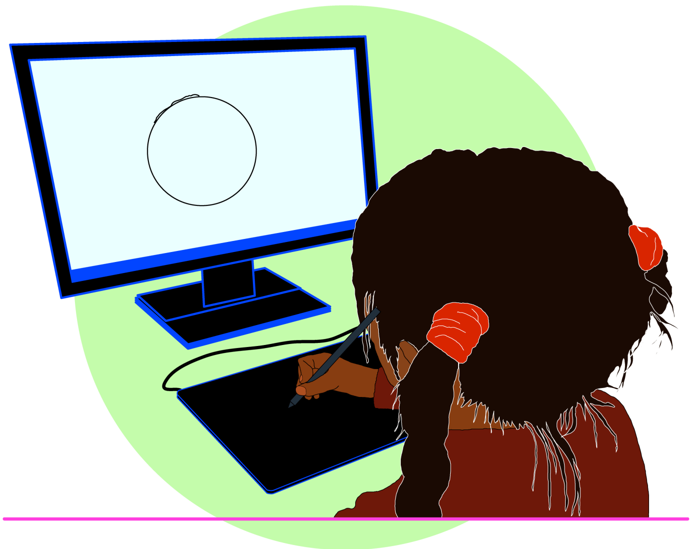


Figure 3.1. Setup. Diagram illustrating the experimental setup. Each subject was seated in front of a monitor set to eye level. Each subject performed both a drawing of a circle as well as a tracing of a circle; the order was randomized across subjects so as to obtain an equal number of subjects that started with the first or the latter. Between the trials, a minute interval was introduced. The subjects executed either tracing or drawing of a circle, while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen.

For all tasks we have specified to trace or draw the circles counterclockwise starting from 12 o'clock as precisely as possible with no regard to the speed of execution. Before starting the task, each subject was asked whether the instructions were understood. Each subject performed both a drawing of a circle as well as a tracing of a circle, the order was randomized across subjects so as to obtain an equal number of subjects that started with the first or the latter. A minute interval was present between the two tasks.

3.2.3 Analysis

Using Matlab, we have developed an algorithm to measure the accuracy of the drawn circles. The algorithm consisted of first finding the centroid of the drawn shape. This was achieved by taking the mean value of all x and y coordinates, the result of which would provide a reference center. From the reference center, points were organized according to their angle and were then reduced to 360 points, having one point per degree This was done in order to reduce the sensitivity to the way the shape was drawn (e.g., parts drawn slower will result in more points). After the point reduction, the mean value of all x and y coordinates were calculated on the remaining point, and the result was considered as the center of the circle. Following that, the distance of each point (prior to the reduction) of the drawing from the center was calculated. These distances were considered as the radii for the drawn circle, the mean value of which would result as the radius of the corresponding perfect circle. Seeing that no indication was provided regarding the size of the circle, the coefficient of variation (CV) of the radii was considered as a measure of the precision of the drawn circle, bearing in mind that for a perfect circle the variability would be zero. The same algorithm was used also for CV analysis of the traced circles.

3.2.4 Statistics

In order to evaluate whether a correlation exists between performances in terms of precision, the Pearson correlation coefficient was used on CVs for circle drawing and tracings. To evaluate eventual differences between school grades a two tailed t-test was used comparing every combination of grades for both tracing and drawing separately. To evaluate potential differences between males and females, a two tailed t-test was used on the performances drawing and tracing separately, for each grade.

3.3 Results

The Pearson correlation coefficient revealed a significant correlation between performances in circle tracing and drawing only for the 1st grade. Specifically, for the first grade R-value was 0.42 p-value<0.001. For the other grades, no significant correlations between the performances were found. For 2nd grade R-value was 0.15 (p=0.29), 3rd grade R-value was 0.12 (p=0.32), 4th grade R-value was -0.17 (p=0.32), and for the 5th grade R-value was 0.06 (p=0.67).

Data dispersion within grades was progressively reduced with age for both tracing and drawing. However, while this reduction is quite evident for tracing, dispersion of drawing precision reduces only moderately (Figure 3.2). Interestingly, data dispersion does not align with the adult level of dispersion (reported by Cohen et al., 2018a, based on 125 observations), although it appears that certain subjects (some as young as 1st graders) already reach adult level performances for either tracing or drawing or both.

CVs in both drawing and tracing showed a gradual reduction with age. Specifically, for the 1st grade, drawing precision averaged 0.22±0.09, gradually reducing to 0.16±0.07 by the 5th grade. A similar yet more prominent trend was revealed for tracing precision with an average CV of 0.17±0.12 measured for the 1st grade, gradually reducing to 0.05±0.02 by the 5th grade (Figure 3.3, 3.4). Comparisons of the performances according to between grades are reported in Figure 3.5. It is possible to note, that while for drawing, no significant differences occur between consecutive grades (e.g., 1st compared to 2nd, 2nd compared to 3rd, etc.), for tracing significant differences were found between the 2nd and 3rd grades (p<0.001), as well as between the 4th and 5th grade (p<0.05).

To examine eventual differences between sexes, a two-tailed t-test was implemented individually for each grade comparing each parameter separately. For the 1st grade, no significant differences were found between males and females for tracing (p=0.59) or drawing (p=0.29). For the 2nd grade, no differences were found for tracing (p=0.26) or drawing (p=0.21). For the 3rd grade, no differences were found for tracing (p=0.79) or drawing (p=0.82). For the 4th grade, no significant differences were found for tracing (p=0.24) or for drawing (p=0.57). For the 5th grade, no significant differences were found for tracing (p=0.73) or for drawing (p=0.21).

Laterality results revealed no significant differences for the first grade (drawing p=0.956, tracing p=0.857) as well as for the third grade (drawing p=0.407, tracing p=0.292) and for the fourth grade (drawing p=0.690, tracing p=0.128). Laterality differences were not evaluated for the second and fifth grades due to the small number of left handed subjects in those groups.

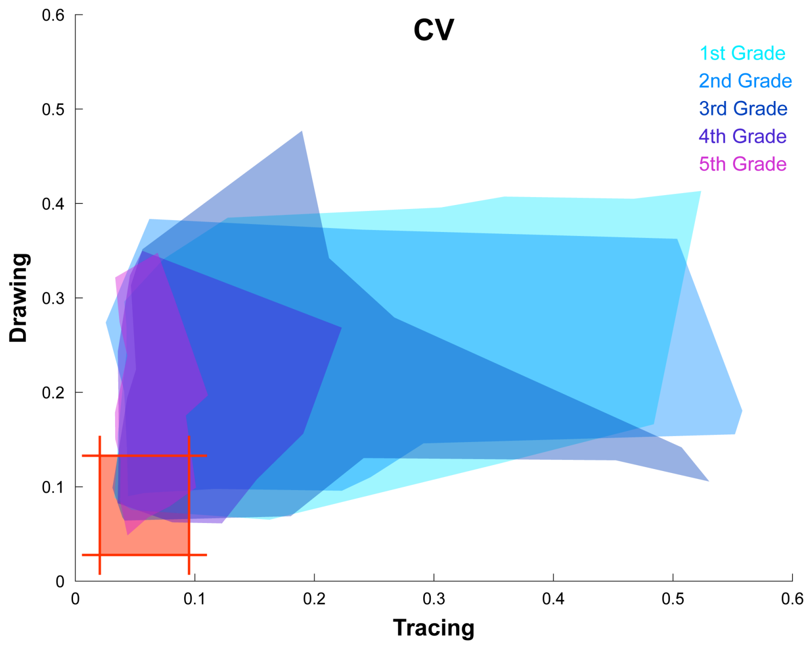


Figure 3.2. Data Dispersion. Illustration of the CV data dispersion for both tracing and drawing tasks per grade. Each colored area encloses all of the performances related to a specific grade. It is possible to note that while there is a gradual reduction in dispersion for tracing precision across grades, reduction in dispersion for drawing precision is very moderate. Moreover, it is evident that some subjects, across all grades, already achieve adult level of performance (red region; as reported in Cohen et al., 2018a).

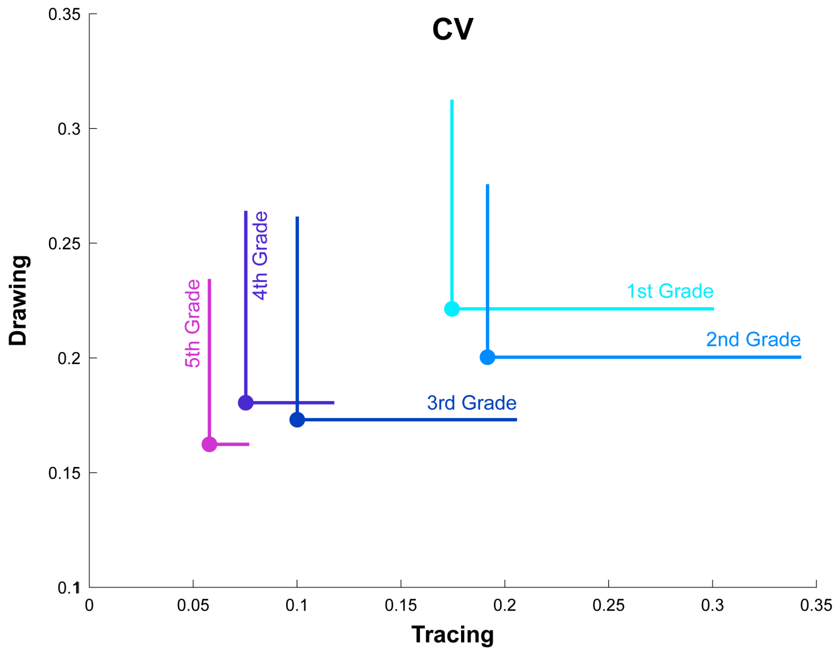


Figure 3.3. Results drawing and tracing precision. Results for drawing and tracing precision are reported as mean CV per grade (dot) and SDs (line). It is possible to see that performances gradually improve both for drawing and for tracing. Moreover, improvement in tracing is much more prominent compared to drawing as evidenced by both bigger reductions in means CV as well as SDs. Greatest improvement appears to occur between the 2nd and the 3rd grades.

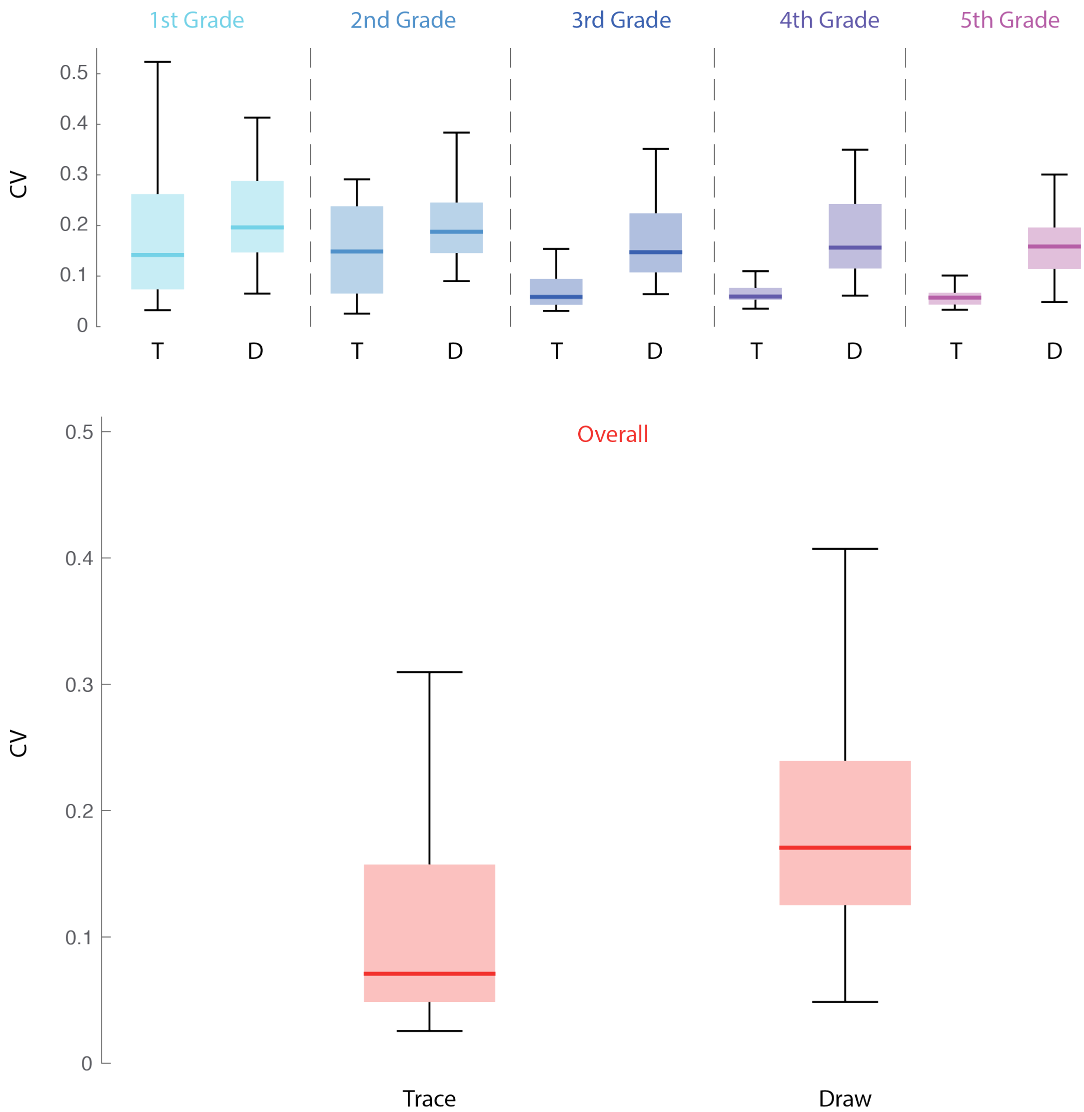


Figure 3.4. Boxplots drawing and tracing precision. Results for drawing and tracing precision are reported. The upper panel represent the CV's results for each grade for tracing (T) and drawing (D) separately. The lower panel shows the overall pooled results (i.e., CV) for tracing and drawing. It is possible to see that performances gradually improve both for drawing and for tracing, with a much more prominent improvement for tracing.

Tracing / Drawing	1st Grade	2nd Grade	3rd Grade	4th Grade	5th Grade
1st Grade	1	p=0.50	**p<0.001**	**p<0.001**	**p<0.001**
2nd Grade	p=0.22	1	**p<0.001**	**p<0.001**	**p<0.001**
3rd Grade	**p<0.05**	p=0.12	1	p=0.17	**p<0.05**
4th Grade	**p<0.05**	p=0.25	p=0.71	1	**p<0.05**
5th Grade	**p<0.001**	**p<0.05**	p=0.46	p=0.29	1

Figure 3.5. Comparison between grade performances. The figure reports the p-values obtained from different comparisons between the grades. The background corresponds to performances in tracing (yellow) and drawing (purple). It is possible to see that for serial comparisons (i.e., 1st vs 2nd grade, 2nd vs 3rd grade, etc.) most significant differences for tracing were found between the 2nd and the 3rd grade, followed by between the 4th and the 5th grade. For drawing on the other hand, no significant differences were found for serial comparisons, though when investigated other combinations, significant differences are found between the 1st grade and the 3rd, 4th, and 5th grades and between the 2nd and the 5th grade, most significant between the 1st and the 5th grade.

3.4 Discussion

This study was concentrated on the investigation of the development of drawing and tracing skills in children. With the exception of the first grade, no correlation was found between the proficiency in drawing and in tracing. As expected, we observed an improvement for both tracing and drawing across ages. Most prominent differences were found between the 2^{nd} (ages 7-8) and the 3^{rd} (ages 8-9) grade for tracing, followed by between the 4^{th} (ages 9-10) and the 5^{th} (ages 10-11) grade, again for tracing. For drawing, significant differences were found when comparing the 5^{th} grade with the 1^{st} and 2^{nd} grades, suggesting that improvement in learning is more gradual compared to tracing. Finally, no differences were found between males and females, confirming previous findings in simple drawing tasks (Blank et al., 1999).

The presence of a moderate correlation in the first grade could indicate that, for children of this age, components of the motor system are still relatively limited. Therefore, the presence of a template or not, though may still induce different cognitive processes, is limited by the output of a still immature system. In fact, it is known that the corticospinal tract, fundamental for movement execution, undergoes a rapid maturation process up to the age of 10, with more rapid changes the smaller the age is (Fietzek et al., 2000; Müller et al., 1991). Also, evidence from corticospinal tracts lesions illustrate the importance of its integrity for movement dexterity (Bleyenheuft et al., 2007; Duque, 2003). Therefore, considering the maturation pattern of the corticospinal tract, it is very likely that the younger subjects included in this study may be more limited in their motor output. In addition, it is known that writing control from ages 5-7 is characterized by the shift from an inability to use sensory feedback to a control mainly based on visual feedback (Palmis et al., 2017). The 1st grade in this study included children between the ages of 6-7, falling exactly within the period of shifting toward a more visual oriented control. As such, it is possible that the moderate correlation present between tracing and drawing, could be due to the fact that while some children have become more visually reliant, others still did not. In the case of the latter, the differences in the presentation of template are not expected to affect the motor output.

Interestingly, improvement in tracing was relatively rapid compared to drawing. The improvement pattern for tracing across the grade fits very well with previously reported results for handwriting in children. Specifically, great differences are to be expected from the age of 7 to the age of 10, a period which is believed to represent a turning point toward a more concrete motor representation of movement, less reliant on visual feedback (Palmis et al., 2017). In accordance, our study revealed the most significant differences between the 2nd (ages 7-8) and the 3rd (ages 8-9), followed by 4th (ages 9-10) and the 5th (ages 10-11) grade. This, however, does not explain the only moderate improvement found for drawing.

Though both tracing and drawing utilize the same effectors, the cardinal difference between drawing and tracing is the presence of a template. Since any deviation from the template is readily evidenced when a template is present, it could favor external focus (i.e., on the movement effect) during the performance, a factor known to improve performance (Marchant, 2010; Wulf, 2007a; Wulf and Lewthwaite, 2010). In fact, it was argued the mere presence of a target during dart throwing could facilitate external focus (Marchant et al., 2007; Wulf, 2013). It should be noted that when tasks are more automatic in nature or relatively simple, the clear benefit of external focus may not be readily observable (Wulf 2013). This may explain why the effect was less prominent in adult findings (Cohen et al., 2018a) who are likely to have a more automatic control when using writing instruments. However, the lack of automatic processes does not guarantee employment of external focus. It was shown that different skill levels benefit differently from internal and external focus, with the less skilled subjects adopting the former (Castaneda and Gray, 2007). In addition, it was argued that when automatic processes are lacking, for example in novice performers, a more conscious control might be necessary in order to avoid gross performance errors (Kal et al., 2015). Therefore, drawing performances, by both lacking a visual anchor along with undeveloped automatic processes, are likely to cause a shift attention toward a more internal focus. As internal focus is known to cause only moderate improvement compared to external focus (Wulf, 2007a), it should be expected that drawing performances would improve more gradually.

It should be considered that beyond the possible contribution of external focus, there could be other factors that may cause the trend observed for tracing. In fact, internally and externally driven movements are thought to involve different brain areas. While for internally cued movements the basal ganglia are thought to play a prominent role, for externally cued the cerebellum is considered to be an important component (van Donkelaar et al., 1999; van Donkelaar and Staub, 2000). More recently, greater involvement of supplementary motor area was found for internally guided tasks, whereas compared to greater premotor cortex involvement during visually guided tasks (Mushiake et al., 1991). Surprisingly, when cerebral activation patterns for drawing and tracing tasks were compared, basal ganglia and cerebellar activity did not differentiate tracing from drawing in the expected manner, furthermore, drawing appeared to recruit areas more associated with cognitively demanding tasks, attention and memory (Gowen and Miall, 2007). Therefore, since regional differences in brain maturation patterns are known to occur (Toga et al., 2006), specifically, areas related with more advanced functions mature later (some in late adolescence) than those related to more basic functions (Gogtay et al., 2004), it is possible that the later maturation of areas more involved in drawing compared to tracing could account for the differences observed between the two.

Though no significant differences were found between right handed and left handed individuals, asymmetry in performance is known to occur in goal directed movements. Specifically, less strong left handed individuals, measured as low scores in the Edinburgh Handedness Inventory (Oldfield, 1971), may present more learning, and consequently a better performance, using their dominant hand compared to strong left handed individuals (McGrath and Kantak, 2016). However, this latter study was concerned with adult subjects, which may be subject lifetime of manipulation and adaptation of right-handed instruments which are much more commonplace than specific left handed-instruments (Flatt, 2008). Since this sort of adaptation is the product of experience, children may possess a much less biased motor biography. In fact, it is known that young children display a weak and inconsistent hand preference which becomes more consistent with age, reaching adult like pattern of handedness between the ages of 10 and 12 years, presumably due to both experience and cognitive maturity (Scharoun and Bryden, 2014). The study presented here was focused mostly on a providing a panoramic view of motor control in children which is easily quantified, however, future studies would certainly benefit from focusing also on handedness and controlling for factors such as experience and cognitive maturity.

It is important to consider that though as a group performances did non align with adult performance, still some subjects do reach adult level of performance (some even as early as the first grade). These individual differences may be due to other factors that were not considered in this study, for example intelligence quotient (Smits-Engelsman and Hill, 2012), socioeconomic status (Klein et al., 2016), specific training (Costa-Giomi, 2005), etc., all of which may indeed influence motor abilities. Though this represents a limitation for this study, the results provided here still paint a very clear and congruent image of the developmental patterns for components of fine motor control.

3.5 Conclusions

Assessing fine motor control during development is important for both asserting normal developmental pattern as well as identifying delays or incongruent development. In this study we have shown that fine motor control could be reliably quantified in school age children using very simple tasks of drawing and tracing. Furthermore, while the results for tracing align with previous findings regarding developmental patterns, those for drawing provide additional insights regarding the development of internally driven movements in children. Though this approach may not substitute a thorough examination of motor skills during development, we believe that, by being both simple and economic (time and financial wise), renders it very suitable for a widespread implementation and population screening.

4 The effect of fidget spinners on fine motor control

Abstract. Fidgeting, defined as the generation of small movements through nervousness or impatience, is one of cardinal characteristic of ADHD. While fidgeting is, by definition, a motor experience still nothing is known about the effects of fidgeting on motor control. Some forms of fidgeting involve also the manipulation of external objects which, through repetition, may become automatic and second nature. Both repetition and practice are important for the acquisition of motor skills and, therefore, it is plausible that the repetitive manipulation of objects may influence motor control and performance. As such, fidget spinners, by being diffuse and prone to repetitive usage, may represent interesting tool for improving motor control. In this study we examine the effect of fidget spinners on fine motor control, evaluated by a spiral-tracing task. We show that the use of fidget spinner indeed seems to have a favorable effect on fine motor control, at least in the short term, although this effect does not seem to be in any way inherent to fidget spinners themselves as much as to object manipulation in general. However, due to their widespread usage, fidget spinner may have the advantage of being an enjoyable means for improving fine motor control.

4.1 Introduction

Fidget spinners are increasing in popularity and, as such, ambiguities regarding their possible effects are emerging. The mechanism behind the spinners is relatively simple. As any spinning apparatus, fidget spinners rotate around a central axis, formed by two rings. By using a ball bearing mechanism instead of simple sliding between the rings, friction may be reduced significantly during rotation. In order to further increase the duration of the rotation, fidget spinners are equipped with three wings (for most spinners) bearing weight distributed equally from the center. This allows to increase the moment of inertia of the spinner and, when an external force (or torque) is applied, results in a rotation that may last for a few minutes (Figure 4.1). Also, by having the wings distant from the center of rotation, as for any lever-based system, less force is needed to induce a sustained rotation.

It is somewhat surprising that such a simple toy is subject to such a huge controversy, anecdotally as shown by social media. This controversy stems from the fact that fidget spinners are being currently marketed as devices that may help in increasing focus and attention, as well as general stress relievers. While some support these claims, e.g., (Isbister, 2017), other believe that fidget spinners are just a toy and, as such, do not possess any beneficial potential, e.g., (Calfas, 2017). Also, fidget spinners are considered to be a source of distraction in classrooms and are currently being banned in some schools throughout the United States (Calfas, 2017; Isbister, 2017). Either way, these anecdotal beneficial claims regarding the spinners have rendered them an attractive mean for children suffering from ADHD and autism, as well as "focus enhancing" devices to the general population.

It should be mentioned however that, though anecdotal, these claims are not completely devoid of a scientific base as hyperactivity is often associated with some form of fidgeting and restlessness (American Psychiatric Association, 2013). Therefore, the assumption that an external device may in some way attenuate hyperactivity and, consequently, maintain the attention seems reasonable. In fact, there are a few studies that have investigated the relationship between attention and fidgeting. Carriere and colleagues (Carriere et al., 2013), have investigated the relationship between fidgeting and mind

Cohen EJ, Bravi R, Minciacchi D (2018) The effect of fidget spinners on fine motor control. Sci Rep. 8(1):3144. doi: 10.1038/s41598-018-21529-0.

wandering (i.e., presence of thoughts unrelated to the current task or decoupled from the external environment; (Xu et al., 2017), finding a strong association between the two, with increase in fidgeting behavior as attention decreases. They have concluded with the hypothesis that fidgeting increases the moment mind wandering takes place. Also, an earlier study found that when questioned, students believe that fidgeting is one of the strongest indicators for reduced attention (Gligoric et al., 2012). Therefore, a close relationship seems to exist between fidgeting and attention, which was shown to be a function of time (Farley et al., 2013).

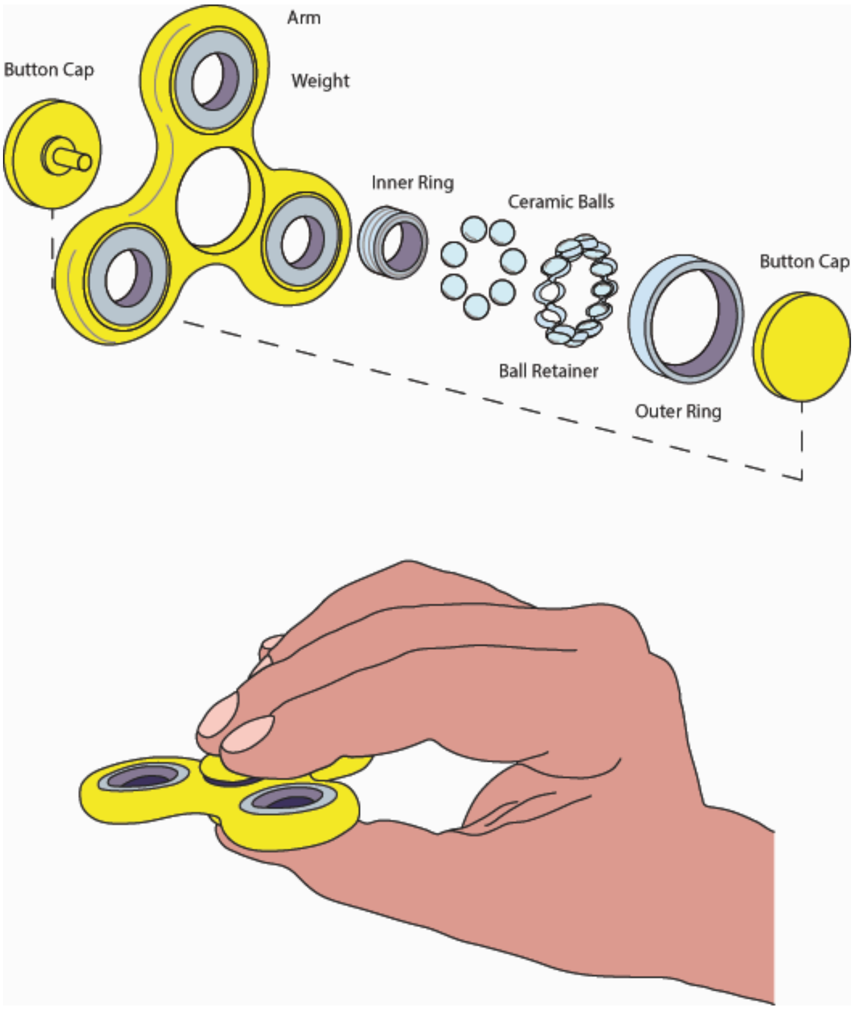


Figure 4.1. A diagram of Fidget Spinner and grip. In the upper panel it is possible to see the components of the fidget spinner, including the ball-bearing mechanism formed by the two rings interposed by ceramic balls, held together by a retainer. The bottom panel illustrates the way that the fidget spinner was asked to be held during the experiment, with the index and third fingers at the top and thumb at the bottom.

More recent studies have further investigated the relationship between fidgeting and attention, trying to evaluate whether fidgeting in itself may modulate attention or only represents a manifestation of its reduction. In fact, fidgeting appears to play a role when cognitive tasks are to be performed. In two separate studies, children with hyperactivity were asked to perform cognitive tasks while their level of activity was being monitored (Hartanto et al., 2016; Sarver et al., 2015). In both studies, a positive correlation was found between the level of activity and task performance, suggesting that fidgeting plays a role in maintaining attention, in hyperactive children but not in typically developed children. In fact, these studies suggested that fidgeting may represent a compensatory mechanism for modulating attention and alertness, as well as augmenting CNS arousal during challenging tasks. This hypothesis is based on a model of ADHD according to which individuals have exhibit a decreased tonic firing of the locus coeruleus-norepinephrine system, which would result in decreased cortical arousal and poor attention performance (Howells et al., 2012). Under this view, an increase in activity, such as fidgeting, in individuals with ADHD may stimulate the system and, consequently, increase arousal (Dishman, 1997; Hartanto et al., 2016; Rapport et al., 2009). Optimal arousal levels were shown to be necessary to maintain attention, and it was suggested that under attentional demanding conditions the level of stimulation could be modulated to optimize cortical excitability (Fischer et al., 2008). Further supporting the hypothesis that fidgeting could indeed represent a mechanism employed by individual with ADHD for maintaining attention by optimizing the level of arousal.

While fidgeting is characterized as the generation of small movements, many forms of fidgeting involve also the manipulation of external objects and seem to represent an important part of our day-to-day lives. As such, studies relative to fidgeting with objects like stress balls (Stalvey and Brasell, 2006), and doodling (Andrade, 2010) have emerged, further demonstrating the positive effect of fidgeting on both attention and concentration. In fact, the benefit of fidgeting activities has led to the design of workspaces for human-computer-interface with enough stimuli to favor fidgeting and, therefore, maintain attention while working (Karlesky and Isbister, 2016).

It should be mentioned that fidgeting was suggested to have also a stress-based origin, as most of the settings in which fidgeting was studied (i.e., those requiring sustained attention) may also be interpreted as stressful (Farley et al., 2013). Moreover, in some people fidgeting appears to mediate the experience of perceived stress (Mohiyeddini et al., 2013; Mohiyeddini and Semple, 2013). According to this view, fidgeting, intended as a manifestation of stress, would be expected to reduce performance in cognitive tasks (Farley et al., 2013). However, this assumption remains as only a speculation for the moment.

When it comes to fidget spinners specifically, it is therefore plausible to assume that the manipulation of these toys may indeed help to increase concentration and attention. However, this is not necessarily achieved by merit of some intrinsic property the spinners themselves as fidgeting, in general, may have this beneficial effect. A different aspect of the spinners may be even more intriguing, seeing that their manipulation requires some level of control and coordination, especially when attempting to balance them as demonstrated by social media. Also, it is known that games in general, and specifically those requiring fine manipulation (e.g., video games), may improve coordination, precision and dexterity (Borecki et al., 2013; Latham et al., 2013). As such, a plausible assumption is that the same may also be accomplished by fidget spinners. Especially when considered that repeated usage of these fidget spinners may render their manipulation automatic. The same as in practice, where the performance of a task eventually becomes second nature as a function of practice. It is well established that practice improves motor performance both in a task specific manner as well as by means of skill transfer (i.e., practice of certain type of task, may improve performance in different tasks that rely on the same type of control) (Schmidt and Lee, 2013). Therefore, fidget spinner manipulation may enhance fine motor control and, seeing that these objects are widely used, they have an added value of improving motor control in a population-based manner. Also, fidget spinners are generally perceived as an enjoyable pastime and thus, adherence is more likely.

It is evident that the spinners possess also some vibratory component to them, which we quantified according to Discrete Fourier Transform magnitude showing the principal component at a frequency of about 10 Hz (although magnitude is likely to vary between different spinners, see Methods). There are various studies that demonstrate that vibration may also affect motor control, e.g., (Ritzmann et al., 2014). Taken together, perhaps the combination of these factors, repeated manipulation and vibration, may in fact be favorable for promoting precision in fine motor control.

4.2 Materials and Methods

4.2.1 Participants

Eighty-one healthy adults were recruited for this study (age: 23.51±2.47 years; 29 males). All participants were right handed (83.64±13.91; laterality score from the Edinburgh Handedness Inventory (Oldfield, 1971)); they were naive to the task and the purpose of the study. All participants were free of documented visual, motor, neurological impairments. The participants were university students who volunteered for the study. Participants were not paid for their participation. The study protocol was approved by the Institutional Ethics Committee (Comitato Etico Area Vasta Centro AOUCareggi, Florence, Italy; Prot. N. 2015/0018234, Rif. 63/12) and all procedures conformed to the code of ethics of the Declaration of Helsinki. All participants gave written informed consent.

4.2.2 Task and Set up

Fine motor control can be tested with spiral drawing that offers a reliable -on the fly- measurement; in addition, by digitizing the procedure, a quantitative objective assessment may be obtained, (Hoogendam et al., 2014; Longstaff and Heath, 2006; Miralles et al., 2006; San Luciano et al., 2016; Sisti et al., 2017). As a quantitative measure, we used a spiral-tracing task to assess for fine motor control before and after using a fidget spinner (i.e., Fidget group), and compared these results to those obtained from a Sham and Control groups (Figure 4.2).

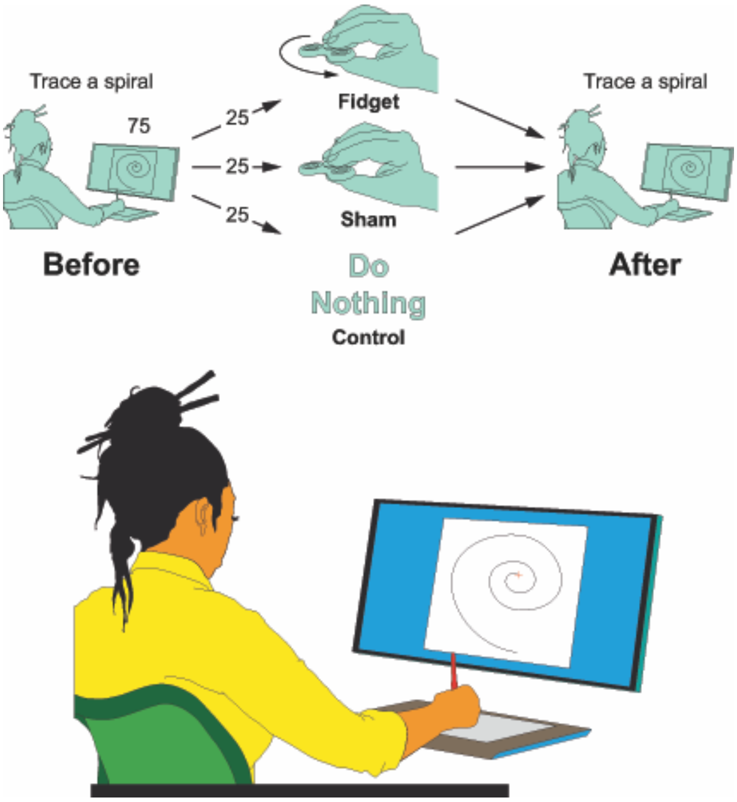


Figure 4.2. Experimental design. The upper panel illustrates the experimental design for this study. All participants were initially asked to trace a spiral (i.e., Before trial). After the first tracing, participants were divided into one of the three groups: Fidget, Sham or Control, and were asked to either rotate the spinner (i.e., Fidget group), hold the spinner (i.e., Sham group) or do nothing (i.e., Control group), for one minute, followed by a second tracing of the spiral (i.e., After trial). The bottom panel illustrates the working station used for the tracing. The graphic pen tablet was placed in front of the screen, and the participants were asked to trace the spiral, while seated, without the support of either wrist, arm, or elbow, in such a way that the only contact was made through the pen on the tablet.

Each participant was tested individually. Participants were randomly assigned to either a Control, Sham or Fidget group (27 participants per group; Fidget -10 males, Sham -8 males, Control -11 males). Before and after each trial, participants were asked to trace a spiral, beginning from the center and going outward, using graphic pen tablet (Wacom Intuos® CTH-690AK, Tokyo, Japan; active area: 216 x 135 mm; Figure 4.2).

To exclude performance differences between genders, the results of the tracings were evaluated by using an unpaired two sample t-test, not revealing any significant differences between genders, independently of group, for both first and second tracings, and also within groups for the second tracing.

The spiral templates were designed for a medial to lateral performance of the dominant hand (e.g., counter-clockwise for the right hand). The participants were instructed to trace the spiral while seated without the support of either wrist, arm, or elbow, in such a way that the only contact was made through the pen on the tablet (Figure 4.2). We also specified to trace the spirals as precisely as possible with no regard to the speed of execution.

For the Fidget group, the trial consisted of rotating the fidget spinner, placed in the dominant hand. Participants were asked to hold the spinner with their thumb, index and third finger and to maintain the spinner horizontal to ground in such a way that the thumb placed at the bottom, and the index and third finger placed at the top of the spinner (Figure 4.1). The reason for maintaining this horizontal position is that this way gravitational forces are equally distributed through the wings of the spinner. Once rotation was initiated, participants were asked to maintain this position for one minute, timed by a stopwatch. For the Sham group, participants were asked to hold the spinner in the same way as for the Fidget group without inducing a rotation and to maintain this position for one minute. For the Control group, participants were asked to do nothing for one minute.

4.2.3 Analysis

We have developed an algorithm using Matlab for spiral analysis. The algorithm consists of serial angle-based calculation of the traced spiral deviations from the template. Points of the tracing (n = 6,643 per traced spiral, normalized to the size of the template) were organized both according to their distance from the spiral center as well as according to the angle. For each point the residual difference between the tracing and the template was measured, considering the template as the expected value (Figure 4.3). Since we are interested only in deviations from the template, residual differences were considered as absolute values. For each tracing the mean residual difference and total area of deviation (considered as the area between the template and the drawn spiral) were calculated.

Quantification of the fidget spinner vibratory component was made with an accelerometer (ADXL330, Analog Devices Inc., Norwood, MA, USA), sensor output was acquired and digitized at 200 Hz through PCI-6071E (12-Bit E Series Multifunction DAQ, National Instruments, Austin, TX, USA) and analyzed with Matlab according to Discrete Fourier Transform.

4.2.4 Statistics

The mean and standard deviation, per group and per trial, were calculated for both mean residual difference (RD) and total area of deviation. A two-way ANOVA was implemented to evaluate the differences, in mean RD and total area, both between groups (i.e., factor 1: Fidget, Sham, and Control) and between trials (i.e., factor 2: Before and After trials). ANOVA analyses were followed by a Bonferroni post-hoc test to confirm the significance of the differences between groups and between trials. Furthermore, the root-mean-square standardized effect, namely Ψ, was calculated as the effect size estimator for ANOVA analysis, which was used as the effect size for power analysis calculation (Steiger, 2004). Statistical power was calculated using G*power 3.1.9 with an α value of 0.05 (Faul et al., 2007).

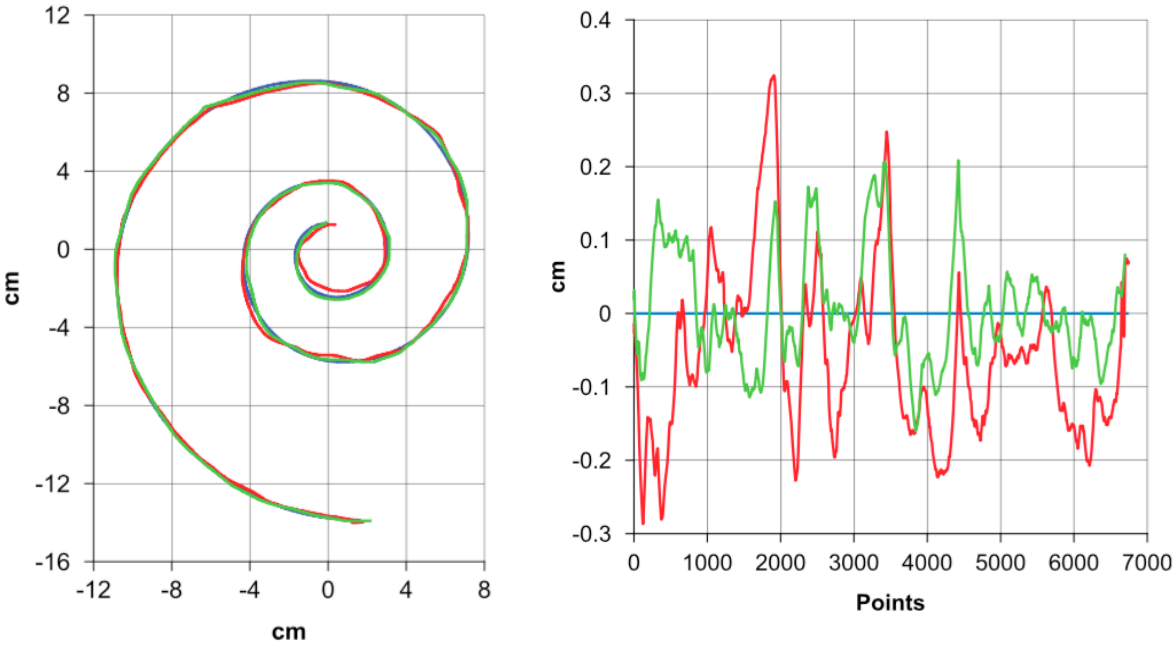


Figure 4.3. Spiral analysis. An example of how the spirals were analyzed. In the left panel, it is possible to see three spirals that correspond to the template (blue), tracing in the Before trial (red), and tracing in the After trial (green). It should be noted that the first tracing was not visible to the participant during the second tracing. In the right panel it is possible to see the differences between the tracings more clearly, with the template corresponding to zero, and the tracings as deviations from the template. In this example it is possible to see an improvement in the After trial (green) compared to the Before trial (red). The participant in this case was part of the Fidget group, with a mean RD of 0.13 cm and a total area of deviation of 3.14 cm2 in the Before trial and 0.09 cm and 2.19 cm2 in the After trial.

4.3 Results

Based on both mean residual difference (RD) and total area of deviation from the template (Figure 4.3), there seems to be a general improvement in the After trial for both Fidget and Sham groups but not for the Control group (Figure 4.4). For the Fidget group, mean RD improved from 0.22±0.08 cm to 0.16±0.05 cm; total area from 5.22±1.95 cm^2 to 3.84±1.27 cm^2. For the Sham group, mean RD improved from 0.20±0.07 cm to 0.16±0.04 cm; total area from 4.85±1.78 cm^2 to 3.85±1.12 cm^2. For the Control group no improvement was found, with mean RD of 0.19±0.07 cm Before and 0.21±0.06 cm After; total area measured 4.60±1.66 cm^2 and 4.92±1.49 cm^2, respectively.

ANOVA analyses preformed on both mean RD and total area of deviation confirmed a significant difference between trials (i.e., factor 2: Before and After; F-values: 7.37 for mean RD and 7.71 for total area, d.f.:1), with p-values of 0.007 (for mean RD) and 0.006 (for total area). Specifically, the within group results for both Fidget and Sham groups were found to be statistically significant for both mean RD (p-values of 0.001 and 0.026, respectively) and total area of deviation (p-values of 0.001 and 0.020, respectively). These results were also confirmed by the Bonferroni post-hoc test. Contrary, the within group results for the Control group were not found to be significantly different between trials (p-values of 0.455 for mean RD and 0.458 for total area; Figure 4.4).

When analyzing the results between groups (i.e., factor 1), no differences between groups were found for the Before trial (i.e., first tracing), with p-values all above 0.05 for both mean RD (p-values of 0.99

for Fidget vs Sham, 1 for Sham vs Control, and 0.41 for Fidget vs Control) and total area (p-values of 1 for Fidget vs Sham and for Sham vs Control, and 0.44 for Fidget vs Control) according to the Bonferroni post-hoc test. However, when analyzing the After trial, significant differences were found between both Fidget vs Control (p-values 0.042 for Mean RD and 0.039 for total area of deviation) and Sham vs Control groups (p-values 0.043 for Mean RD and 0.041 for total area of deviation). No statistical differences were found between the Fidget and Sham groups for the After trial (p-values of 1 for both Mean RD and Total area of deviation). The statistical power relative to the sample in this study was found to be 87.7%, with a calculated effect size estimator Ψ value of 0.389 (Steiger, 2004).

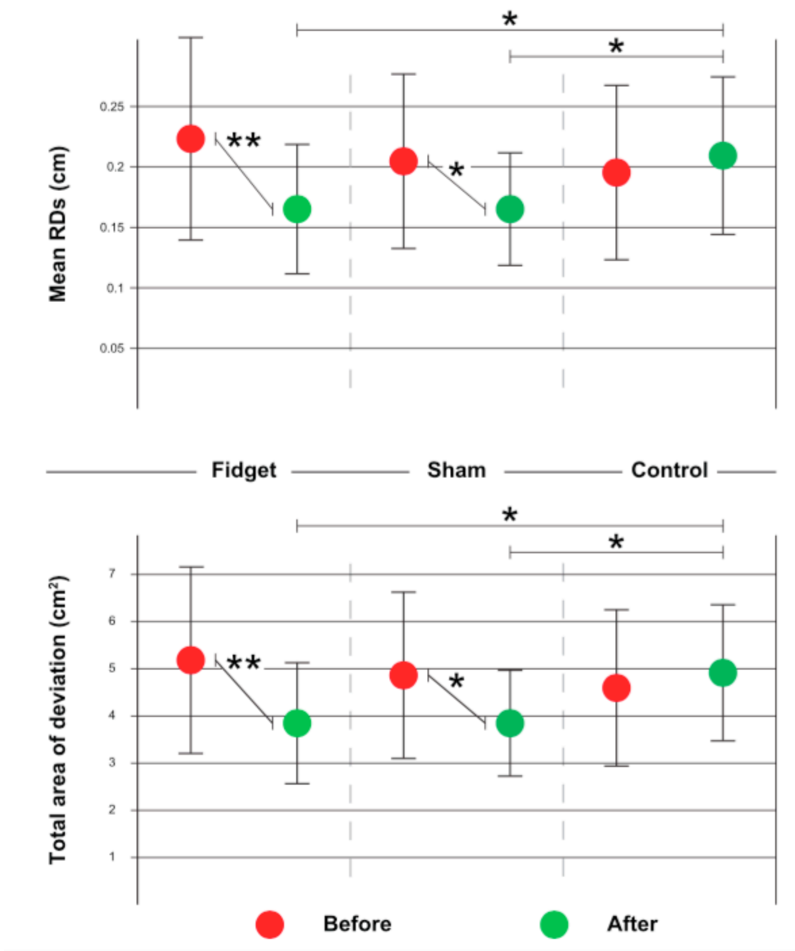


Figure 4.4. Results. Circles represent the group mean and vertical bars indicate the standard deviation. Circles are color coded according to trial (red for Before, green for After). It is possible to see that for both Fidget and Sham groups there is a significant improvement in the After trial with p-values <0.01 (**) for the Fidget group and <0.05 (*) for the Sham group for both mean RD (upper panel) and total area of deviation (lower panel). Also, it is possible to see a significant difference in the After trial, for both mean RD and total area of deviation, between Fidget and Control groups and Sham and Control groups with p-values <0.05, but not between Fidget and Sham groups.

4.4 Discussion

Our results suggest that the use of fidget spinners may indeed better fine motor control to a certain extent, as shown by the within group analysis. However, it would be imprudent of us not to consider the fact that this general improvement was also evident for the Sham group. Taken together, these results suggest that fine motor control may be related more to the general manipulation of objects and not necessarily inherent to fidget spinners themselves. Considering our sample of young healthy subjects, our results should apply to all subjects. It is possible, that in certain special groups, such as that of ADHD, the effects could be even greater, seeing that fidgeting in general was already shown to have a beneficial effect on this type of population. However, this remains as a mere speculation for the moment that may be elucidated by future studies.

The observed improvement in performance for the Fidget and Sham groups may be due to an additional attentional component on the motor effector related to handling of the fidget spinner between trials. This may explain why improvements were found in both Fidget and Sham groups but not in the Control group. In fact, by examining dual task paradigms it is evident that while performing a motor task concurrent with a cognitive task, some modifications to the motor performance occur, suggesting that the any motor task, even when not fully concentrated, requires allocation of attentional resources for the performance (Abernethy, 1988; Guillery et al., 2013; Saling and Phillips, 2007). Also, object manipulation specifically was shown to require the integration of sensory, motor and cognitive systems (Hesse and Deubel, 2011; McBride et al., 2012). Moreover, it was shown that both internal and external focus may affect motor performance, with the latter being more effective in improving performance (Porter et al., 2010; Wulf and Prinz, 2001). Therefore, it is possible that the handling of the fidget spinner between trials may contribute to divert the attention toward the handling hand (i.e., internal focus) or the fidget spinner itself (i.e., external focus). Consequently, a higher level of performance may be achieved faster and retained more effectively (Wulf, 2007b).

Another possibility would be that while handling the object, the motor areas responsible for the movement during the task remain active. It was shown that activation of motor areas, even when no movement is occurring (e.g., motor imagery), may influence performance (Guillot and Collet, 2008; Karni et al., 1998). Also, when developing motor skills, it was shown that executing different tasks may help in improving a specific skill by means of skill transfer when the same effectors are used (Schmidt and Lee, 2013; Seidler and Noll, 2008). Under this view, the handling of the fidget spinner between trials, by keeping the same motor areas activated, may be comparable to practice by means of skill transfer and, therefore, improve performance in successive trials. A general improvement due to trial repetition may be excluded seeing that the Control group did not demonstrate an improvement between trials. An fMRI study could provide information relative to this hypothesis. Also, it would be interesting to evaluate the amount of attention allocated during the use of fidget spinners by a dual task paradigm. Perhaps by doing this, the effect would be better characterized and, consequently, also controlled.

In our study we tried to obtain a homogeneous group of individuals, all being young adults free from any reported neurological or visual impairments that may interfere with the task. However, there are other variables that may influence motor performance that were not evaluated in this study. It was shown that motor and cardiovascular fitness as well as academic skills are related and could influence one another (Haapala et al., 2014). Also, motivation was shown to be a determining factor for success when developing motor skills (Schmidt and Lee, 2013). Therefore, it is possible that by evaluating and/or controlling these variables some specific correlations may emerge. We assume that by our choice of the sample, the motor fitness, motivation, and age would be relatively similar among subjects, and therefore, would not affect the present research. However, it would be interesting to test if the effect present reported here would also be present in other types of groups with different motor and cardiovascular fitness (e.g., professional athletes vs sedentary individuals) and age (e.g., children vs adults).

It should also be considered, that our study was concentrated only on the immediate effect and, therefore, we cannot predict whether these effects are also long lasting. While this remains as an open question, it is also true that the continuous manipulation of objects may eventually better dexterity

(Borecki et al., 2013; Latham et al., 2013; Magallón et al., 2016; Sarver et al., 2015; Schmidt and Lee, 2013). In fact, when manipulating objects, the mechanical properties of both hand and object must be accounted for. This is made simple for a rigid object that is held firmly in the hand, as movement of the object is equivalent to controlling the movement of the hand whereas for non-rigid objects, movement of the object is made by the interaction between hand and internal dynamics of the object (Dingwell et al., 2002). The manipulation of unknown objects (i.e., unknown dynamics) is made by estimation of either the dynamics of the object or employment of different strategies for control, both of which are based on past experiences (Dingwell et al., 2002). Therefore, it is possible to assume that the longer and more varied is the manipulation of object, the easier would be the successive manipulation of new objects. This way, continuous manipulation will add to the repertoire of experiences and strategies for future human-object interactions, especially when considering that experience is a determining factor for the success of a planned motor response (Metcalf et al., 2014). Further supporting this notion is the fact that when the physical properties of the arm are altered by an object, the internal model of dynamics of the adapted arm to the new physical condition is maintained (Gordon et al., 1993; Sainburg et al., 1999; Witney et al., 2000). This type of adaptation may indeed influence the predictability of the object's dynamics in future human-object interactions, which was suggested to be a primary criterion for strategy selection (Nasseroleslami et al., 2014). When these concepts are combined with skill transfer, it is probable that a continuous manipulation of objects may indeed influence dexterity and motor control. Examples for this can be found when examining the effects of video games as well as chopsticks on dexterity (Borecki et al., 2013; Chen and Chang, 1999; Latham et al., 2013; Rosser et al., 2012). Therefore, it is possible that the repetitive manipulation of fidget spinners may influence motor control. Moreover, by being a toy that is considered to be enjoyable, fidget spinners may stimulate even more people to utilize them, much more efficiently than refine exercises aimed to improve fine motor control.

5 3D reconstruction of human movement in a single projection by dynamic marker scaling

Abstract. The three dimensional (3D) reconstruction of movement from videos is widely utilized as a method for spatial analysis of movement. Several approaches exist for a 3D reconstruction of movement using 2D video projection, most of them require the use of at least two cameras as well as the application of relatively complex algorithms. While a few approaches also exist for 3D reconstruction of movement with a single camera, they are not widely implemented due to tedious and complicated methods of calibration. Here we propose a simple method that allows for a 3D reconstruction of movement by using a single projection and three calibration markers. Such approach is made possible by tracking the change in diameter of a moving spherical marker within a 2D projection. In order to test our model, we compared kinematic results obtained with this model to those with the commonly used approach of two cameras and Direct Linear Transformation (DLT). Our results show that such approach appears to be in line with the DLT method for 3D reconstruction and kinematic analysis. The simplicity of this method may render it approachable for both clinical use as well as in uncontrolled environments.

5.1 Introduction

The clinical assessment of biomechanical parameters is fundamental for both rehabilitation and prevention. As such, the need for objectivity when evaluating appears to be of great importance. However, more than often the assessment of such parameters is still more subjective than warranted, limited to a simple observation by the examiner of the movements performed and scoring the performance according to various clinical scales e.g., (Claesson et al., 2017; Ferrarello et al., 2013; Lussiana et al., 2017; Sibley et al., 2011). To overcome this difficulty, various instruments exist that allow for more objective measurements. These instruments vary in complexity and in costs, from simple manual goniometers to refined automatic kinematic assessments tools e.g., (Cancela Carral et al., 2017; Nussbaumer et al., 2010). However, when evaluating complex multi-segmental movements frequently the use of the more expensive and refined tools is called for.

One of the corner stones of biomechanical evaluation is the dynamic study of the body in its entirety during movement along with a three dimensional (3D) reconstruction, often achieved by means of some acquisition system, from simple video cameras to complex capture systems e.g., (Baskwill et al., 2017; Mustapa et al., 2017). Such evaluation generally requires dedicated spaces and, frequently, trained personnel for its operation. Therefore, the introduction of low-cost, flexible, and simple tools for dynamic analysis and 3D reconstruction of full body movement may provide the basis for a much wider implementation of these types of biomechanical assessments, in both clinical use as well as in uncontrolled environments.

Cohen EJ, Bravi R, Minciacchi D (2017) 3D reconstruction of human movement in a single projection by dynamic marker scaling. PLoS One. 12(10):e0186443. doi: 10.1371/journal.pone.0186443.

The use of video for kinematic analysis of human movement represents a simple tool for biomechanics studies. While not as accurate as optical capture systems, it does provide easily obtainable valid data at a lower cost and does not require highly trained personnel for its operation, see (Chèze, 2014); therefore, it may satisfy some of the prerequisites for a widespread implementation. One of the issues regarding video analysis is the reconstruction of the movement in a three dimensional (3D) space, commonly requiring the use of at least two cameras. However, while two cameras are able to localize markers in 3D, more than often some of the markers may be hidden during capturing and, therefore, provide partial information and/or necessitate the addition of more cameras, causing an increase in costs. Also, in order to use two cameras, adequate space must be dedicated that allows for a complete acquisition.

Several approaches have been proposed for 3D reconstruction from video cameras. Widely used is Direct Linear Transformation (DLT) that, with a minimum of 6 calibrated markers, is able to link the information provided by two cameras to reconstruct a 3D space (Abdel-Aziz and Karara, 1971). The comparison between the DLT method and other approaches is beyond the scope of this paper; for comparisons and considerations between calibration methods see (Remondino and Fraser, 2006). This approach, however, does have its downsides. The first already mentioned, is the obligated use of at least 2 cameras. The second is that, when relating image points to object points, a series of constants must be used. These constants for each camera are represented by the projection coordinates, global coordinates, and a series of coefficients that relate the two. Therefore, for each point we have 5 knowns (i.e., 2 for the projection and 3 for global coordinates) and 11 unknowns (i.e., coefficients) per camera. These coefficients, or DLT parameters, are expressed by two equations per projection point. To find these unknown parameters, at least 11 equations are needed, per camera. This can be done by adding calibration points. For each additional calibration point, two new equations are introduced, while the DLT parameters remain the same. Therefore, by using 6 calibration points, which yield 12 equations, we are able to solve for the DLT parameters, for a detailed explanation of the DLT method see (Abdel-Aziz and Karara, 1971). Therefore, to calibrate the system according to the DLT method, a minimum of 6 accurately placed calibration points are needed, and we have to create the transformation matrix for each point, which may result in quite a tedious procedure. Also, when a marker is not visible on one camera the reconstruction cannot be made for said marker.

An appealing alternative is the reconstruction of movement by using a single camera. Not only for the reduction in number of cameras, and therefore costs, but also in cases in which a single camera is used for 2D analysis, a 3D reconstruction may provide additional information from the same recording. An example for this is gait analysis, where only a sagittal view is considered e.g., (Castelli et al., 2015; Yang et al., 2016) leaving the information obtained as partial. A few studies have addressed the issue of 3D reconstruction by a single projection, providing different methods e.g., (Ambrósio et al., 2001; Bowden et al., 1998; Howe et al., 1999; Wei et al., 2012) Worth noting is the work of Yang and Yuan (Yang and Yuan, 2005), in which by adding kinematic constraints associated with a human biomechanical model the authors were able to reconstruct a 3D movement from a single camera quite precisely. However, this approach is based on the same principals as the DLT method and therefore requires the solution for 11 parameters. The reduction of the DLT principals to a single camera with the added kinematic constraints as well as the need for anthropometric data further increased the complexity of this method, rendering it less approachable for personnel with no mathematical background. Also, the use of kinematic constraints renders each calibration subject-specific, and not setup specific, which may cause a great increase in the time for preparation and analysis.

Another general issue that merits attention is the use of the commercially available cameras for which, with the advances in video technology, the accuracy of video-obtained data has increased and more low cost alternatives to specialized cameras have emerged. In fact, the use of webcams and action cameras have been successfully implemented for biomechanical analysis of movement (Bernardina et al., 2016; Krishnan et al., 2015). For these types of cameras, more than often information relative to the intrinsic properties of the camera (e.g., focal length, sensor specifications) is not readily available and, consequently, some reconstruction methods may not be employed, as also mentioned by (Yang and Yuan, 2005).

In a clinical setting, the implementation of an objective biomechanical assessment is still far from widespread. This may be due to a series of factors. As mentioned earlier, most of the elaborated systems for biomechanical analysis require a dedicated space e.g., (Riberto, 2013), which is far greater than that found in a typical examination room, let alone at patient's bedside or during house calls. Even for a two camera setup, the space required to assure visibility of the entire body, though variable between cameras, exceeds that of a common examination room.

In single camera-based approaches space is not an issue. However, the increase in complexity for implementation of these methods, due to the reduction in cameras, may greatly limit their usage. When considering that healthcare professionals are concentrated on specific field of expertise, it is not surprising that the most may not possess adequate knowledge or preparation for the application of said methods.

Another general consideration is that the majority of calibration processes are setup-specific, meaning that once the cameras are calibrated they cannot be moved which reduces the mobility of the system and, therefore, may obstacle a common day-to-day use in dynamic environments, such as those found in clinical practice.

In addition, as costs and resources are also to be considered, acquisition of specialized cameras specific for movement analysis is not always possible. Especially today, where most portable devices are able to provide fairly decent video recordings at hand's reach (Boissin et al., 2015), acquisition of specialized equipment may and should be avoided when possible.

When taking all of these considerations together, it is obvious that in order to render an objective biomechanical assessment widespread, a simple, mobile instrument that is camera independent and does not necessitate any specific background is needed.

Here we propose a simple approach that requires a minimum of 3 markers for calibration and is able to reconstruct movement in a 3D space with a single projection. Such algorithm is based on the scaling effect provided by a two dimensional projection. Seeing that the scaling effect occurs throughout the movement, we called this method dynamic marker scaling (DMS). This approach is independent from the intrinsic properties of the camera and may be widely implemented. In order to test the validity of the DMS method, we compared it to the commonly used DLT method with two cameras.

5.2 Materials and Methods

5.2.1 Subject and Task

A normal subject (female, age 25, height 167 cm, 47 kg) was analyzed for linear and angular kinematics of the entire body during a simple lifting task of a box (dimensions 10 x 4 x 2 cm, 100g). No indication was provided to the subject regarding how the task is to be performed. The experimental protocol conformed to the requirements of the Federal Policy for the Protection of Human Subjects (U.S. Office of Science and Technology Policy) and Declaration of Helsinki, and has been approved by the Research Ethics Board of our Institution (Local Ethics Committee, Azienda Ospedaliero Universitaria Careggi, Florence, Italy). The participant provided informed consent in written form.

5.2.2 Cameras

Three cameras were used for data acquisition (GoPro Hero 5 Black), 2 for the DLT method and one for the DMS method. The DLT cameras were positioned orthogonally from one another forming a 45° from the center of the working area at a distance of 220 cm from the center point. The camera used for the DMS method was placed at a distance of 272 cm and frontal to the center of the working area (Figure 5.1). In order to compare the same movement for DLT and DMS, all three cameras were synchronized by using GoPro Smart Remote control. Video acquisition was set for resolution of 1080p at 120 frames per second for the DLT and DMS cameras. Other settings included: Field of view- Narrow, Color-flat, WB-3000K, ISO-1200, EV Compensation- -0.5.

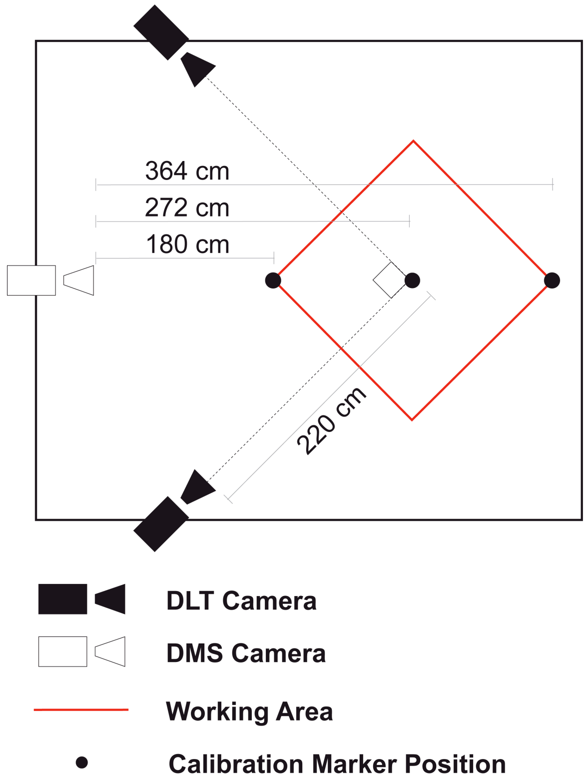


Figure 5.1. Setup. A diagram of camera placement for acquisition. The cameras used for DLT were placed at a 45° angle from the center point, while the DMS camera was placed frontal to the working area (in red). Also, placement of the calibration markers for the DMS method are shown.

5.2.3 Calibration

For DLT calibration 19 spherical markers were placed at known locations, fixed to a static structure thus distributing the markers throughout the working area (Figure 5.2). For the DMS method, three spherical markers were placed on the ground at known distances from the camera (180 cm, 272 cm, and 364 cm, Figure 5.1). The distances were chosen to delineate the working area. All of the markers used in this study were 2.4 cm in diameter. For implementation, our algorithm requires the following parameters: marker height (simplified by placing markers on the ground), marker diameter, camera height (considered from ground to lens center, measured at 90.6 cm), marker distance from camera's plane (i.e., ground distance). Seeing that scaling of objects occur in reference to the center of the camera's lens, the actual camera distance was calculated from the measured ground distances (as the ground distance and camera height are known, see Figure 5.3). According to this calculation, a ground marker placed at 180 cm has a camera distance equivalent of 201.51 cm, considering a camera height of 90.6 cm. Therefore, if a marker at 180 cm (ground distance) is known to have a certain diameter when projected, any marker that measures the same diameter can be considered to be placed at a distance of 201.51, in any direction, from the camera's center (i.e., camera distance; Figure 5.4).

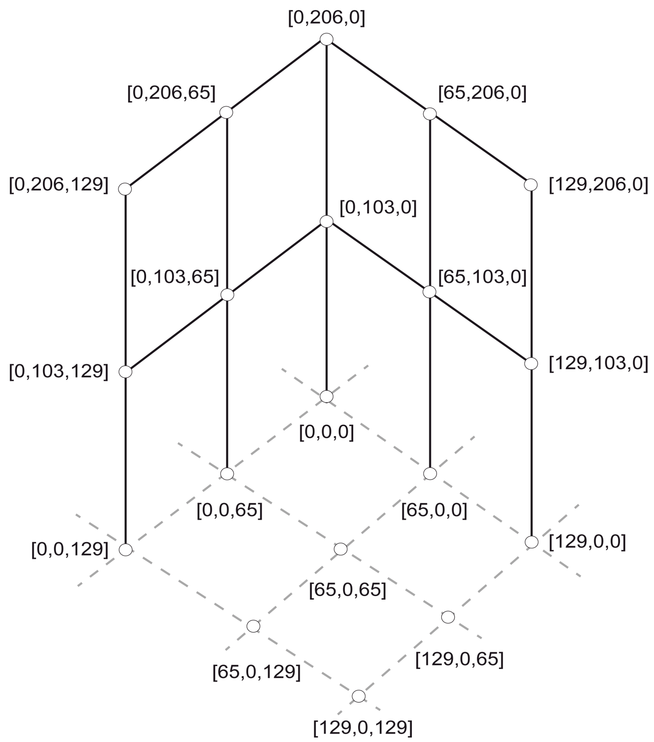


Figure 5.2. DLT setup. A diagram of the placement of calibration markers for the DLT method. A static structure formed by two fixed orthogonal frames was built to delineate the working area, to which markers were fixed at known positions. For each marker, global coordinates in cm are shown in the parenthesis as XYZ.

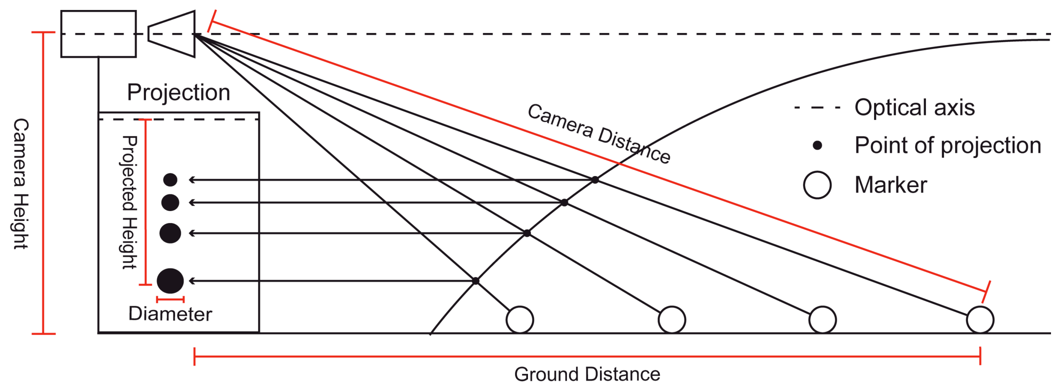


Figure 5.3. Relationship between position and projections. A diagram describing differences between actual positions of markers, relative to the camera, and their projections. Camera Height is considered as the measured height from the ground to the lens center. Camera Distance is considered as the distance between the marker's center and the center of the camera's lens. Ground Distance is considered as the distance from the marker's center to the camera's plane. Also shown are differences in projection height, where more distant markers are projected higher than closer ones, as well as diameter changes relative to distance, with closer markers appearing bigger than more distant ones.

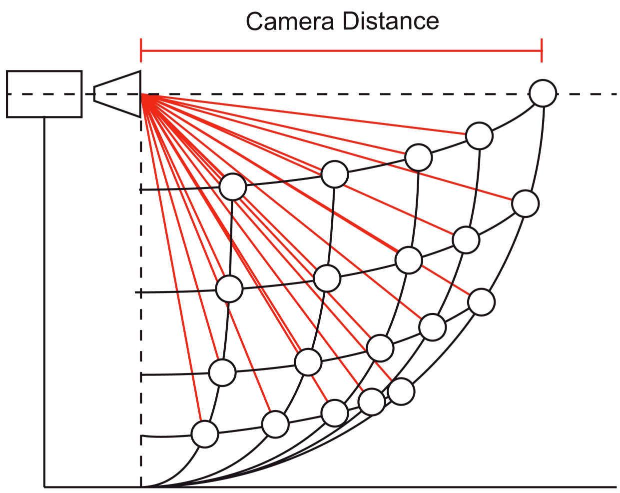


Figure 5.4. Camera distance. A diagram demonstrating that when a marker measures a certain diameter, said marker will have a specific camera distance independent from its direction. Corresponding camera distances are shown in red lines, all of which are equal to the measured camera distance. An example from our measurements is a projected diameter of 24 pixels, and a corresponding camera distance of 203.56 cm, in any direction.

Calibration for conventional cameras is usually based on a perspective projection model, known as the pinhole camera model. While calculation based on a pinhole camera model can be solved for with simple projection equation (e.g., $u=fX/Z$, $v=fY/Z$; where u and v are the projected coordinates, X, Y, and Z are the real world coordinates, and f is the focal length), due to camera parameters that don't match the pinhole model (e.g., large aperture, lens distortion, etc.) as well as our scope to create a camera independent model (i.e., that does not rely on prior knowledge of the intrinsic parameters of the camera, specifically the focal length) the equation needs to be made more general. As such, for a dynamic analysis through marker scaling the following premise was considered. There is an inverse relationship between marker size and its distance from the camera (i.e., marker diameters grows as the distances reduces; Figure 5.5). Therefore, two asymptotes are present according to these conditions allowing for an implementation of a negative power function based on:

$$f(x)=x^{-1}$$

where $f(x)$ represent the camera distance, and x represents the marker's projected diameter. By including a scaling factor and noise effect the resulting function is:

$$f(x)=ax^{b}+c$$

where b is a negative number. During the formulation of our model, we have conducted several trials in which markers were placed at different distances, and their projected diameters measured. The results obtained with this function appeared to be in line with our measurements. To test the goodness of fit of our function we used the curve fit tool of Matlab, plotting 13 measurements of distances and diameters. Our calculated coefficients matched those obtained with the curve fit tool, with an R^2 and adjusted R^2 values of 0.999, a root mean squared error value of 0.07, and a sum of squared errors of prediction value of 0.04 (see Figure 5.6). In order to solve for our equation, seeing that there are 3 unknown coefficients, a minimum number of 3 known points is needed. While the choice to use a power function may be reasonable enough, it is still arguable how accurate this function may be. However, considering the fact that we are interested only in results occurring within a limited numerical range (i.e., working area), and that our calibration markers were placed at the limits and center of said range, measurements obtained by the function are expected to be relatively accurate.

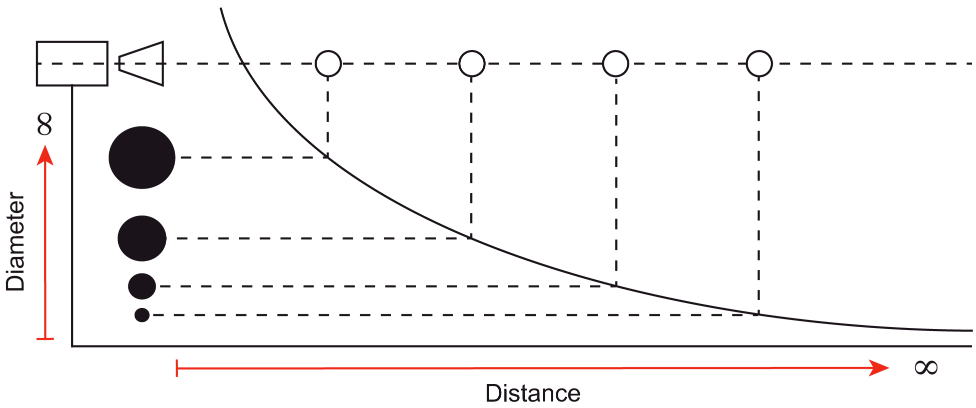


Figure 5.5. Relationship between diameter and distance. A diagram describing the relationship between a marker's camera distance and its diameter. The curve of this relationship takes the form of an inverse power function. From this function it is possible to see that the closer the marker is to the camera center, its size approaches infinity and as its diameter approaches zero, the distance grows to infinity. In the figure, we have included also some of the measurements obtained by us relative to the marker's camera distance (in cm), and its projected diameter (in pixel).

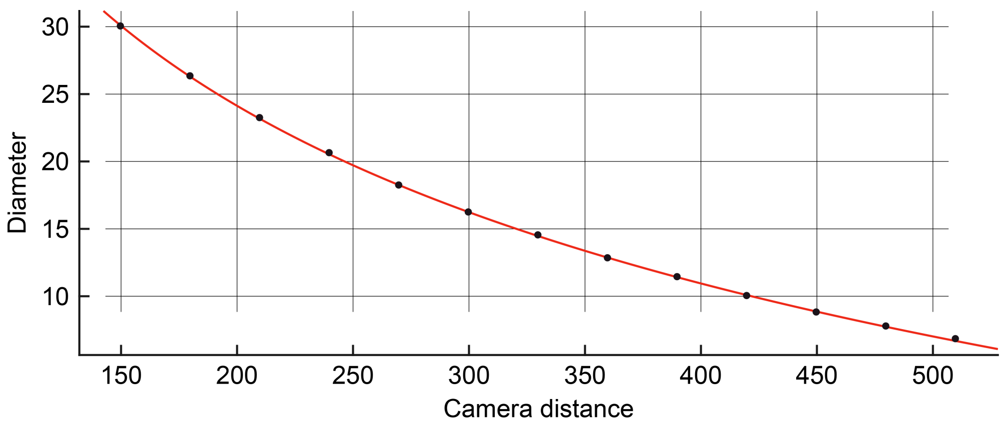


Figure 5.6. Goodness of fit of function. Plotted values of paired measurements of camera distances (in cm) and corresponding diameters (in pixels). The red curve represents the function that was fitted to the measurements. For the goodness of fit values, see text.

After resolving for the camera distance, a correction factor should be used for the Y and X axes seeing that, due to perspective distortion, objects more distant from the camera appear closer to the center (i.e., optical axis). For example, on the Y axis, more distant objects appear higher when placed below the optical axis of the camera, and lower than they above (Figure 5.3). On the X axis, more distant objects appear more medial whereas closer objects appear more lateral. In order to resolve for perspective, the known marker diameter can be used. By taking the projected diameter of a marker and calculating the projected distance of that marker from a reference point (for simplicity we used the axes origins), we can quantify that same distance in terms of projected diameter instead of pixels. Seeing that the actual diameter of the marker is known, the conversion of that measurement into centimeters is made by a simple multiplication which could be expressed by the following equation: *actual(Y)=(projected(y) /projected(diameter))* * *actual(diameter)*. By using a spherical marker the same approach can be used for both the X and Y axes, this concept is exemplified in Figure 5.7.

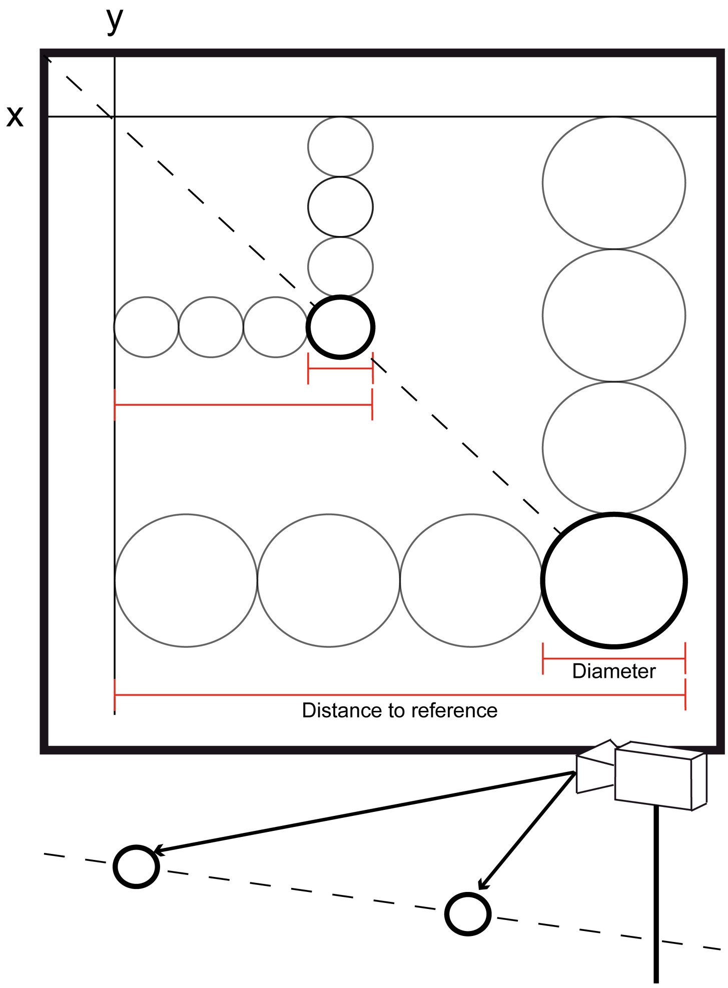


Figure 5.7. Perspective correction. A diagram describing the correction for perspective distortion. By using the measured projected diameter of a marker as well as the distance to some reference point, it is possible to calculate the ratio between projected diameter and distance to the reference. As the real marker diameter is known, it is possible to multiply the ratio by the real diameter, therefore obtaining the actual distance from the reference. This may be applied to both the X and Y axes. In the diagram we can see two markers (bold circles), that are placed at different distances from the camera (as shown at the bottom of the figure) and that in their projection (bold circles in the frame) appear to have a different diameter (with more distant marker having a smaller projected diameter), and a different localization (with the more distant marker appearing higher and more medial). As we can see the markers are effectively placed one behind the other (in the bottom of the figure) and, in fact, when calculating the ratio between projected diameter and distance to the reference, both present the same ratio meaning that in reality are placed one behind the other (i.e., having the same X and Y global coordinates).

After obtaining data relative to the X and Y axes, a conversion of the measured camera distances obtained into distances from the camera's plane (i.e., Z axis) is necessary. This conversion can be made by using the Pythagorean theorem, with the measured camera distance and the obtained Y value.

5.2.4 Data acquisition

For a full body analysis of the movement, 12 joints were considered (ankle, knee, hip, shoulder, elbow, and wrist joints) and additional markers were placed on the head, feet and trunk for a total of 16 points of interest (see Figure 5.8). To assure joint tracking, 2 markers were placed per joint (3 for the knees and ankles). For both DLT and DMS methods, marker tracking was done manually using the open source software Tracker (http://physlets.org/tracker/). The data was extracted from Tracker as x-y coordinates for each tracked point which were then analyzed using Matlab.

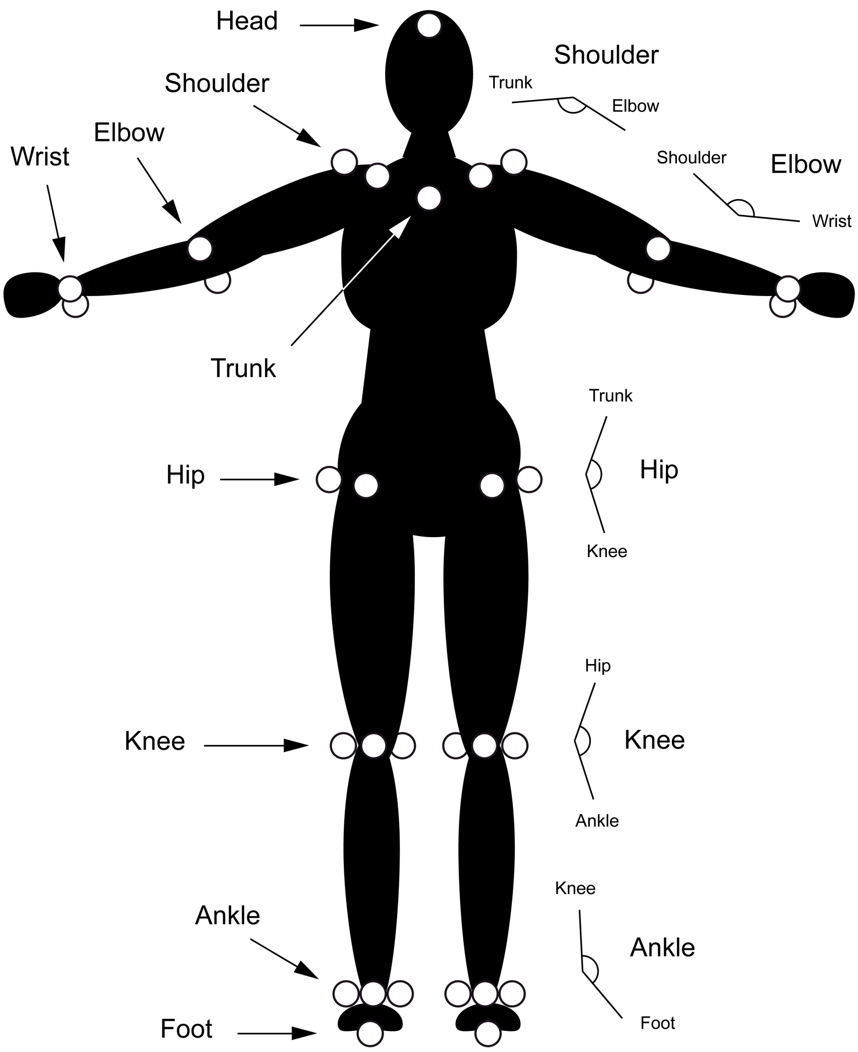


Figure 5.8. Marker placement. A diagram illustrating marker placement on the subject. As shown, 16 points were taken into consideration with 2 markers per joint for shoulders, elbows, wrists, and hips 3 markers per joint for the knees, and ankles, and a single marker for the head, trunk and left and right feet. Also shown are the joint angles, illustrated in the right part of the diagram; angles are named according to the joint at the vertex.

For DMS analysis, other than the coordinates of the marker, we are also interested in its diameter and, therefore, tracking points were placed at each side of the marker. Thus, by calculating the difference between the two tracked points, the marker's diameter may be retrieved (Figure 5.9). The use of spherical markers for diameter acquisition provides the advantage that the dimensions of the marker do not change with movement. As long as the marker is half visible, data regarding its distance may be retrieved. Also, by using spherical markers, the perspective correction for both X and Y axes is simplified significantly.

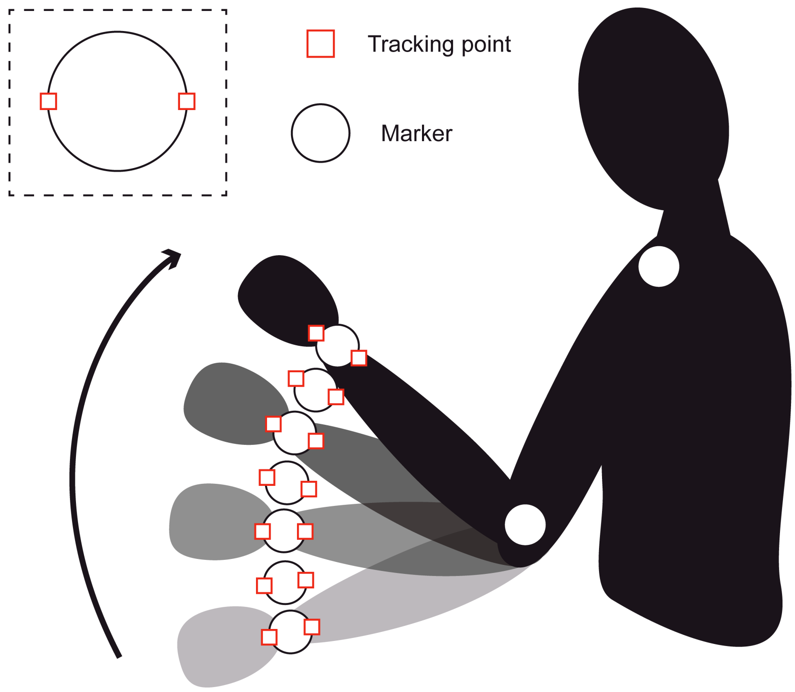


Figure 5.9. Marker diameter acquisition. A diagram demonstrating marker diameter acquisition. Each side of the marker is tracked for every frame.

5.2.5 Analysis

The basis of biomechanical analysis from video recorded data is the extraction of kinematic parameters. Of these parameters fundamental data are represented by the change in joints positions and angles over time, from which it is possible to calculate other kinematic parameters such as linear and angular velocities, accelerations as well as a more in depth analysis via inverse dynamics for kinetic data. In order to calculate for the various kinematic parameters, we have constructed an algorithm with Matlab. Seeing that the DLT and DMS methods are calibrated differently, we limited our analysis to linear displacement and angles, both of which are independent from the coordinate system used.

Linear displacement was calculated as the change in position from the starting position for every point in time. In order to resolve for displacement in a three dimensional space, a vectorial calculation is necessary. Therefore, the change in position for every frame was calculated for each axis separately (e.g., x_i-x_0). Then the three dimensional displacement for a frame was calculated as the square root of the sum of the changes in position of each axis squared.

Angle calculation was made by taking the 3D coordinates of three points at a time, considering the middle point as the vertex. First, the rays were calculated as the vectors between the first to middle and middle to third points. Then the norm of dot and cross products of the vectors was obtained, and the four-quadrant inverse tangent of the norm was found giving the angle for the three points in radians, which was then converted to degrees.

The following angles were considered for each side of the body: ankle (foot-ankle-knee), knee (ankle-knee-hip), hip (knee-hip-trunk), shoulder (trunk-shoulder-elbow), elbow (shoulder-elbow-wrist), Figure 5.8.

5.2.6 Statistics

The coefficient of determination (R^2) was used to determine the closeness of fit between measurements obtained with the DLT and the DMS methods. The residual differences between the two methods were measured for each joint in order to quantify the magnitude of the differences, reported here as mean, standard deviation (SD), and maximal residual difference (RD). Although usually used to determine the noninferiority or equivalence between treatments (Walker and Nowacki, 2011), we believe that an equivalence test may help to better characterize the level of similarity between the two methods. Therefore, a Two One-Sided Test (TOST) was implemented to better define the equivalence between the two methods (Rogers et al., 1993). Seeing, however, that the equivalence margins are not defined in current literature for this type of analysis, we have used the equivalence test to find said margins. This way, we hope to provide at least some quantification of the accuracy between measurements, which may benefit future studies in this field.

5.3 Results

The two approaches, overall, provided relatively similar results. The 3D reconstructions acquired from both methods along with the image sequence of the real movement are shown in Figure 5.10 whereas graphical representations of the results are shown in Figure 5.11 and Figure 5.12.

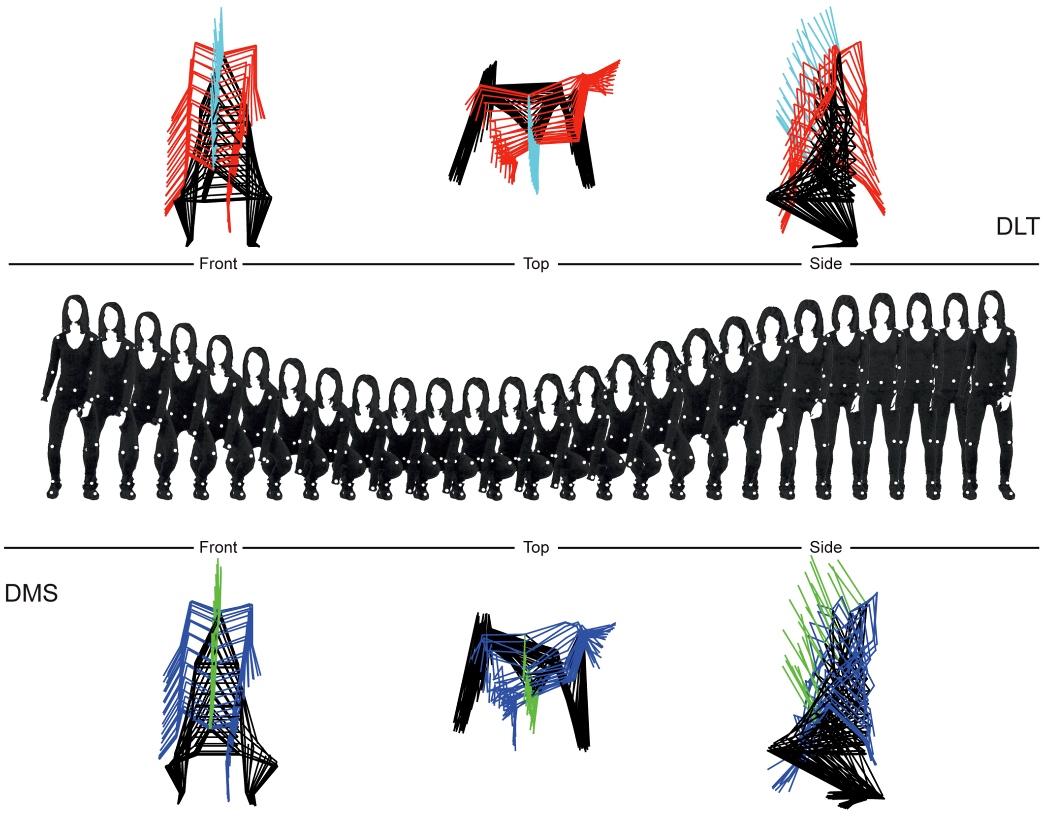


Figure 5.10. A reconstruction of the movement from both the DLT and DMS methods. The actual action, as sequenced images is displayed along with the reconstruction for each method. For simplicity, only 1 every 10 frames is shown for reconstructions and image sequence. Reconstructions are shown in three different points of view: front, top, and side views. To differentiate between body segments, different colors were used for the lower extremities (black), upper extremities (red for DLT and blue for DMS) and head (cyan for DLT and green for DMS).

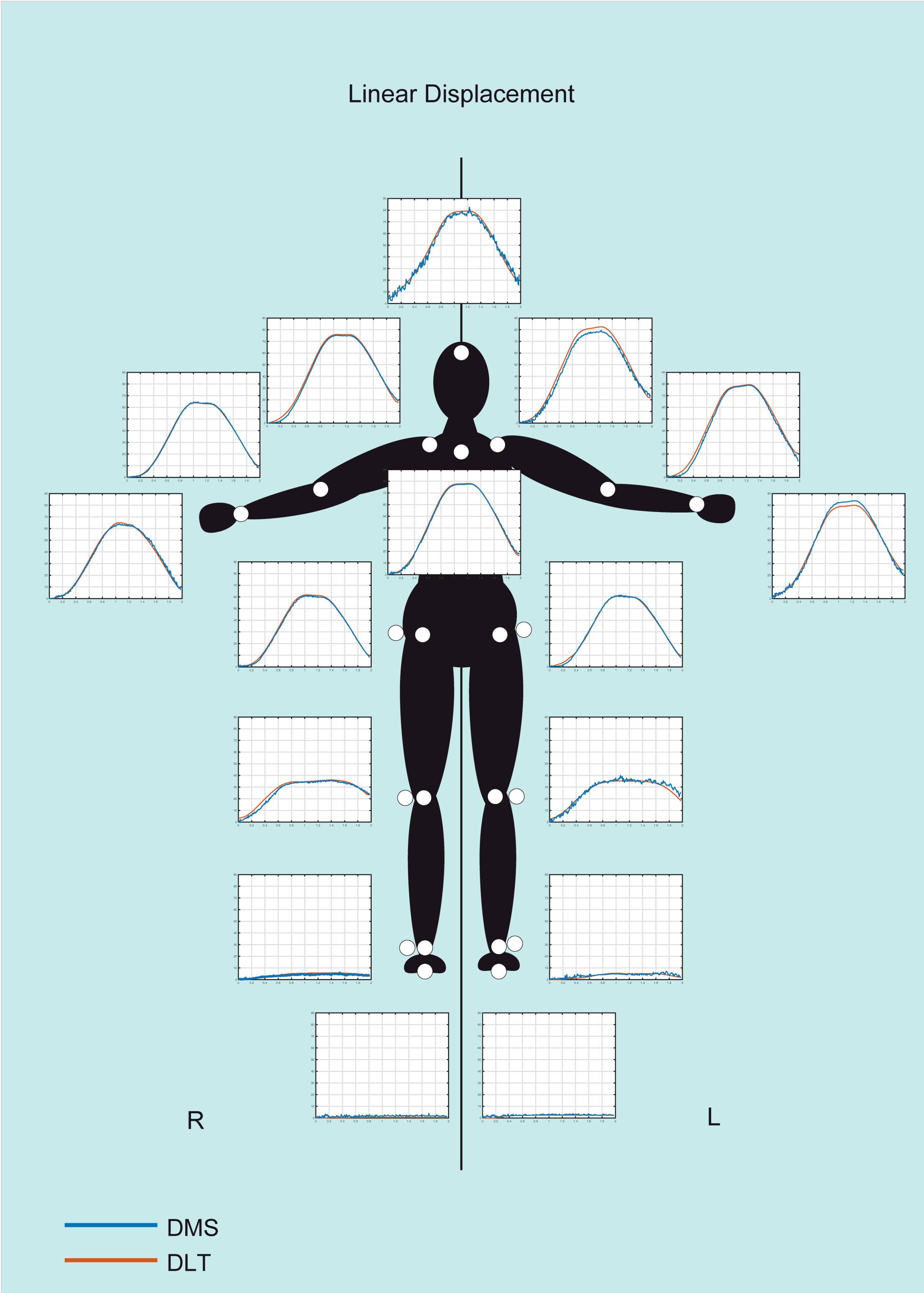


Figure 5.11. Comparison between the DLT and DMS methods for linear displacement. DLT results (red lines) and the DMS results (blue lines) are shown in the graphs. Graphs represent the amount of displacement for each joint (in cm, from 0 to 90 cm) over time (in seconds).

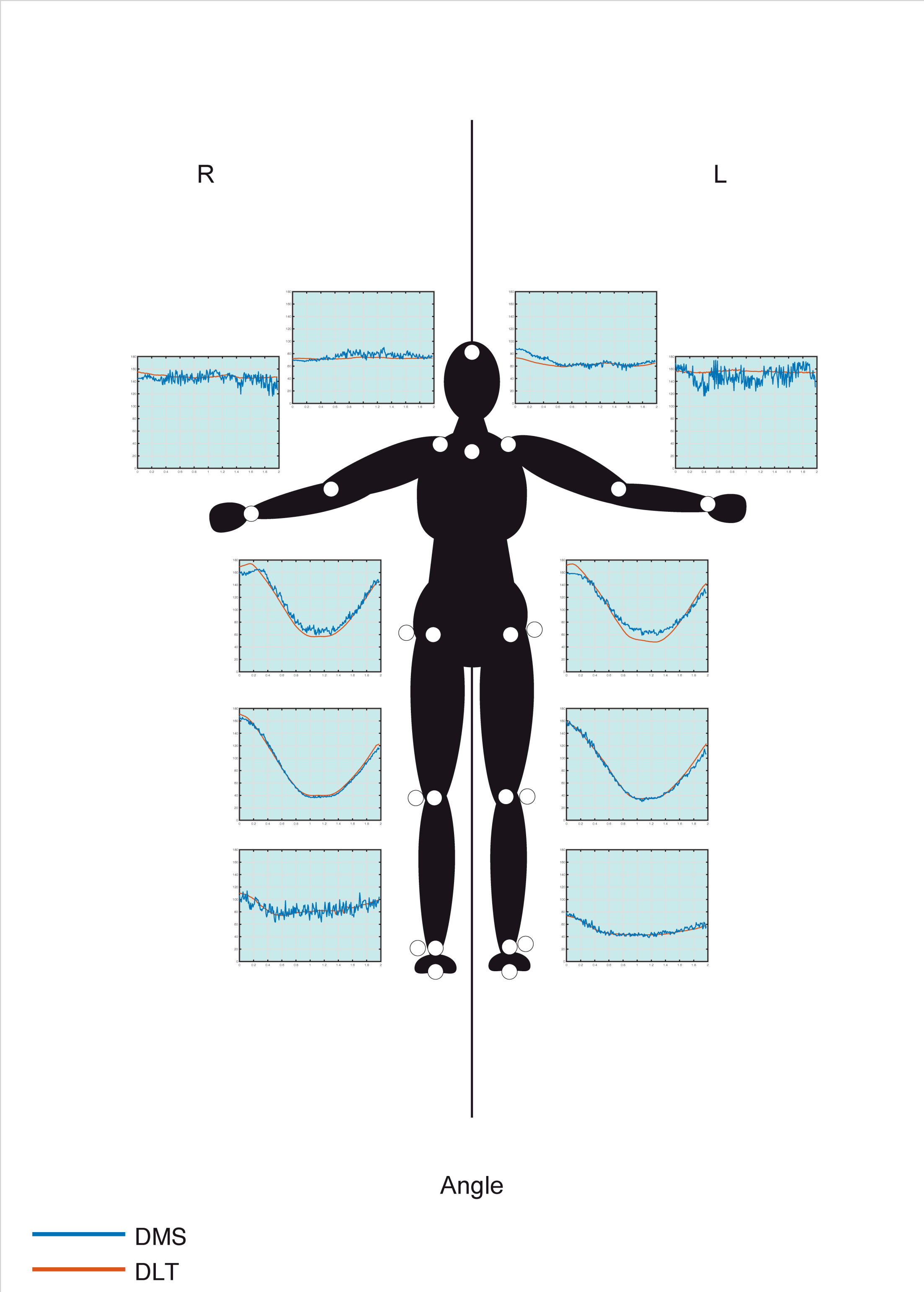


Figure 5.12. Comparison between the DLT and DMS methods for angles. DLT results (red lines) and the DMS results (blue lines) are shown in the graphs. Graphs represent the angle measured (in degrees, from 0 to 180) over time.

For linear displacement, R^2 values were all above 0.9 (ranging from 0.92 to 0.99), with the exception of the left ankle (measuring 0.7), right and left foot (measuring 0.14 and 0.53 respectively). Mean RDs ranged from 0.45 to 3.3 cm with SDs ranging from 0.35 to 1.53 cm (see Table 5.1). Also, TOST values were found to be significant for all points when the equivalence margins were set to ±7.2 cm. The margins were found after repeated measurements revealed equivalence between methods for all points, considering a p-value of 0.05.

Table 5.1. Results linear displacement

	R^2	Mean RD	Max RD	SD
Head	0.99	2.30	7.67	1.39
Trunk	0.99	0.81	2.50	0.54
Left Shoulder	0.99	3.30	5.98	1.53
Left Elbow	0.99	2.10	6.97	1.38
Left Wrist	0.99	2.00	4.20	1.23
Left Hip	0.99	0.65	2.74	0.58
Left Knee	0.96	1.57	7.21	1.53
Left Ankle	0.70	0.84	3.87	0.69
Left Foot	0.53	0.49	2.71	0.50
Right Shoulder	0.99	1.49	3.54	0.83
Right Elbow	0.99	0.45	2.33	0.32
Right Wrist	0.99	1.14	4.02	0.79
Right Hip	0.99	0.83	2.01	0.53
Right Knee	0.98	1.52	4.90	1.22
Right Ankle	0.92	0.47	1.49	0.35
Right Foot	0.14	1.21	3.29	0.57

For angles, R^2 values were more dispersed (see Table 5.2), with highest values measured for the hips, knees, and left ankle (ranging from 0.91 to 0.99). Intermediate values were measured for the two shoulders and right ankle (ranging from 0.22 to 0.73), whereas low values were measured for left and right elbows (0.01 and 0.025, respectively). Mean RDs were all under 10 degrees with SDs values measuring less than 6 degrees, with the exception of the left elbow which measured a mean RD of 11.64 (SD 8.32) degrees. TOST values were found to be significant for all angles when the equivalence margins were set to ±10.009 degrees after repeated measurements revealed equivalence between methods for all angles, considering a p-value of 0.05.

Table 5.2. Results angles

	R^2	Mean RD	Max RD	SD
Left Shoulder	0.73	4.87	15.86	4.47
Left Elbow	0.01	11.64	38.03	8.32
Left Hip	0.98	9.48	19.84	5.22
Left Knee	0.98	3.08	16.07	3.17
Left Ankle	0.91	2.39	10.58	1.81
Right Shoulder	0.25	4.49	16.24	3.37
Right Elbow	0.011	6.71	30.18	5.08
Right Hip	0.97	7.29	18.70	4.20
Right Knee	0.99	3.10	11.07	1.97
Right Ankle	0.46	6.15	23.521	4.70

5.4 Discussion

For the most part, the results obtained with the DMS method appear to be in line with the DLT method. For linear displacement, greater differences were present for less mobile joints (i.e., feet and ankles). However, when considering the mean RDs, they were all under 1.5 cm. This difference is relatively low, especially when considering that the highest mean RD was registered for the left shoulder (measured 3.3 cm). This is further emphasized when considering the SDs, which were all low for both feet and ankles (0.35-0.69 cm) along with maximal RD of 1.49-3.87 cm. Compared to other joints, highest SD was registered to the left shoulder (1.54 cm), and highest maximal RD measured to the head (7.76 cm). This type of trend is to be expected seeing that measurements for less mobile points are more susceptible to small differences, especially when considering that both methods are an approximation of the real values, and as such, are more likely to present greater differences for fixed points.

For angles measured between the two methods, the data also seem to suggest that for the less active joints (in angular terms), results differ greatly compared to the more active joints. In fact, according to their R^2 values, the joints may be divided into three groups in terms of activity: highly active (knees, hips, and ankles), moderately active (shoulders), lowly active (elbows). The exception in this case was the right ankle, which presented an R^2 value of 0.46, however, when looking at the graph it is evident that this value is mostly due to dispersion (Figure 5.12). The level of activity of the joints may also be seen by the sequenced images of the movement, in which the elbows appear to be at a relatively stationary angle compared to the other joints, followed by the shoulders (Figure 5.10). When examining the graphs obtained from the angular measurements, it is possible to see that the general trend appears to be very similar between methods (Figure 5.12), with greater data dispersion for the DMS method compared to the DLT method. As for linear displacement, also in this case it appears that as the measurement in question is more stationary, greater differences ensue. With that in mind, still all of the mean RDs between methods were under 10 degrees, with the exception of the left elbow measuring at 11.64 degrees. Such difference may easily be attributed to relatively smaller differences between the position of joints, where even slight movements may greatly influence the angles measured, which is further magnified the more stationary the measurement is.

Some general limitations provided by both the DLT and the DSM method should be noted. As pointed earlier, video analysis produces less accurate results compared to other systems, such as optical capture systems (Chèze, 2014). Also, it is well known that a marker-based measurement may result in inaccuracies due to inaccurate placement, skin movement, attachment on loose clothing etc. In fact, alternative markerless-based approaches are emerging to overcome these difficulties (Ceseracciu et al., 2014).

As for specific limitation of the DMS method, as demonstrated by the graphs, is that measurements for the DMS method present a greater dispersion of data. This is mostly due to the fact that a more precise measurement is needed in order to retrieve the markers diameters and, by being a pixel-based measurement, it is more likely that the diameters measured will be skewed from one frame to another, especially when objects are more distant or less mobile. Moreover, dispersion of data may be the result of inaccuracies in acquisition due to contrast issues within the video, which may limit the visibility of contours of the markers. The importance of adequate contrast between marker and surrounding is emphasized also in other works e.g., (Ceseracciu et al., 2014; Magalhaes et al., 2013). In fact, in our experience a higher dispersion of data was found for the joints in which contrast between the marker and the surroundings was lowest (i.e., head, trunk, wrists).

These inaccuracies of the DMS methods may, however, be substantially reduced by increasing the resolution of acquisition as well as the frames per seconds. The new commercial cameras, such as action cameras, provide a resolution up to 4K at 30 frames per second (reduced when frames per second are increased), which is sufficiently high to reduce measurement errors. Also, a manual tracking of the markers, instead of the automated algorithms of various software, may further increase the accuracy of the method. Finally, data dispersion may be reduced either by applying adequate filters or data smoothing.

Still, it should be considered that the DLT method also has its own inherent errors as the transformation from R2 to R3 based on only a few markers remains as only an approximation, which may be reduced by increasing the number of calibration markers. Worth mentioning is the fact that in this study we compared the DLT method calibrated according to 19 points to the DMS method, calibrated with only three diameters.

5.5 Conclusions

The DMS method appears to provide relatively similar results compared to the DLT method, at least when gross movements are concerned. This method may be used alongside the DLT method in cases in which markers become hidden in one of the cameras. This way, by calibrating the cameras also according to the DMS method, data relative to said marker may still be salvaged. Also, the algorithm presented here may be of value for acquisition of data in specific tasks such as gait, that when is studied with a single camera, only the sagittal plane is considered (e.g., (Castelli et al., 2015; Yang et al., 2016). This way information that may be obtained from a frontal plane is eliminated. Perhaps the biggest advantage of the DMS method is that the entire calibration process is very simple compared to other approaches of 3D reconstruction with a single camera, or multiple cameras in general, which translates in rapidly obtained data. Also, the use of a single camera and three markers renders it much more mobile than other methodologies. This may be of value especially when the goal of the measurements is to provide a general estimation of the movement rather than a precise description. As pointed out in a recent review by Hewett and Bates (Hewett and Bates, 2017), preventive biomechanical interventions may help in reducing the incidence of various musculoskeletal injuries, referred by the authors as "preventive biomechanics". Therefore, having some measurement in a clinical setting may help in identifying those people who might benefit the most from preventive interventions. The simplicity and mobility of the DMS method may render it as an adequate instrument for widespread this type of clinical use or in other uncontrolled environments.

6 Visuomotor perturbation in a continuous circle tracing task: novel approach for quantifying motor adaptation

Abstract. The study of motor adaptation certainly has advanced greatly through the years, and helped to shed light on the mechanisms of motor learning. Most paradigms used to study adaptation employ a discrete approach, where people adapt in successive attempts. Continuous tasks on the other hand, while known to possess different characteristics than discrete ones, have received little attention regarding the study motor adaptation. In this paper, we test for adaptation using a continuous circle tracing task with a visuomotor gain perturbation. To examine feasibility of this task, 45 normal subjects divided into 3 groups were tested for adaptation, aftereffects and generalization. The results appear to be in line with the requisites for visuomotor adaptation to gain perturbations. Specifically, all subjects exhibited a gradual adaptation when faced with a perturbation as well as opposite aftereffects once the perturbation was removed. Aftereffects tended to persist unless veridical feedback was given. The task generalized well both in size and in space. We believe that this task, by being continuous, could allow for a thorough investigation of visuomotor adaptation to gain perturbations in particular, and perhaps be expanded to other types of adaptations as well, especially when used alongside with discrete tasks.

6.1 Introduction

Motor adaptation refers to the process by which behavior is modified to accommodate a certain perturbation encountered. It is thought to occur not by a simple error correction mechanism, but by a modification of internal representations based on predictions of the eventual outcome of the movement itself (Izawa et al., 2008). This adaptive process requires the brain to make several assessments regarding the perturbation it is facing. The first of which is whether the perturbation is systematic or transient in nature (Haith and Krakauer, 2013). The distinction between the two will determine whether a change in behavior is necessary, as transient perturbations should not elicit an adaptive response and would therefore be solely compensated. Systematic perturbations on the other hand, would merit a consequent change in behavior, as the perturbation cannot not be attributed to randomness (Berniker and Kording, 2008). This would result in a gradual improvement following the abrupt presentation of the perturbation. If adaptation has occurred, then once the perturbation is removed, reverting back to normal performance would occur at a certain delay, what is commonly known as “aftereffects” (Weiner et al., 1983), resulting in errors opposite to those present initially when the perturbation was introduced. Furthermore, if indeed an internal representation was modified, the adapted behavior would be expected to generalize also to other circumstances (Shadmehr, 2004; Shadmehr and Mussa-Ivaldi, 1994).

The study of motor adaptation commonly employs the use of discrete tasks (e.g., reaching), operating on a trial-to-trial basis, evaluating the trial-by-trial learning or cumulative learning over successive trials. This approach is inherently long and may require hundreds of trials e.g., (Inoue et al., 2015), although, it was suggested that even a few trials may produce long-term retention in some cases (Huberdeau et al., 2015; Krakauer et al., 2000). Still, when using a trial-by-trial approach, the presence of an inter-trial interval is inevitable. Though this interval was shown to be an important factor for

Cohen EJ, Wei K, Minciacchi D (2019) Visuomotor perturbation in a continuous circle tracing task: novel approach for quantifying motor adaptation. Sci Rep. 9:18679. doi: 10.1038/s41598-019-55241-4.

learning, as it may affect the decay of learning, the extent by which it may affect learning is not well characterized (Kim et al., 2015; Kitago et al., 2013). Still, the mere presence of an inter-trial interval, by leaving room for preparation time which could influence the extent of learning (Haith et al., 2015), may represent a confounding factor when interpreting results and, therefore, must be meticulously controlled if we wish to compare subjects.

In addition, a trial-by-trial assessment is accompanied by several uncertainties regarding the performance. For example, when moving to different directions, as is often the case in reaching adaptation paradigms e.g., (Huang et al., 2018; Maschke et al., 2004; Mostafavi et al., 2014; Smith and Shadmehr, 2005; Taylor et al., 2014), each trial is accompanied by an initial uncertainty regarding the location of the target. A second uncertainty is related to the nature of the perturbation, whether it is persistent (i.e., always present) and consistent (i.e., always of the same magnitude). The third is whether the perturbation is specific to a single direction, or present in all directions equally. Although, subjects will eventually adapt also in noisy environments and conditions, these uncertainties are likely to generate compensatory responses that are not a manifest of adaptation per se. This is evidenced in force field perturbation paradigms where people use impedance control against uncertain perturbation (Franklin et al., 2003; Orbán and Wolpert, 2011; Thoroughman and Shadmehr, 1999). While impedance does reduce as the the internal model is learned and updated (Takahashi et al., 2001), it could potentially contaminate the results when the adaptation period is limited. Though it remains debatable whether and to what extent impedance control plays a role in other adaptation paradigms (e.g., rotation perturbation), uncertainty surely plays an important role in motor adaptation and all of these factors may affect both performance as well as the interpretation of data.

It is possible to eliminate some of these uncertainties. For example, testing for a single direction, may eliminate the uncertainty regarding the target's location as well as the perturbation specificity. However, which direction is better? direction specificity was shown to play an important role in adaptation (Jiang et al., 2018; Yin et al., 2016) and, as such, the elimination of different directions may produce incomplete results, especially when considering that baseline performance is already direction specific. On the other hand, testing more directions will reduce use-dependent learning (Diedrichsen et al., 2010) and increase the number of trials.

It should be noted that these "issues" related to discrete tasks may also be desired, especially when we wish to examine certain specific aspects relative to components of motor adaptation. For example, the modulation of inter-trial interval may be used to favor explicit components of learning e.g., (Haith et al., 2015). Moreover, under certain circumstances, we may wish to examine the effects of a certain direction on adaptation and, therefore using different directions may be important (Jiang et al., 2018). However, if we do wish to conduct a study in which the effects of these factors are reduced, we could opt to use motor adaptation that involves continuous movements e.g., (Bruijn et al., 2012; Reisman et al., 2007; Schmid et al., 2011; Van Ooteghem et al., 2008). In fact, continuous adaptation does not require preparation time and, as such, should provide more consistent results by removing this confounding factor. Moreover, as the movement is continuous, any uncertainty related to either direction or the perturbation itself is eliminated. Trial-by-trial decay of learning might also be reduced, thus adaptation can potentially be achieved rapidly.

In this paper, we examined motor adaptation to a visuomotor gain perturbation using a continuous task of circle tracing. This specific task was chosen since it was shown to provide consistent results across measurements (Cohen et al., 2018a). Moreover, by being a simple and continuous task it may greatly reduce any confounding factors related to inter-trial interval as well as, by being a circle, to direction biases and specificity. Though the circle-drawing task was previously used to assess explicit and implicit motor adjustments (Sülzenbrück and Heuer, 2009). The persistence as well as extent of adaptation were not adequately addressed. To overcome these issues, we have examined adaptation for a large perturbation and for a longer period, as well as two types of generalizations.

6.2 Materials and Methods

6.2.1 Participants

45 healthy adults were recruited for this study (age: 20.35±2.98 years; 21 males). All participants were right handed. Participants were naive to the task and the purpose of the study, and free of documented neurological impairments. All participants reported to have a corrected-to-normal visual acuity. The study protocol was approved by the Institutional Review Board of Peking University and all procedures conformed to the code of ethics of the Declaration of Helsinki. All participants gave written informed consent and were paid for their time.

6.2.2 Set up and Task

Participants were presented a circle template projected on a monitor mounted vertically in front of them at eye level (Figure 6.1). A black paperboard occluded vision of the hand. On the circle template (5.4 cm in radius) a small red moveable circle represented the starting point. The participants were instructed to executed tracings of a circle, using graphic pen tablet (Wacom Intuos® PTK-1240, Tokyo, Japan; active area: 462 x 305 mm), while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen. Further instructions included tracing the target circle counterclockwise as fast as they can while still being accurate. Before starting the task, each participant was asked whether the instructions were understood. Once participants positioned themselves at the correct point, the small circle turned to green indicating the start of the trial and the cursor became invisible. During execution, the cursor position, represented by the small circle, was visible. The cursor trajectory was also visible, and was reset every revolution. The position of the small circle as well as the cursor trajectory will be referred to as cursor feedback. Each participant was tested individually.

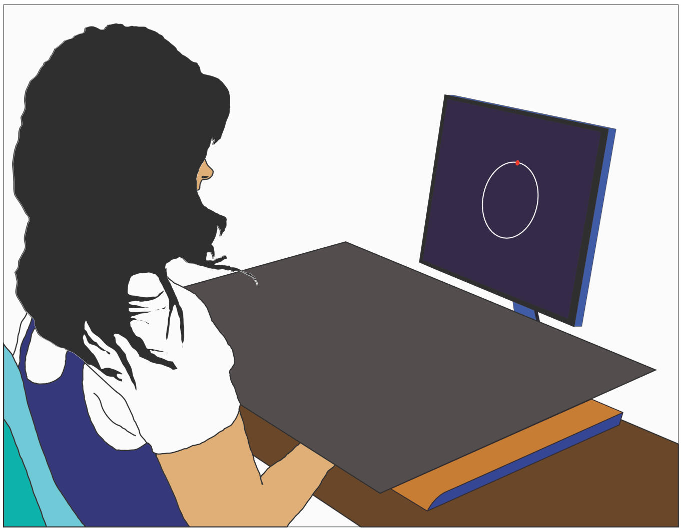


Figure 6.1. Setup. Diagram illustrating the experimental setup. Each subject was presented a circle template projected on a monitor in front of her/him at eye level. A black paperboard occluded vision of the hand. The subjects executed tracings of a circle, while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen.

6.2.3 Experimental Design

Subjects were divided into three groups (n=15/group; 7 males/group), two generalization groups (size and spatial generalization; i.e., Size and Shift), and a post-adaptation group (i.e., Post; Figure 6.2).

Subjects were trained to adapt to a gain perturbation of the cursor position about the origin of the circle. To achieve robust effect, perturbation was set to 250% gain, causing the desired tracing of the circle to be 40% of the original circle size (40% of 5.4 cm i.e., 2.16 cm in radius). In the generalization group each session consisted of the following trials: familiarization (10 revolutions of a circle with veridical cursor feedback), baseline (10 revolutions of a circle with veridical cursor feedback), baseline no feedback (i.e., Baseline NF; 10 revolutions of a circle with no cursor feedback), training (50 revolutions of a circle with a gain perturbation of 250% of the cursor), aftereffects (10 revolutions of a circle with no cursor feedback), and generalization (2 trials each consisting of 10 revolutions with no cursor feedback).

For the Shift group, the target circle's template was shifted 10 cm to the left or to the right of the original circle, one trial for each. For Size group, the circle's template presented was either bigger (150% of original radius, i.e., 8.14 cm) or smaller (50% of original radius, i.e., 2.71 cm), one trial for each. For Size and Shift groups each subject performed both generalization trials related to the group (either large and small size or left and right shift, respectively), along with aftereffects trial. For these groups, the order of the aftereffects and generalization trials was randomized.

In the Post group, each subject participated in one session consisting of baseline (10 revolutions with veridical cursor feedback), training (50 revolutions with gain perturbation of 250% of the cursor) and a post-adaptation trial (10 revolutions of a circle with veridical cursor feedback).

6.2.4 Analysis

Following data collection, circle tracing analysis consisted of calculation of traced circle radii, measured as point distances from the template's center (i.e., radius). For each measured radius, deviations from the template's radius (i.e., reference radius) were also calculated (i.e., residual difference; RD) and are presented as percent deviation from the expected radius (i.e., % radius difference; %RD; Figure 6.3). Point direction was calculated as the angle difference from the starting position, considering the circle center as the vertex. Since subjects may present certain biases for specific direction (Classen et al., 1998; Haar et al., 2015; Huang et al., 2011; Jax and Rosenbaum, 2007), the mean error per angle was calculated for the baseline performance. Following that, the baseline performance was subtracted from the measurements of all other trials in an angle specific manner. For the generalization group, since aftereffects and generalizations had no feedback, baseline NF was used as a measurement for potential biases for these trials. The amount of learning was derived from %RD of the expected adapted radius and is presented as %Learning, where 100% represents a complete adaptation (i.e., %RD equals zero for the expected adapted radius). Learning rate was estimated as the %Learning averaged over the first 3 revolutions of the training trial.

6.2.5 Statistics

To evaluate any potential between-group difference a One-Way ANOVA was implemented on the average %RD of the baseline performance of each subject. To evaluate any differences that may relate to adaptation between groups a One-Way ANOVA was also implemented on the %Learning during training for each subject.

To evaluate the immediate extent of learning, a two-tailed t-test of %Learning was conducted comparing the mean of last 3 revolutions during training with the first evolution of the following trials (i.e., aftereffects, generalization, post-adaptation). As a measure of the significance of decay, the average of first 3 revolutions of each trial was compared with the average last 3 revolutions of said trial using a two-tailed t-test. To evaluate potential within trial decay in the generalization groups, the average %Learning of the last 3 revolutions of the aftereffects and generalization trials was also calculated and compared with the average of the first 3 revolutions using a two-tailed t-test.

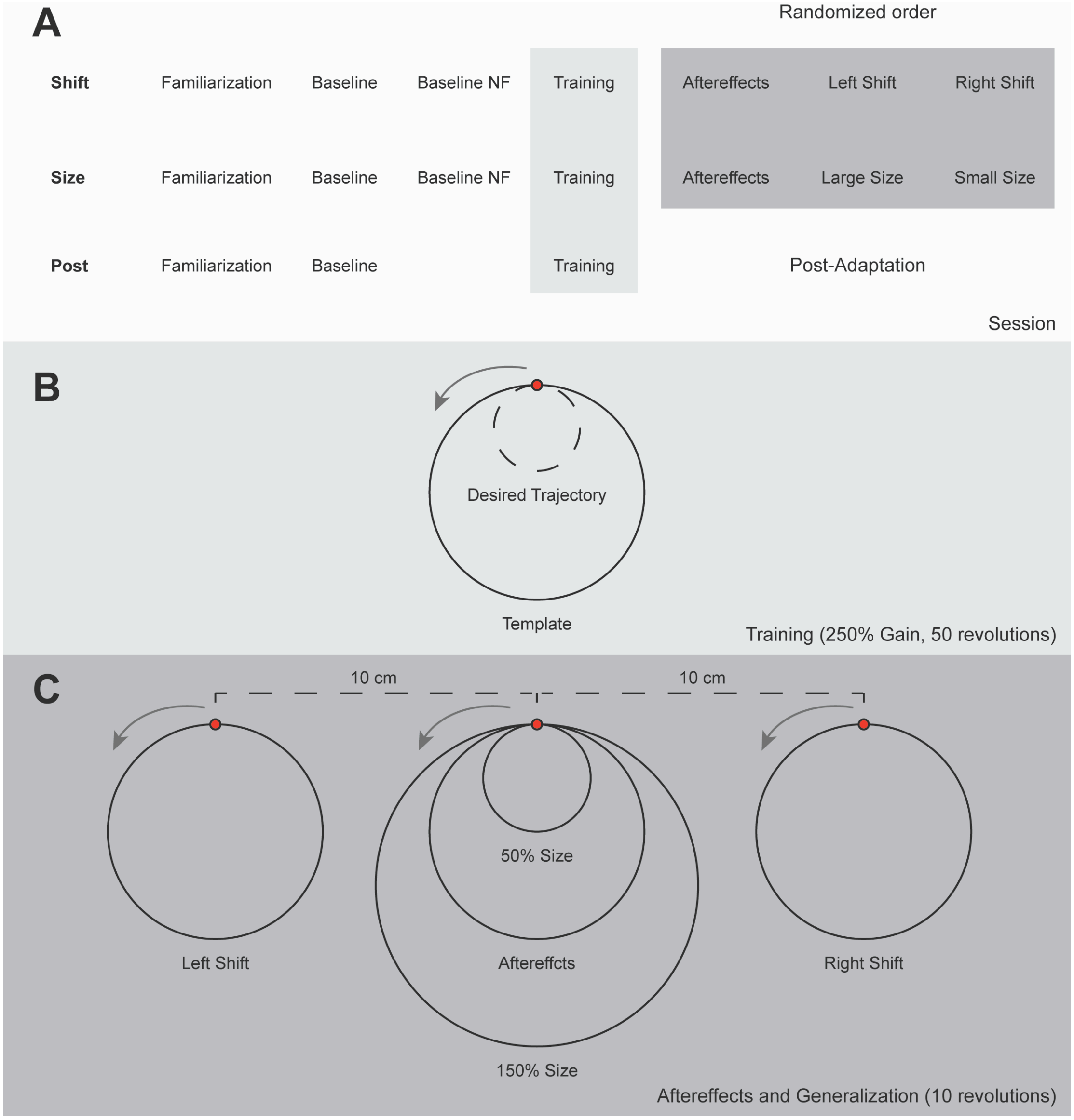


Figure 6.2. Experimental design. A. Schematics of the session organization. Subjects were divided into one of three groups: Shift, Size and Post. For both Shift and Size groups, the session consisted of the following trials: familiarization (10 revolutions with veridical feedback), baseline (10 revolutions with veridical feedback), no feedback baseline (Baseline NF; 10 revolutions with no feedback), training (50 revolutions with 250% gain perturbation to cursor feedback), aftereffects and two generalization trials (left and right shift for Shift group, large and small size for Size group, each consisting of 10 revolutions with no feedback). The order of the last 3 trials (i.e., aftereffects and generalization trials) was randomized. For the Post group, the session consisted of the following trials: familiarization, baseline, training and post-adaptation (10 revolutions with veridical feedback). B. A diagram demonstrating the circle template presented to the subjects. During the trial, the cursor position was represented by the small circle (shown in red). Subjects were asked to trace the circle according to the template. During the baseline trial the desired trajectory corresponded to the circle template. During training, a 250% gain perturbation to the cursor feedback was introduced. In order to match the template subjects needed to draw a circle 40% smaller than the original (i.e., desired trajectory; represented by the dashed line). C. Diagram showing the different templates used for the aftereffects and generalization trials. In these trials no feedback was presented. For the aftereffects, the circle's template presented was the same size as the original, located at the same place (i.e., Aftereffects). For Shift group, the circle's template was of the same size, shifted to the left (i.e., Left Shift) and to the right (i.e., Right Shift). For Size group, the circle's template was 50% the size of the original (i.e., 50% Size) and 150% the size of the original (i.e., 150% Size) presented at the same place as the original.

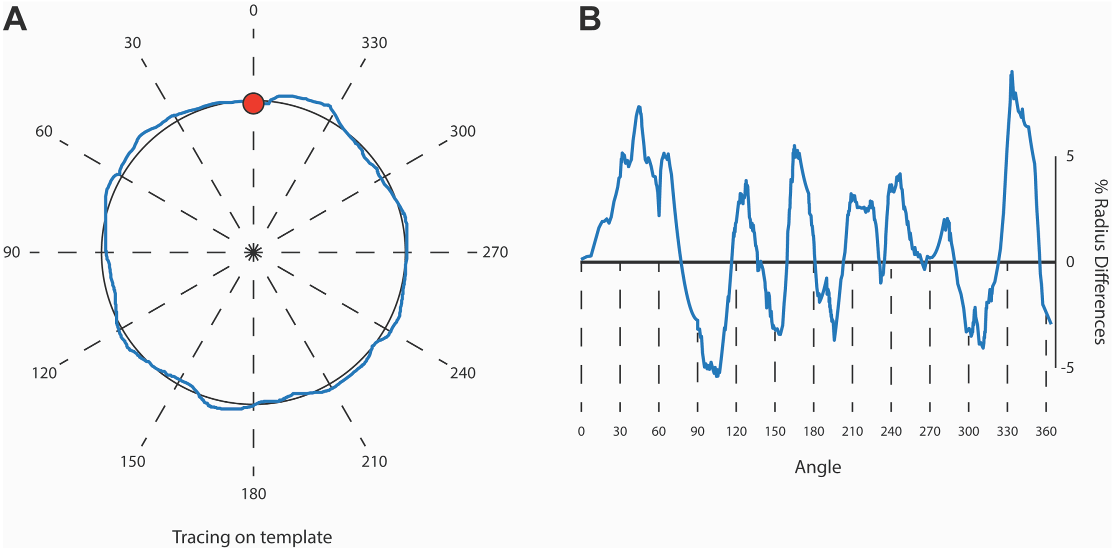


Figure 6.3. Circles analysis. An example of the calculation of the precision of a traced circle. A. A complete revolution of a traced circle drawn counterclockwise (blue line) on a template is shown. The center of the template was used to measure the radius of each point on the tracing. B. For each angle of the circle the template's radius was subtracted from the measured radius at that specific angle in order to obtain the Radius Difference, which was divided by the template's radius to obtain % Radius Difference for every direction of the circle over time.

6.3 Results

The adaptation and subsequent tests of aftereffect and generalization were performed in a couple of minutes. Across all subjects and trials, average completion time for the entire session was 126.32±35.7 seconds.

First, we found no significant differences in baseline performance between groups ($F_{2,42} = 0.88$, $p = 0.42$, one-way ANOVA). Baseline precision (measured as %RD) across subjects averaged -1.81±3.87%. For every subject, baseline performance was shown to be relatively consistent with small variation across revolutions as shown by the change in SD of the %RD across revolutions for every subject averaging 4.72±1.69%.

During the training trial, all subjects, in all groups, showed an immediate increase in error upon the introduction of visuomotor gain adaptation, averaging 39.2±35.8 %Learning for the first revolution. Then, they exhibited a gradual reduction in error, with an average learning rate of 64.4 ±21.6% by the end of the third revolution. Also in this case no significant differences were found between groups ($F_{2,42} = 0.61$, $p=0.54$, one-way ANOVA). As a measure of the extent of learning during training, the average of the last 3 revolutions was calculated for each group and measured 95.2±9% for Size group, 92.3±12% for Shift group and 98.9±5.6% for Post group. At the end of the session, all our subjects reported to be aware of the perturbation.

The immediate extent of learning following training for the Size group averaged 108±24.1% for the aftereffects trial, 86.1±32.7% for the small size, and 104.5±21.3% for the large size (Figure 6.4), all of which were not found to be significantly different compared to the average of the last 3 revolutions during training ($p=0.1$, $p=0.33$, and $p=0.17$). For the Shift group, extent of learning averaged 88.4±25.3% for the aftereffects trial, 94.2±31.6% for left shift and 91.8±30.7% for right shift (Figure 6.5). Also in this case no significant differences were found between the trials and the last 3 revolutions of the training trial ($p=0.53$, $p=0.82$, and $p=0.94$, respectively). These results suggest that generalization to size may have a more robust effect compared to spatial generalization, as the values for both aftereffects and large size trials were larger than 100% learning. For the Post group, immediate extent of learning averaged 94.3±29.3% (%Learning of the first revolution; Figure 6.6), not showing any significant differences with the average of last 3 revolutions of training (p=0.57).

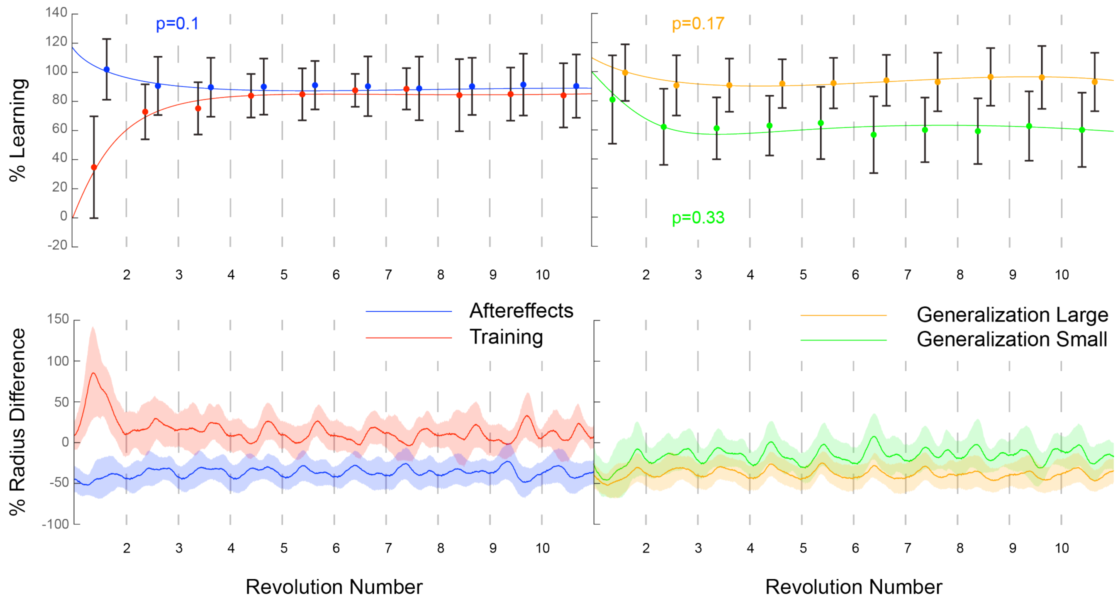


Figure 6.4. Results Size group. Results obtained for the Size group (n=15) presented as %Learning (upper panel) and % Radius difference (lower panel). On the left side are the results obtained from both training (red; only first 10 revolutions) and aftereffects (blue), whereas the right side are the results obtained from the large generalization (orange) and small generalization (green). For %Learning, the dots represent the revolution's mean whereas the error bar represent the standard deviation for said revolution; the solid lines illustrate the general trend during the trials. In the lower panel % Radius difference are presented as mean (line) and standard deviation (shaded areas). P-values refer to the performance of the last 3 revolutions of training compared to the first 3 revolutions of the other trials. It is possible to note that subjects maintain their adapted state throughout with the exception of the small generalization, in which values demonstrated a slight reduction in adaptation.

No significant within trial decay was found for any of the trials of the Generalization groups. Specifically, aftereffects measured as %Learning of the adaptive state, averaged 83.4±24% for the first three revolutions, decaying to 80.3±23.9% (p=0.15) for Shift, and 102±20.3%, decaying to 99.4±20.6% (p=0.21) for Size. For Shift group, %Learning averaged 87.6±30.3% for left shift, decaying to 85±27.1% (p=0.42); for right shift %Learning averaged 85.9±26.2%, decaying to 81.7±22.6% (p=0.11). For Size group, small size averaged 73.2±27.1%, decaying to 65.8±26.1% by the last 3 revolutions (p=0.13). For large size %Learning averaged 98.6±21% and presented no decay, reaching 100.2±24.4% (p=0.6) by the last 3 revolutions. In sum, generalization across sizes and space was large with small decay over time.

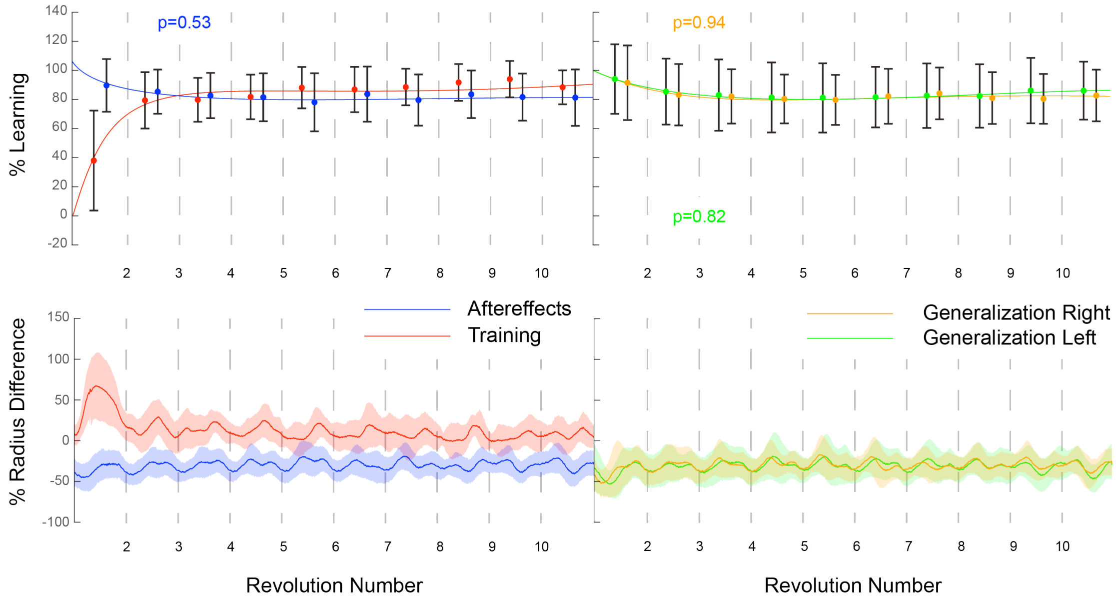


Figure 6.5. Results Shift group. Results obtained for the Shift group (n=15) presented as %Learning (upper panel) and % Radius difference (lower panel). On the left side are the results obtained from both training (red; only first 10 revolutions) and aftereffects (blue), whereas the right side are the results obtained from the right generalization (orange) and left generalization (green). For %Learning, the dots represent the revolution's mean whereas the error bar represent the standard deviation for said revolution; the solid lines illustrate the general trend during the trials. In the lower panel % Radius difference are presented as mean (line) and standard deviation (shaded areas). P-values refer to the performance of the last 3 revolutions of training compared to the first 3 revolutions of the other trials. It is possible to note that subjects maintain their adapted state throughout all trials with a very small decay.

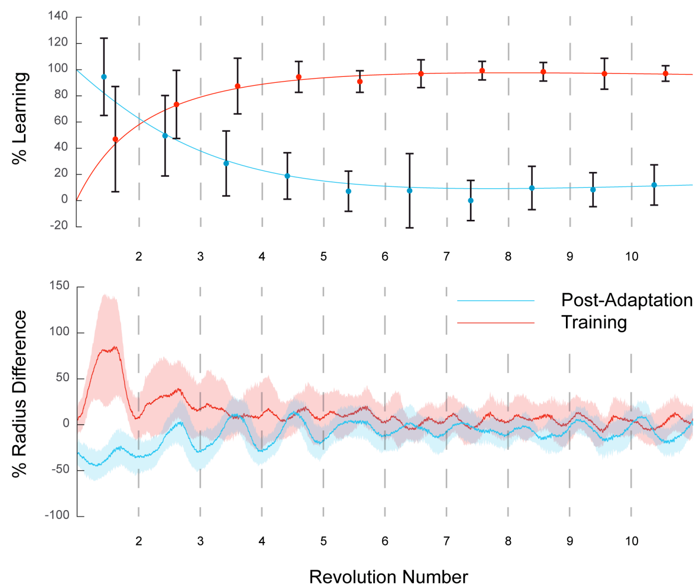


Figure 6.6. Results Post-adaptation group. Reported are the results obtained for the Post group (n=15). Results for training (red) and post-adaptation (blue) are shown reported as mean (dots) and standard deviations (error bars) of %Learning (upper panel) and mean (lines) and standard deviations (shaded areas) of % Radius difference of the expected radius (for training is 40% of the original). As expected, the two trials present opposite trends with training initially having larger radii gradually reducing and post-adaptation having smaller radii gradually increasing.

To examine decay across trials for the generalization groups, the average of each trial according to its order was calculated as %Learning of the last 3 revolutions. For the first trial after training, %Learning averaged 92.7±26.6%, for the second 85.5±25.9% and for the third 77.4±25.9%. Revealing an inter-trial decay of learning of ~7.5%.

For the Post group, as expected, subjects presented opposite trends during training and post-adaptation as shown by the change in %RD. For training, initial %RD for the first 3 revolutions averaged 29.4±20.5% than expected radius (69.3±26.5 %Learning). For post-adaptation, subjects initially performed smaller radii, averaging -20.9±9.8% (57.2±23.9 %Learning) by the third revolution. These trials presented converging trends as they continued and by the tenth revolution %RD values measured 4.1±8.2% for training and -6.9±5.3% (for post-adaptation) (Figure 6.6). It should be noted that even though a large perturbation was used, which could favor the formation of an explicit strategy, the non-immediate return to baseline in the Post group suggests that an internal model was indeed updated.

6.4 Discussion

The results in this study appear to satisfy the prerequisites for visuomotor adaptation to gain perturbations. Specifically, we observed a gradual reduction in error after the introduction of the perturbation as well as the presence of opposite aftereffects once the perturbation was removed. Furthermore, the task generalized in space and in size, showing a relatively small decay in time. Interestingly, the extent of adaptation appears to be long lasting when no veridical feedback is presented, as shown by the by both high retention of adaptation as well as low decay during generalization.

The presence of long lasting aftereffects is somewhat reminiscent to prism adaptation, in which, unless veridical feedback is provided, adaptation tends to persist or present a slow decay (Hatada et al., 2006). Since the common denominator between prism adaptation and circle tracing adaptation appears to be that both are continuous processes, it is possible that long lasting aftereffects would be related to this feature. In fact, it is widely accepted that skill acquisition in continuous tasks is better retained than discrete ones (Schmidt and Lee, 2011), though whether this holds true for motor adaptation remains debatable. The similarity with prism adaptation however raises a few questions, as prism adaptation was shown to have effects extending beyond visuomotor parameters, e.g., visuospatial, visuoverbal, tactile perception, spatial attention as well as mental imagery (Berberovic et al., 2004; Farnè, 2002; Maravita et al., 2003; Rode et al., 2001), suggesting that the global representation of space is modified. In contrast to prism adaptation, since there is only spatially-bounded alteration to visual perception in the circle tracing task, a global modification to the representation of space is unlikely, therefore an extension to non-visuomotor parameters appears improbable. However, since visuomotor remapping does cause the effector-space interaction to be modified, it is possible that some of the effects present in this tracing adaptation, by being long-lasting, could transfer to other non-trained tasks within the motor domain, similarly to prism adaptation (Jacquin-Courtois et al., 2008; Tilikete et al., 2001).

Using this task, several of the issues related to discrete measurements indeed may be eliminated. Specifically, there is no inter-trial interval and, as such, any issue related to preparation time (Haith et al., 2015) or decay of learning is minimized (Kim et al., 2015; Kitago et al., 2013). Furthermore, since the perturbation in this case is evident and consistent, the uncertainties related to the nature of the perturbation are greatly reduced. Also, the use of a circle, by covering all possible directions, reduces direction-related issues. It should be considered however, that depending on the nature of the study, the characteristics of the discrete measurements may indeed be desired in order to investigate certain aspects related to motor adaptation. Therefore, the implementation of a continuous approach could not substitute a discrete one, and the two are best implemented alongside.

The continuous approach holds an additional advantage compared to other paradigms. In reaching paradigms, it is important to consider the possibility of inaccuracies between measurements, both within a single study as well as between labs. A simple example from reaching adaptation paradigms is whether the reach angle is calculated at end point or at peak velocity. Seeing that this discrepancy is known, some studies integrate these two measurements e.g., (Haar et al., 2015). This would result in an operational tool for assessment, but not a precise one. Similarly, discrepancies may also derive from how the start position of a reaching movement is defined (i.e., subjects' actual start position or an imposed start point). If 4 mm around an imposed starting position is defined as the area of starting position e.g., (Jiang et al., 2018), the maximum deviation of actual start position from the imposed starting position alone can generate a 6.5° direction deviation between measurements with a reaching distance of 70 mm. As there is no consensus regarding the area around the center for the starting point, these deviations could be even greater e.g., (Huang et al., 2018). All of these minor issues could confound the learning data and its interpretations. In the circle tracing paradigm, since the measurement for adaptation is continuous, these possible inaccuracies are eliminated, as the starting point is constant and the target is uniform across all measurements.

A general limitation of this study is the use of a single type of perturbation, i.e., a visuomotor gain perturbation. It should be noted that not all perturbations are alike. Specifically, gain perturbations are adapted quicker and generalize better than visuomotor rotation perturbation (Krakauer et al., 2000). As such, the results presented in this study cannot be extended also to other types of perturbations (e.g., visuomotor rotation). However, we believe that future studies would indeed benefit from the evaluation of a visuomotor rotation perturbation using a continuous task as suggested in this study. Furthermore, it should be noted that a continuous task also presents limitations compared to a discrete one (e.g., directional generalization cannot be tested using a continuous task). Therefore, considering the differences between discrete and continuous tasks, it would be interesting to examine motor adaptation using a combination of both continuous and discrete tasks. This could permit a more thorough investigation of transfer from one modality to the other, as well as to better characterize the differences between the two. Finally, it should be noted that, granted the size of the perturbation used in this study, the observed adaptation may be due to strategic learning. Under this view, it is possible that subjects would demonstrate strategic adjustments, sensitive to goal based performance error, during the experiment rather than adaptation proper, sensitive to prediction errors between desired and actual consequences of planned movement (Taylor and Ivry, 2012). We should consider however, that the line between gradual adaptation and strategy formation is not easy to define. Explicit report of strategy in the current paradigm (if there is any) will be hard to put into numbers. If we assume the Post group explicitly knew about the gain change when they suddenly received veridical feedback after adaptation, they can pull off their strategy during this washout (i.e., post-adaptation). In this case, if an explicit strategy can fully account for the reported adaptation, we should observe an abrupt de-adaptation. However, this is not what we observed. Even though we indeed saw this group de-adapted faster than other groups, their de-adaptation was still gradual. Thus, we postulate that learning performance here contains implicit learning. Just like rotation adaptation, the relative size of explicit and implicit components might be a function of perturbation size (gain size here). However, this question shall be left for future studies.

7 Predicting behavior not learning: how initial state can predict execution patterns during motor learning

Abstract. Motor learning is integral for our day-to-day interaction with the outside world. As such much effort has been put on the identification of factors that may determine learning. However, as the main focus of current research is based on a single outcome measure for learning, current models for predicting learning from initial state variables have produced contrasting results. Here by investigating the interplay between parameters of the execution throughout performance, we examine the predictability of behavior during learning from the initial state in a repeated continuous circle tracing task. This was achieved by decomposing an outcome variable into different components whose combination is able to numerically determine movement outcome. By identifying movement components of speed and duration, we have created an execution space and divided the subjects according to their initial performance in that space into speed preference, duration preference, and no-preference groups. We found that performances tend to follow the shape of the solution manifold and, furthermore, are dependent on the initial location within the execution space.

7.1 Introduction

Motor learning is integral part of our day-to-day lives, from picking up a phone to playing a piano, the ability to learn is fundamental to our interaction with the world. As such understanding what may determine learning or how learning may be predicted has provoked great interest in current research. Commonly, motor learning is studied by introducing a task and measuring how well it is performed (or how much error is reduced) across trials. Following that, learning rate (how fast does the error reduce) and learning extent (how much of the error is reduced) may be determined. While examining learning is relatively straight forward, predicting learning is by far more challenging.

There are several studies that have investigated whether the initial conditions of certain aspects of performance may influence/determine learning. Most debated is the role of motor variability, which is considered to be an indicator of exploration during learning (Barbado Murillo et al., 2012; Manor et al., 2010; Zhou et al., 2013). It was suggested that the larger the initial variability the faster learning in both reward-based as well as error-based learning (Barbado Murillo et al., 2017; Wu et al., 2014). However, when considering individual differences in learning, predictive power of initial variability may be limited. In fact, (He et al., 2016) argued that inter-individual differences in initial variability could not predict learning rate. It should be considered that initial motor variability is not the only factor that could condition the initial state of performance and learning. A number of factors from working memory (Bisagno and Morra, 2018), visual processing (Baweja et al., 2015), visual-motor connectivity (Mattar et al., 2018), to the influence of previous experience (Witney et al., 2001) and age (Trewartha et al., 2014) were shown to influence motor learning. Therefore, it is clear that in order to predict learning between individuals, a different approach should be implemented.

Cohen EJ, Wei K, Minciacchi D (2019) Predicting behavior not learning: how initial state can predict execution patterns during motor learning. Under Review

As previously stated, examination of motor learning is commonly based on measuring learning rate e.g., (Dhawale et al., 2017; He et al., 2016; van Beers, 2012). Since learning rate is defined by a single measure of outcome (i.e., error reduction), it cannot fully describe how execution evolves nor how execution may support learning. Therefore, if our attention is only outcome oriented, we cannot fully understand the processes governing it. Awareness of this issue is well known, in fact, performance decomposition methods have been developed specifically with the idea of focusing on execution (Cusumano and Cesari, 2006; Furuki and Takiyama, 2019; Latash et al., 2002; Muller and Sternad, 2004). However, the vast majority of these methods was applied only to discrete tasks.

Though discrete tasks, by evaluating performance on a trial-by-trial basis, are extremely useful in dissecting the relationship between error and correction (and consequently learning), some fundamental differences are present between discrete and continuous tasks which may impede transfer of knowledge derived from discrete tasks. In fact, in the continuous tasks, pre-movement planning is less important, consequently there is an ongoing regulation of control (Schmidt and Lee, 2005). Therefore, when it comes to exploration patterns, it is possible that in a continuous task subjects can only make incremental changes, as tasks are to be performed smoothly, therefore, abrupt changes in performance (e.g., following an unsuccessful trial) are less likely to occur. In discrete tasks on the other hand, as more time is present to elaborate previous performance, subsequent performances may vary greatly. In fact, it was shown that reducing inter-trial interval and pre-movement planning, people tend to reduce their strategic learning but rely on incremental error-based learning (Haith et al., 2015; Kim et al., 2015). Therefore, it is likely that certain aspects of performance in a continuous task, by being more incrementally driven, could indeed be predicted by the initial state.

In this study we take an execution-centric approach for motor learning in a continuous task, investigating the interplay between execution variables throughout the performance, regardless of the outcome. For this purpose, a circle tracing task was asked to be performed as fast and accurate as possible. Given the continuous nature of the task, we hypothesize that no abrupt changes in behavior are expected, and therefore execution pattern could be determined by the initial state and remain relatively fixed throughout the performance. Therefore, when no specific indication is given, both the initial state within the execution space as well as by the shape of the solution manifold would determine subjects' performance.

7.2 Material and Methods

7.2.1 Participants

40 healthy adults were recruited for this study (age: 20.27±2.93 years; 17 males). All participants were right handed. Participants were naive to the task and the purpose of the study, and free of documented neurological impairments. All participants reported to have a corrected-to-normal visual acuity. The study protocol was approved by the Institutional Review Board of Peking University and all procedures conformed to the code of ethics of the Declaration of Helsinki. All participants gave written informed consent and were paid for their time.

7.2.2 Set up and Task

Participants were presented a circle template projected on a monitor mounted vertically in front of them at eye level (Figure 7.1). A black paperboard occluded vision of the hand. On the circle template (2.27 cm in radius) a small red moveable circle represented the starting point. The participants were instructed to executed tracings of a circle, using graphic pen tablet (Wacom Intuos® PTK-1240, Tokyo, Japan; active area: 462 x 305 mm), while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen. Further instructions included tracing the target circle counterclockwise as fast and as accurate as possible.

Before starting the task, each participant was asked whether the instructions were understood. Once participants positioned themselves at the correct point, the small circle turned to green indicating the start of the trial and the cursor became invisible. During execution, the cursor position, represented by the small circle, was visible. The cursor trajectory was also visible, and was reset every revolution. Each participant was tested individually and was asked to continuously trace the circle without stopping. Once 48 revolutions of the circle were traced, the trial ended automatically.

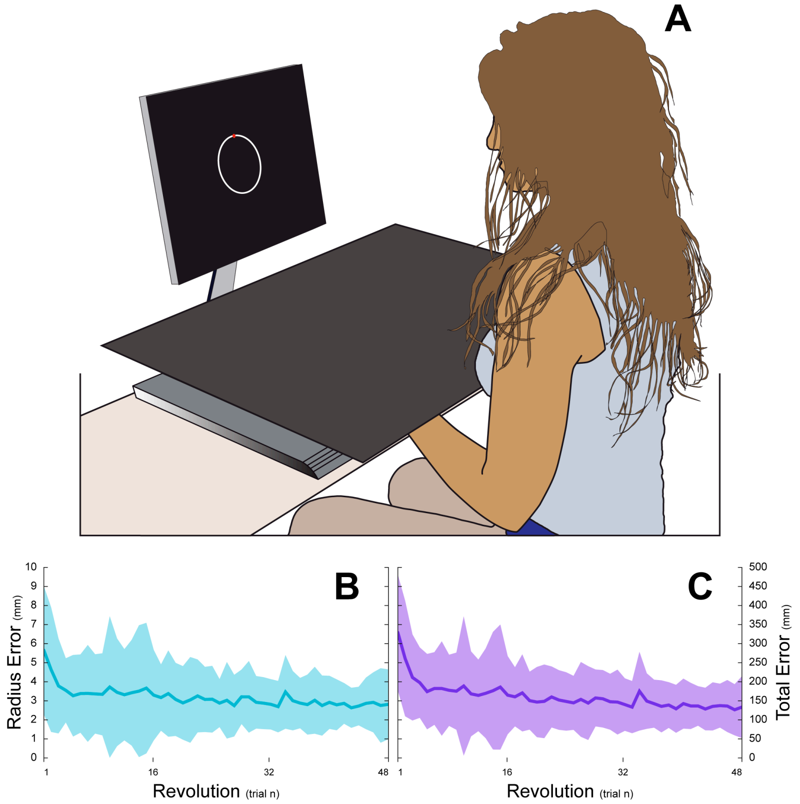


Figure 7.1. Setup and Error Reduction. A. Diagram illustrating the experimental setup. Each subject was presented a circle template projected on a monitor in front of her/him at eye level. A black paperboard occluded vision of the hand. The subjects executed tracings of a circle, while seated without the support of either wrist, arm, or elbow, in such a way that the only contact with the tablet was made through the pen. B-C. Results for radius error (B) and for total error (C) per revolution for all subjects, it is possible to see that both radius and total errors gradually reduce during the task.

7.2.3 Analysis

7.2.3.1 Circle analysis

Circle tracing analysis consisted of calculation of traced circle radii, measured as point distances from the template's center (i.e., radius). For each measured radius, deviations from the template's radius were also calculated (i.e., radius error) which were used to calculate the mean radius error for each revolution. The sum of the radius errors for each revolution was considered as the total error. In addition, for each revolution the travelled distance distance was calculated. This measure was further used along with the duration of each revolution to estimate the speed for said revolution (derived from Speed = Distance / Duration). Finally, for evaluation of inter-trial differences, the differences between two successive revolutions were calculated, for both duration and speed.

7.2.3.2 Speed Profile

The number of peaks within the speed profile of the entire performance of each subject was used as an estimate for movement smoothness (Balasubramanian et al., 2015; Teo et al., 2002). Speed data of the performances was first filtered using local regression with weighted linear least squares and a 1st degree polynomial model setting, span was set for 1% of the dataset's length. Following that using Matlab, the find peaks algorithm was implemented in order to calculate the number of peaks.

7.2.3.3 Timing variability

In order to evaluate a timing variability within the performances, the detrended windowed lag-one autocorrelation (detrended-wγ(1)) was used on the measured duration of each revolution for each subject (Lemoine and Delignières, 2009). We computed wγ(1) over a window of the 30 first points, moving the window by one point, all along the sets. For each point moved the data was first linearly detrended on the window, and then the lag-one autocorrelation was computed. Following that the mean detrended-wγ(1) was calculated for each subject, and was considered as an estimator of the overall autocorrelation.

7.2.3.4 Creation of execution space, solution manifold, and group division

The execution space was created by pairing the possible values of each of the execution variables. The limits of the space were chosen *a posteriori* following the examination of the dataset and were set to maximum values of 2.2 sec for duration, and 600 mm/sec for speed. Creation of the solution manifold was based on paired possible values of the execution variables the yielded a distance equal to the circle circumference (142.85 mm). The absolute difference between the measured distance of each pair of variables and that of the circumference was calculated, and the results were plotted on the execution space (Figure 7.2), the closer the difference was to 0, the whiter the area corresponding to the combination of variables. A k-means algorithm was used in order to divide subjects into groups based on their initial performance, specifically based on speed and duration values. The reason for choosing k-means clustering was that it does not require any prior assumption regarding the performance.

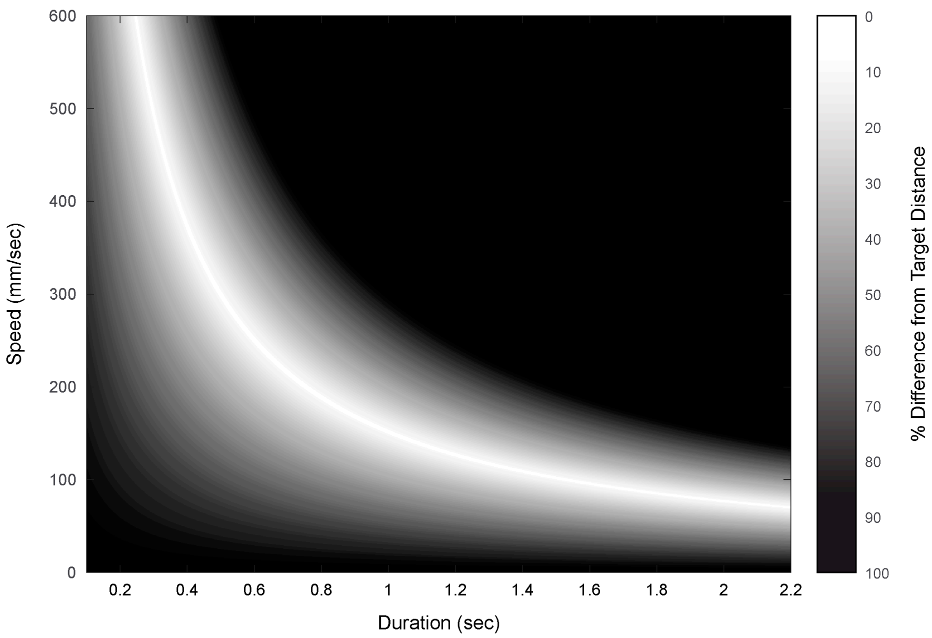


Figure 7.2. Solution Manifold. Within the possible combination of the execution variables (duration and speed), the most congruent combinations with the target distance create the solution manifold (represented in white). The better the combination of the variables is (i.e., the closer their combination yields the target distance) the whiter the area is.

7.2.4 Statistics

To evaluate the significance of the improvement of the performance a paired sample t-test was implemented on the initial error and end error for both radius error as well as for total error. All eventual differences between groups were evaluated using a two-tailed t-test on the inter-trial differences for speed and duration, as well as on the peak numbers in the speed profiles and on the detrended-wγ(1) values.

7.3 Results

As a first measure, we have evaluated the task execution according to the instructions. We assume that if the instructions were indeed followed, there should be a gradual reduction in error. In fact, the initial radius error for the first revolution measured 5.65±3.35 mm, reducing to 2.81±1.83 mm by the last revolution (Figure 7.1B), total error reduced from 329.2±151.7 mm to 133.47±81 mm (Figure 7.1C). This improvement was further evidenced by using paired sample t-test revealing significant differences between the initial error and end error for both radius error ($p<0.001$) as well as total error ($p<0.001$).

In order to examine exploration patterns within the data, an execution space is needed to be created. To achieve this, first a result variable is to be chosen. This variable must represent some measure that could be compared with the desired outcome. In the circle tracing task, since the distance travelled each revolution could be readily compared with the target distance (i.e., circumference of the template circle), it was chosen as the result variable. Following this, two execution variables are to be chosen. The relationship of these execution variables must be able to quantify the result variable. When examining the measurable quantities retrieved in this task (i.e., trajectory and time), as well as the result variable, it seems fitting to define the execution variables from the distance and time relationship (i.e., Speed=Distance/Duration). Consequently, as the distance measure is considered as the result variable, we may use Speed and Duration as the execution variables. This allows for the creation of an execution space based on the various combination of speed and duration, and solution manifold for the combination yielding zero discrepancy between the circumference of the target circle and the given combination (Figure 7.2).

The solution manifold within the execution space assumes curved conformation. Furthermore, it is possible to see that the solution manifold becomes larger the closer it is to the curve change point (calculated as the point on the manifold with shortest distance from the origin, measured 0.8 sec and 192 mm/sec). Meaning that more combinations around the change point would have a minor error (greater tolerance) compared to other regions. Also, the closer performances get to that point, small variations in one variable correspond to small changes in the other (as opposed to other areas in which small variations in one variable may cause large variations in the other). Considering this shape, if performances do indeed respect the architecture of the solution manifold, there should be a tendency to converge toward the change point. With that logic, we have computed the deviation from that point throughout the performances for both speed and duration, both reducing to values close to zero. Specifically, for speed the absolute initial difference measured 7.04±87.13 mm/sec, reducing to 2.63±62.7 mm/sec, for duration the absolute initial difference of 0.266±0.35 sec, reduced to 0.0021±0.23 sec. A quiver plot further demonstrate this trend (Figure 7.3).

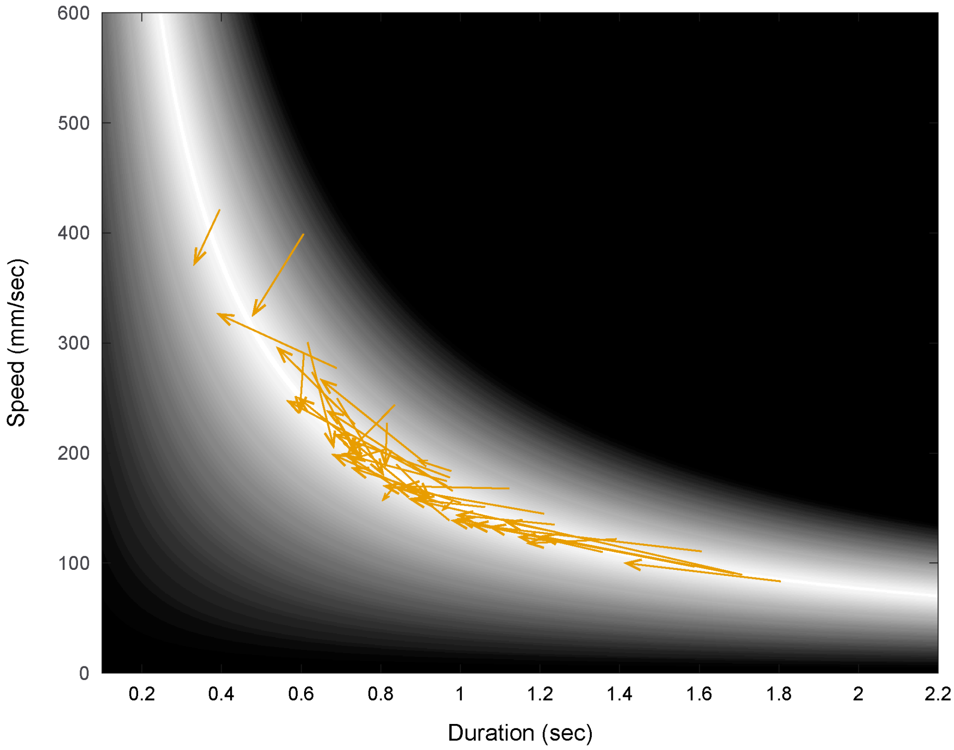


Figure 7.3. Quiver plot. A quiver plot was obtained by taking the mean of the first 3 revolution and the last 3 revolutions for each subjects. It is possible to see that there is a general tendency of the performances toward the curve change point.

Examination of the solution manifold appears to suggest that if the manifold were divided into 2 parts at the changing point, one part would correspond to relatively small changes in speed with large changes in duration, and the second part with the opposite trend. From this, 2 strategies emerge, the first is that of maintaining a relatively constant speed, the other of maintaining a relatively constant duration. Furthermore, the quiver plot seems to suggest that there is no change in strategy throughout the performance. This means where subject land on the execution space, would very likely determine said subject's exploration pattern. To examine this hypothesis, we have first divided the subjects into 3 groups using k-means algorithm, using only the speed and duration of the first revolution (Figure 7.4A). The reason for 3 groups instead of 2 is that subjects landing on the area of maximum tolerance, are not expected to show any preference. The 3 groups obtained were that of steady speed (i.e., Speed Preference, SP; n=9), steady duration (i.e., Duration Preference, DP; n=8), and No Preference (i.e., NP; n=23). Particularly, the average duration measured 0.63±0.01 sec for the DP group, 1.2±0.12 sec for the SP group and 0.8±0.04 sec. The average speed measured 254±16 mm/sec for the DP group, 122±9.1 for the SP group and 195±7.6 for the NP group. Both duration and speed were found to be significantly different between all groups ($p<0.001$).

If strategies are indeed fixed, there should be a minimal change in duration for the DP group along with large changes in duration for the SP group (Figure 7.4B). The opposite should be visible when examining the speed parameter (Figure 7.4C). Since using the speed and duration values would evidently be significantly different since the values themselves are already very different (Figure 7.4). We have examined inter-trial difference to evaluate the consistency of each parameter (speed and duration) throughout the performance for each subject. A two-tailed t-test was implemented on the inter-trial differences for each parameter. Both values were found to be significantly different between the groups (Figure 7.5A, 7.5B). Specifically, the mean inter-trial difference for duration were low for the DP group compared to the SP (0.137±2.134 msec and 10.88±5.7 msec, respectively, $p<0.001$); the mean inter-trial difference for speed presented the opposite trend, with larger differences for DP group compared to the SP group (2.081±0.413 mm/sec and 0.531±0.473 mm/sec, respectively, $p<0.001$). Inter-trial differences for the NP group presented intermediate values (5.6±4 msec for duration and 0.67±1.24 mm/sec for speed). Significant differences between the NP group and the DP were found for both duration and speed ($p<0.05$ and $p<0.001$, respectively), whereas between the NP and the SP groups significant differences were found for duration but not for speed ($p<0.05$ and $p=0.73$, respectively).

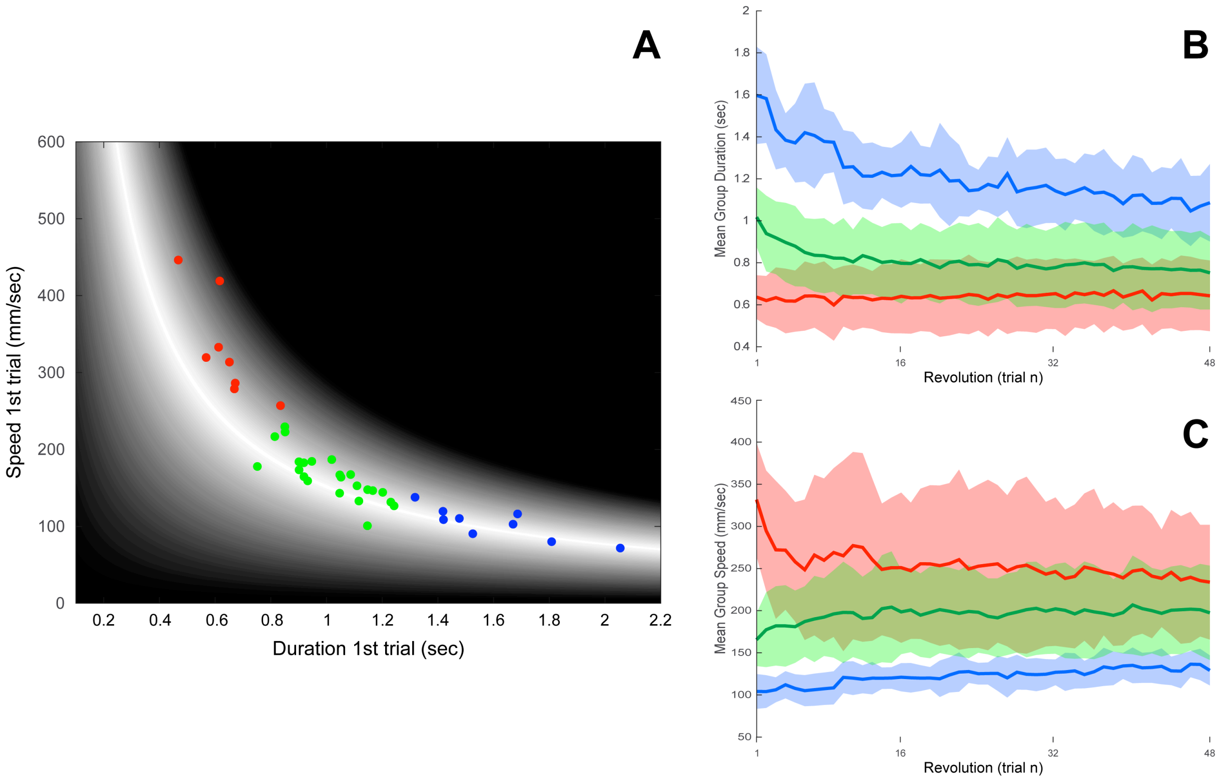


Figure 7.4. Group Division. Subjects into 3 groups following the implementation of k-means on the speed and duration values of the first revolution. **A.** scatter plot of the speed and duration values obtained on the first revolution, every dot represents a subject and is colored according to the k-means division into a Duration Preference group (i.e., DP; n=8; red), Speed Preference group (i.e., SP; n=9; blue) and No Preference Group (i.e., NP; n=23; green). **B.** Duration results throughout the performance for the 3 groups. It is possible to note that the DP group (red) remains relatively stable compared to the SP group (blue). **C.** Speed results throughout the performance for the 3 groups, demonstrating that SP group (blue) remains relatively stable compared to the DP group (red).

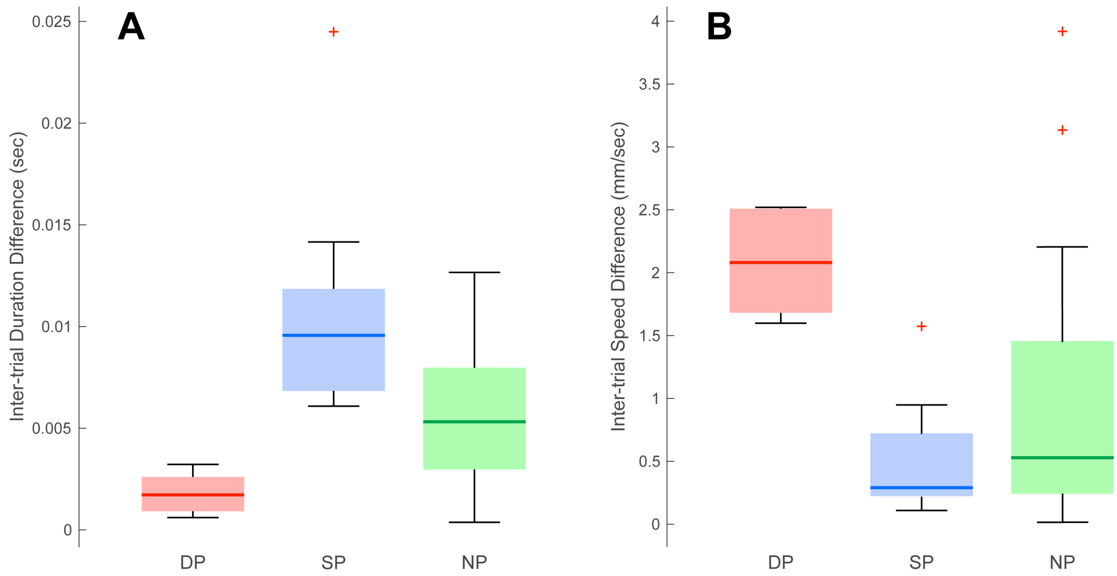


Figure 7.5. Inter-Trial Differences. Box plot representing the group inter-trial differences for duration (**A**) and for speed (**B**). It is possible to see that for duration, DP group (red), present very small differences compared to SP (blue), suggesting that DP group maintains the duration relatively constant. The opposite trend is visible for speed in which the SP group (blue) presents smaller differences compared to the DP group (red). The NP group (green) represents an intermediate between the groups for both duration (**A**) and speed (**B**). Red crosses represent extreme outliers.

To broaden our examination of the potential differences between the groups, the number of peaks within the speed profiles for each group were evaluated revealing that a smoother performance is present for the SP (124.8±7.2 average peaks) regarding speed compared to the DP group (145.8±18.4). Also in this case, the NP group presented intermediate values (131.7±13.1). Significant differences were found between DP and SP groups ($p<0.001$) as well as between DP and NP group ($p<0.05$), but not between the SP and NP groups ($p=0.15$). Interestingly, even though performances were generally longer for the SP group, still the number of peaks was lower compared to the DP group.

In addition, we have implemented a timing variability analysis using a detrended windowed lag(1)-autocorrelation (detrended-wγ(1)) on the duration values of the 3 groups. For the DP group, with the exception of 2 subjects, values were negative (-0.138±0.255), suggesting that the group as a whole is more event-based type of control, driven by an internal representation of time. For the SP group, values were invariably positive (0.290±0.211), suggestive for a more emergent base type of control, driven by effector dynamics. The NP group represented the intermediate case with both positive and and negative values (with 9 subjects showing negative values, group average 0.105±0.223). All groups were found to be significantly different from each-other ($p<0.05$). However, only the SP group was found to be significantly different from 0 ($p<0.05$).

7.4 Discussion

One of the largest mysteries in motor control is that of why and how a certain movement comes about during performance. In this paper we have shown that when focusing on the execution, several patterns seem to emerge which remain relatively stable throughout the performance (Figure 7.4, 7.5).

Surprisingly, even though the chosen execution variables (speed and duration) in our task are dependent, their modifications throughout the performance are independent. As such, the identified patterns were those of maintaining a relatively constant speed or a relatively constant duration. We have further demonstrated that performance according to these patterns follow the shape of the solution manifold and, by doing so, remain relatively constant (Figures 7.3 and 7.4). This suggests that the initial state of the performance within the execution space is sufficient to determine or predict the entire performance.

The findings provided by this study do demonstrate the existence of different task-related execution strategies. In the case of the task here presented, this optimization is guided by one measure which is either duration or speed. It is important to consider that these two execution variables possess different characteristics, which could suggest different types of control. While duration is defined by a periodic measure (i.e., interval between repetition) and is maintained best when controlled periodically (Elliott et al., 2009; Studenka et al., 2012), speed on the other hand is a more dynamic measure which is controlled continuously. This view may suggest that the SP group utilizes a more active type of control whereas the DP group a more intermittent one. In fact, examination of the peak number within the speed profile of the performances revealed a lower number of peaks for the SP compared to the DP, suggesting a smoother performance (Balasubramanian et al., 2015; Teo et al., 2002). Also, the positive detrended-w$\gamma(1)$ values for the SP further support the notion of a more dynamic type control, compared to negative values for the DP group which are suggestive for a more discrete type of control (Repp and Steinman, 2010).

There is a plethora of possible explanations as to why a performance may occur in a certain way. In this study we have focused mostly on the existence and modification of execution patterns. However, since these patterns are determined already at the beginning of the performance, it is possible that subjects present certain biases/inclination toward a certain pattern, which then after would determine their initial location. In fact, it is known that while the possibilities for movement execution are infinite, most subjects tend to demonstrate certain stereotypical patterns and, therefore, the abundance of solutions is more apparent than actual (Franklin and Wolpert, 2011). Furthermore, the notion of individual biases was demonstrated to occur for certain aspects of a motor performance. For example, individual directional biases were found to occur for reaching (Wolpert et al., 2011). Biases are not the only example for some certain inherent preference that subject may possess. It was also shown that feedback reliance is not equal among individuals (Cohen et al., 2018a). Therefore, it is also possible that subjects possess some estimation of their own control, and consequently, by being aware of their own limitations would be more inclined toward one direction or the other.

A few limitations of this study should be noted. The first, it is important to note that while the execution variables in this task demonstrate differences, these variables are chosen. Therefore, by choosing different variables there is also the possibility for other patterns to emerge. Also, it should be considered that performances are likely to greatly vary depending on the task as well as the task requirements. While this study was concentrated on a continuous task, discrete tasks are likely to produce different results. Though a side by side comparison of the two was not included in this study, it would be interesting to examine whether subjects maintain performance patterns also across tasks. Finally, though this study focused on a group division of the subjects, this decision was made in order to evidence the differences, however, we believe that data regarding execution patterns may also be viewed as a continuum.

7.5 Conclusions

How a movement is performed during learning is an important aspect for both motor control and learning in general. Finding ways to identify and describe the determining factors for a movement is indeed a challenging mission. Though there are different factors that were suggested to influence and/or predict learning, by focusing solely on learning (rate or extent) as an outcome measure, their predictive power may be limited. Here we shifted the focus away from "how well a task is performed", and investigated the differences in "how the task is performed" between individuals. Indeed, we identified two specific patterns for the given task suggestive for engagement of different types of control. We believe that by examining the execution patterns employed, it could be easier to understand which aspects of performances could be improved and individual differences could be better investigated.

8 General Conclusions

If the history of intelligence testing teaches us anything is that any transition from theory to practice entails numerous attempts as well as different approaches before consolidating it. For motor intelligence, though conceptually as old as intelligence itself, was not pursuit with the same vigor and consequently remains mostly theoretical. It is important to consider, however, that the effort of quantification and stratification of the population is only justified when a certain larger purpose is present. When it comes to intelligence, this stratification allowed for early identification of individuals who may require special assistance, as well as those who could be pushed forward. In other words, the general purpose of quantifying intelligence is that of helping individuals to reach their full potential, and it remains the same also for motor intelligence. Especially nowadays, where movement related research has advanced greatly, while at the same time, there are still certain lacunas when it comes to understanding how to use movement and how it influences us in the day to day life. These themes, perhaps due to their nature and the difficulties they entail, are often left behind. However, we must always consider that the consolidation of any theoretical concept is a collective endeavor, which requires both refinements of theory and practice. As such, it is thanks to works like those of Berendrsen and Hand that help to keep the concept alive. Parallel to that, we should pursuit a more practical approach as well.

Though what I present in this thesis are only initial steps, I hope that this work would help to stimulate other researchers to seek more quantification methods which could be of value for evidencing individual differences and, more in general, for motor intelligence. Considering the already existing taxonomies in motor control, stratification for many domains of motor control is still lacking (e.g., gross and fine motor skills, discrete and continuous skills, open and closed loop skills etc.) and may represent an objective for future studies. Surely, this is a long path that should be followed with correlational studies between abilities as well as between other, perhaps more cognitive, aspects of movement. Still, according to many, this is a path worth pursuing.

References

Abdel-Aziz, Y., Karara, H., 1971. Direct linear transformation from comparator coordinates into object space coordinates in close-range photogrammetry, in: Proceedings of the Symposium on Close-Range Photogrammetry. Falls Church, VA: American Society of Photogrammetry, pp. 1–18.

Abernethy, B., 1988. Dual-task methodology and motor skills research: Some applications and methodological constraints. J. Hum. Mov. Stud. 14, 101–132.

Almeida, L.S., Prieto, M.D., Ferreira, A., Ferrando, M., Ferrandiz, C., Bermejo, R., Hernández, D., 2011. Structural invariance of multiple intelligences, based on the level of execution. Psicothema 23, 832–8.

Ambrósio, J., Abrantes, J., Lopes, G., 2001. Spatial reconstruction of human motion by means of a single camera and a biomechanical model. Hum. Mov. Sci. 20, 829–851. https://doi.org/10.1016/S0167-9457(01)00056-2

American Psychiatric Association, 2013. Diagnostic and statistical manual of mental disorders, 5th ed. American Psychiatric Publishing, Arlington, VA.

Andrade, J., 2010. What does doodling do? Appl. Cogn. Psychol. 24, 100–106. https://doi.org/10.1002/acp.1561

Balasubramanian, S., Melendez-Calderon, A., Roby-Brami, A., Burdet, E., 2015. On the analysis of movement smoothness. J. Neuroeng. Rehabil. 12, 112. https://doi.org/10.1186/s12984-015-0090-9

Barak, S., Duncan, P.W., 2006. Issues in selecting outcome measures to assess functional recovery after stroke. NeuroRX 3, 505–524. https://doi.org/10.1016/j.nurx.2006.07.009

Barbado Murillo, D., Caballero Sánchez, C., Moreside, J., Vera-García, F.J., Moreno, F.J., 2017. Can the structure of motor variability predict learning rate? J. Exp. Psychol. Hum. Percept. Perform. 43, 596–607. https://doi.org/10.1037/xhp0000303

Barbado Murillo, D., Sabido Solana, R., Vera-Garcia, F.J., Gusi Fuertes, N., Moreno, F.J., 2012. Effect of increasing difficulty in standing balance tasks with visual feedback on postural sway and EMG: Complexity and performance. Hum. Mov. Sci. 31, 1224–1237. https://doi.org/10.1016/j.humov.2012.01.002

Bardid, F., Rudd, J.R., Lenoir, M., Polman, R., Barnett, L.M., 2015. Cross-cultural comparison of motor competence in children from Australia and Belgium. Front. Psychol. 6, 964. https://doi.org/10.3389/fpsyg.2015.00964

Baskwill, A., Belli, P., Kelleher, L., 2017. Evaluation of a Gait Assessment Module Using 3D Motion Capture Technology. Int. J. Ther. Massage Bodywork 10, 3–9.

Bavdekar, S., 2015. Writing the Discussion Section: Describing the Significance of the Study Findings. J. Assoc. Physicians India 63, 40–42.

Baweja, H.S., Kwon, M., Onushko, T., Wright, D.L., Corcos, D.M., Christou, E.A., 2015. Processing of visual information compromises the ability of older adults to control novel fine motor tasks. Exp. Brain Res. 233, 3475–3488. https://doi.org/10.1007/s00221-015-4408-4

Beery, K., Beery, N., 2010. The Beery-Buktenica developmental test of visual-motor integration (Beery VMI).

Benjaminse, A., Otten, B., Gokeler, A., Diercks, R.L., Lemmink, K.A.P.M., 2017. Motor learning strategies in basketball players and its implications for ACL injury prevention: a randomized controlled trial. Knee Surgery, Sport. Traumatol. Arthrosc. 25, 2365–2376. https://doi.org/10.1007/s00167-015-3727-0

Berberovic, N., Pisella, L., Morris, A.P., Mattingley, J.B., 2004. Prismatic adaptation reduces biased temporal order judgements in spatial neglect. Neuroreport 15, 1199–1204. https://doi.org/10.1097/00001756-200405190-00024

Berendsen, B.M., Meeteren, N.L.U. van, Helders, P.J.M., 2002. Towards Assessment of “Motor Intelligence”: A Kick-off for Debate. Adv. Physiother. 4, 99–107.

https://doi.org/10.1080/140381902320387513

Bernardina, G.R.D., Cerveri, P., Barros, R.M.L., Marins, J.C.B., Silvatti, A.P., 2016. Action Sport Cameras as an Instrument to Perform a 3D Underwater Motion Analysis. PLoS One 11, e0160490. https://doi.org/10.1371/journal.pone.0160490

Berniker, M., Kording, K., 2008. Estimating the sources of motor errors for adaptation and generalization. Nat. Neurosci. 11, 1454–1461. https://doi.org/10.1038/nn.2229

Binet, A., Simon, T., 1904. Méthodes nouvelles pour le diagnostic du niveau intellectuel des anormaux. Annee. Psychol. https://doi.org/10.3406/psy.1904.3675

Bisagno, E., Morra, S., 2018. How do we learn to “kill” in volleyball?: The role of working memory capacity and expertise in volleyball motor learning. J. Exp. Child Psychol. 167, 128–145. https://doi.org/10.1016/j.jecp.2017.10.008

Blank, R., Miller, V., von Voss, H., von Kries, R., 1999. Effects of age on distally and proximally generated drawing movements: a kinematic analysis of school children and adults. Dev. Med. Child Neurol. 41, S0012162299001243. https://doi.org/10.1017/S0012162299001243

Bleyenheuft, Y., Grandin, C.B., Cosnard, G., Olivier, E., Thonnard, J.-L., 2007. Corticospinal dysgenesis and upper-limb deficits in congenital hemiplegia: a diffusion tensor imaging study. Pediatrics 120, e1502-11. https://doi.org/10.1542/peds.2007-0394

Boake, C., 2002. From the Binet–Simon to the Wechsler–Bellevue: Tracing the History of Intelligence Testing. J. Clin. Exp. Neuropsychol. 24, 383–405. https://doi.org/10.1076/jcen.24.3.383.981

Boissin, C., Fleming, J., Wallis, L., Hasselberg, M., Laflamme, L., 2015. Can We Trust the Use of Smartphone Cameras in Clinical Practice? Laypeople Assessment of Their Image Quality. Telemed. e-Health 21, 887–892. https://doi.org/10.1089/tmj.2014.0221

Bonoti, F., Vlachos, F., Metallidou, P., 2005. Writing and Drawing Performance of School Age Children. Sch. Psychol. Int. 26, 243–255. https://doi.org/10.1177/0143034305052916

Borecki, L., Tolstych, K., Pokorski, M., 2013. Computer Games and Fine Motor Skills, in: Advances in Experimental Medicine and Biology. pp. 343–348. https://doi.org/10.1007/978-94-007-4546-9_43

Bowden, R., Mitchell, T., Sarhadi, M., 1998. Reconstructing 3d pose and motion from a single camera view, in: British MAchine Vision Conference. Southampton, UK, pp. 904–913.

Brace, D., 1930. Measuring motor ability. AS Barnes, New York, NY.

Bravi, R., Del Tongo, C., Cohen, E.J., Dalle Mura, G., Tognetti, A., Minciacchi, D., 2014. Modulation of isochronous movements in a flexible environment: Links between motion and auditory experience. Exp. Brain Res. 232, 1663–1675. https://doi.org/10.1007/s00221-014-3845-9

Bravi, R., Quarta, E., Del Tongo, C., Carbonaro, N., Tognetti, A., Minciacchi, D., 2015. Music, clicks, and their imaginations favor differently the event-based timing component for rhythmic movements. Exp. Brain Res. 233, 1945–1961. https://doi.org/10.1007/s00221-015-4267-z

Brazis, P., Masdeu, J., Biller, J., 2007. Localization in clinical neurology, 6th ed. Lippincott Williams & Wilkins, Philadelphia.

Bruijn, S.M., Van Impe, A., Duysens, J., Swinnen, S.P., 2012. Split-belt walking: adaptation differences between young and older adults. J. Neurophysiol. 108, 1149–1157. https://doi.org/10.1152/jn.00018.2012

Bruininks, R., Bruininks, B., 2005. Bruininks- Oseretsky test of motor pro ciency, second edition (BOT-2).

Calfas, J., 2017. Do Fidget Spinners Really Help With ADHD? Nope, Experts Say. Money.

Callaghan, M.J., Selfe, J., Bagley, P.J., Oldham, J.A., 2002. The Effects of Patellar Taping on Knee Joint Proprioception. J Athl Train 37, 19–24.

Cancela Carral, J.M., Pallin, E., Orbegozo, A., Ayán Pérez, C., 2017. Effects of Three Different Chair-Based Exercise Programs on People Older Than 80 Years. Rejuvenation Res. 20, 411–419. https://doi.org/10.1089/rej.2017.1924

Carriere, J.S.A., Seli, P., Smilek, D., 2013. Wandering in both mind and body: Individual differences in mind wandering and inattention predict fidgeting. Can. J. Exp. Psychol. Can. Psychol. expérimentale 67, 19–31. https://doi.org/10.1037/a0031438

Carroll, J.B., 1993. Human cognitive abilities, Human cognitive abilities. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511571312

Castaneda, B., Gray, R., 2007. Effects of Focus of Attention on Baseball Batting Performance in Players of Differing Skill Levels. J. Sport Exerc. Psychol. 29, 60–77. https://doi.org/10.1123/jsep.29.1.60

Castelli, A., Paolini, G., Cereatti, A., Della Croce, U., 2015. A 2D Markerless Gait Analysis Methodology: Validation on Healthy Subjects. Comput. Math. Methods Med. 2015, 1–11. https://doi.org/10.1155/2015/186780

Cattell, R., 1941. Some theoretical issues in adult intelligence testing. Psychol. Bull. 38, 592.

Ceseracciu, E., Sawacha, Z., Cobelli, C., 2014. Comparison of Markerless and Marker-Based Motion Capture Technologies through Simultaneous Data Collection during Gait: Proof of Concept. PLoS One 9, e87640. https://doi.org/10.1371/journal.pone.0087640

Chen, H.M., Chang, J.J., 1999. The skill components of a therapeutic chopsticks task and their relationship with hand function tests. Kaohsiung J. Med. Sci. 15, 704–9.

Chèze, L., 2014. The Different Movement Analysis Devices Available on the Market, in: Kinematic Analysis of Human Movement. John Wiley & Sons. https://doi.org/10.1002/9781119058144.ch2

Chorba, R.S., Chorba, D.J., Bouillon, L.E., Overmyer, C.A., Landis, J.A., 2010. Use of a functional movement screening tool to determine injury risk in female collegiate athletes. N. Am. J. Sports Phys. Ther. 5, 47–54.

Claesson, I.M., Grooten, W.J., Lökk, J., Ståhle, A., 2017. Assessing postural balance in early Parkinson's Disease—validity of the BDL balance scale. Physiother. Theory Pract. 33, 490–496. https://doi.org/10.1080/09593985.2017.1318424

Classen, J., Liepert, J., Wise, S.P., Hallett, M., Cohen, L.G., 1998. Rapid Plasticity of Human Cortical Movement Representation Induced by Practice. J. Neurophysiol. 79, 1117–1123. https://doi.org/10.1152/jn.1998.79.2.1117

Cohen, E.J., Bravi, R., Bagni, M.A., Minciacchi, D., 2018a. Precision in drawing and tracing tasks: Different measures for different aspects of fine motor control. Hum. Mov. Sci. 61, 177–188. https://doi.org/10.1016/j.humov.2018.08.004

Cohen, E.J., Bravi, R., Minciacchi, D., 2018b. The effect of fidget spinners on fine motor control. Sci. Rep. 8, 3144. https://doi.org/10.1038/s41598-018-21529-0

Collier, G.L., Ogden, R.T., 2004. Adding drift to the decomposition of simple isochronous tapping: An extension of the Wing-Kristofferson model. J. Exp. Psychol. Hum. Percept. Perform. 30, 853–872. https://doi.org/10.1037/0096-1523.30.5.853

Costa-Giomi, E., 2005. Does Music Instruction Improve Fine Motor Abilities? Ann. N. Y. Acad. Sci. 1060, 262–264. https://doi.org/10.1196/annals.1360.053

Cusumano, J.P., Cesari, P., 2006. Body-goal Variability Mapping in an Aiming Task. Biol. Cybern. 94, 367–379. https://doi.org/10.1007/s00422-006-0052-1

Deary, 2012. 125 Years of Intelligence in The American Journal of Psychology. Am. J. Psychol. 125, 145. https://doi.org/10.5406/amerjpsyc.125.2.0145

Deary, I.J., 2001. Human intelligence differences: a recent history. Trends Cogn. Sci. 5, 127–130. https://doi.org/10.1016/S1364-6613(00)01621-1

Dhawale, A.K., Smith, M.A., Ölveczky, B.P., 2017. The Role of Variability in Motor Learning. Annu. Rev. Neurosci. 40, 479–498. https://doi.org/10.1146/annurev-neuro-072116-031548

Diedrichsen, J., White, O., Newman, D., Lally, N., 2010. Use-Dependent and Error-Based Learning of Motor Behaviors. J. Neurosci. 30, 5159–5166. https://doi.org/10.1523/JNEUROSCI.5406-09.2010

Dingwell, J.B., Mah, C.D., Mussa-Ivaldi, F.A., 2002. Manipulating Objects With Internal Degrees of

Freedom: Evidence for Model-Based Control. J. Neurophysiol. 88, 222–235. https://doi.org/10.1152/jn.2002.88.1.222

Dishman, R.K., 1997. Brain monoamines, exercise, and behavioral stress: animal models. Med. Sci. Sport. Exerc. 29, 63–74. https://doi.org/10.1097/00005768-199701000-00010

Duque, J., 2003. Correlation between impaired dexterity and corticospinal tract dysgenesis in congenital hemiplegia. Brain 126, 732–747. https://doi.org/10.1093/brain/awg069

Elliott, M.T., Welchman, A.E., Wing, A.M., 2009. Being discrete helps keep to the beat. Exp. Brain Res. 192, 731–737. https://doi.org/10.1007/s00221-008-1646-8

Faber, J., Fonseca, L.M., 2014. How sample size influences research outcomes. Dental Press J. Orthod. 19, 27–29. https://doi.org/10.1590/2176-9451.19.4.027-029.ebo

Farley, J., Risko, E.F., Kingstone, A., 2013. Everyday attention and lecture retention: the effects of time, fidgeting, and mind wandering. Front. Psychol. 4. https://doi.org/10.3389/fpsyg.2013.00619

Farnè, A., 2002. Ameliorating neglect with prism adaptation: visuo-manual and visuo-verbal measures. Neuropsychologia 40, 718–729. https://doi.org/10.1016/S0028-3932(01)00186-5

Faul, F., Erdfelder, E., Lang, A.-G., Buchner, A., 2007. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behav. Res. Methods 39, 175–191. https://doi.org/10.3758/BF03193146

Ferrarello, F., Bianchi, V.A.M., Baccini, M., Rubbieri, G., Mossello, E., Cavallini, M.C., Marchionni, N., Di Bari, M., 2013. Tools for Observational Gait Analysis in Patients With Stroke: A Systematic Review. Phys. Ther. 93, 1673–1685. https://doi.org/10.2522/ptj.20120344

Fietzek, U.M., Heinen, F., Berweck, S., Maute, S., Hufschmidt, A., Schulte-Mönting, J., Lücking, C.H., Korinthenberg, R., 2000. Development of the corticospinal system and hand motor function: central conduction times and motor performance tests. Dev. Med. Child Neurol. 42, S0012162200000384. https://doi.org/10.1017/S0012162200000384

Firestone, W. a., 1993. Arguments for Generalizing Applied to Qualitative Research. Educ. Res. 22, 16–23.

Fischer, T., Langner, R., Birbaumer, N., Brocke, B., 2008. Arousal and Attention: Self-chosen Stimulation Optimizes Cortical Excitability and Minimizes Compensatory Effort. J. Cogn. Neurosci. 20, 1443–1453. https://doi.org/10.1162/jocn.2008.20101

Flanagan, D.P., Dixon, S.G., 2014. The Cattell-Horn-Carroll Theory of Cognitive Abilities, in: Encyclopedia of Special Education. John Wiley & Sons, Inc., Hoboken, NJ, USA. https://doi.org/10.1002/9781118660584.ese0431

Flanders, M., Mrotek, L.A., Gielen, C.C.A.M., 2006. Planning and drawing complex shapes. Exp. Brain Res. 171, 116–128. https://doi.org/10.1007/s00221-005-0252-2

Flatt, A.E., 2008. Is Being Left-Handed a Handicap? the Short and Useless Answer Is "Yes and No." Baylor Univ. Med. Cent. Proc. 21, 304–307. https://doi.org/10.1080/08998280.2008.11928414

Fleishman, E., 1964. The structure and measurement of physical fitness. Prentice Hall, Englewood Cliffs, NJ.

Folio, M., Fewell, R., 2000. Peabody develop- mental motor scales: Examiner's manual (2nd ed).

Franklin, D.W., Osu, R., Burdet, E., Kawato, M., Milner, T.E., 2003. Adaptation to Stable and Unstable Dynamics Achieved By Combined Impedance Control and Inverse Dynamics Model. J. Neurophysiol. 90, 3270–3282. https://doi.org/10.1152/jn.01112.2002

Franklin, D.W., Wolpert, D.M., 2011. Computational Mechanisms of Sensorimotor Control. Neuron 72, 425–442. https://doi.org/10.1016/j.neuron.2011.10.006

Frisch, S., 2014. How cognitive neuroscience could be more biological-and what it might learn from clinical neuropsychology. Front. Hum. Neurosci. 8. https://doi.org/10.3389/fnhum.2014.00541

Furuki, D., Takiyama, K., 2019. Decomposing motion that changes over time into task-relevant and task-irrelevant components in a data-driven manner: application to motor adaptation in whole-body movements. Sci. Rep. 9, 7246. https://doi.org/10.1038/s41598-019-43558-z

Galton, F., 1885. On the Anthropometric Laboratory at the Late International Health Exhibition. J. Anthropol. Inst. Gt. Britain Irel. https://doi.org/10.2307/2841978

Gardner, H., 2006. Multiple Intelligences: New Horizons in Theory and Practice. Basic Books, New-York.

Gatouillat, A., Dumortier, A., Perera, S., Badr, Y., Gehin, C., Sejdić, E., 2017. Analysis of the pen pressure and grip force signal during basic drawing tasks: The timing and speed changes impact drawing characteristics. Comput. Biol. Med. 87, 124–131. https://doi.org/10.1016/j.compbiomed.2017.05.020

Genon, S., Reid, A., Langner, R., Amunts, K., Eickhoff, S.B., 2018. How to Characterize the Function of a Brain Region. Trends Cogn. Sci. 22, 350–364. https://doi.org/10.1016/j.tics.2018.01.010

Gentile, A.M., 1972. A Working Model of Skill Acquisition with Application to Teaching. Quest 17, 3–23. https://doi.org/10.1080/00336297.1972.10519717

Gingerich, A., Regehr, G., Eva, K.W., 2011. Rater-Based Assessments as Social Judgments: Rethinking the Etiology of Rater Errors. Acad. Med. 86, S1–S7. https://doi.org/10.1097/ACM.0b013e31822a6cf8

Gligoric, N., Uzelac, A., Krco, S., 2012. Smart Classroom: Real-time feedback on lecture quality, in: 2012 IEEE International Conference on Pervasive Computing and Communications Workshops. IEEE, pp. 391–394. https://doi.org/10.1109/PerComW.2012.6197517

Gogtay, N., Giedd, J.N., Lusk, L., Hayashi, K.M., Greenstein, D., Vaituzis, A.C., Nugent, T.F., Herman, D.H., Clasen, L.S., Toga, A.W., Rapoport, J.L., Thompson, P.M., 2004. Dynamic mapping of human cortical development during childhood through early adulthood. Proc. Natl. Acad. Sci. 101, 8174–8179. https://doi.org/10.1073/pnas.0402680101

Gordon, A.M., Westling, G., Cole, K.J., Johansson, R.S., 1993. Memory representations underlying motor commands used during manipulation of common and novel objects. J. Neurophysiol. 69, 1789–96. https://doi.org/10.1152/jn.1993.69.6.1789

Gottfredson, L., Saklofske, D.H., 2009. Intelligence: Foundations and issues in assessment. Can. Psychol. Can. 50, 183–195. https://doi.org/10.1037/a0016641

Gowen, E., Miall, R.C., 2007. Differentiation between external and internal cuing: An fMRI study comparing tracing with drawing. Neuroimage 36, 396–410. https://doi.org/10.1016/j.neuroimage.2007.03.005

Gowen, E., Miall, R.C., 2006. Eye-hand interactions in tracing and drawing tasks. Hum. Mov. Sci. 25, 568–585. https://doi.org/10.1016/j.humov.2006.06.005

Guillery, E., Mouraux, A., Thonnard, J.-L., 2013. Cognitive-Motor Interference While Grasping, Lifting and Holding Objects. PLoS One 8, e80125. https://doi.org/10.1371/journal.pone.0080125

Guillot, A., Collet, C., 2008. Construction of the Motor Imagery Integrative Model in Sport: a review and theoretical investigation of motor imagery use. Int. Rev. Sport Exerc. Psychol. 1, 31–44. https://doi.org/10.1080/17509840701823139

Haapala, E.A., Poikkeus, A.M., Tompuri, T., Kukkonen-Harjula, K., Leppanen, P.H., Lindi, V., Laaka, T.A., 2014. Associations of Motor and Cardiovascular Performance with Academic Skills in Children. Med. Sci. Sport. Exerc. 46, 1016–1024. https://doi.org/10.1249/MSS.0000000000000186

Haar, S., Donchin, O., Dinstein, I., 2015. Dissociating Visual and Motor Directional Selectivity Using Visuomotor Adaptation. J. Neurosci. 35, 6813–6821. https://doi.org/10.1523/JNEUROSCI.0182-15.2015

Haith, A.M., Huberdeau, D.M., Krakauer, J.W., 2015. The Influence of Movement Preparation Time on the Expression of Visuomotor Learning and Savings. J. Neurosci. 35, 5109–5117. https://doi.org/10.1523/JNEUROSCI.3869-14.2015

Haith, A.M., Krakauer, J.W., 2013. Model-based and model-free mechanisms of human motor learning. Adv. Exp. Med. Biol. 782, 1–21. https://doi.org/10.1007/978-1-4614-5465-6_1

Hands, B., McIntyre, F., Parker, H., 2018. The General Motor Ability Hypothesis: An Old Idea Revisited. Percept. Mot. Skills 125, 213–233. https://doi.org/10.1177/0031512517751750

Hardwick, R.M., Rottschy, C., Miall, R.C., Eickhoff, S.B., 2013. A quantitative meta-analysis and review of motor learning in the human brain. Neuroimage 67, 283–297. https://doi.org/10.1016/j.neuroimage.2012.11.020

Hartanto, T.A., Krafft, C.E., Iosif, A.M., Schweitzer, J.B., 2016. A trial-by-trial analysis reveals more intense physical activity is associated with better cognitive control performance in attention-deficit/hyperactivity disorder. Child Neuropsychol. 22, 618–626. https://doi.org/10.1080/09297049.2015.1044511

Hatada, Y., Miall, R.C., Rossetti, Y., 2006. Two waves of a long-lasting aftereffect of prism adaptation measured over 7 days. Exp. Brain Res. 169, 417–426. https://doi.org/10.1007/s00221-005-0159-y

He, K., Liang, Y., Abdollahi, F., Fisher Bittmann, M., Kording, K., Wei, K., 2016. The Statistical Determinants of the Speed of Motor Learning. PLOS Comput. Biol. 12, e1005023. https://doi.org/10.1371/journal.pcbi.1005023

Head, M.L., Holman, L., Lanfear, R., Kahn, A.T., Jennions, M.D., 2015. The Extent and Consequences of P-Hacking in Science. PLOS Biol. 13, e1002106. https://doi.org/10.1371/journal.pbio.1002106

Henderson, S., Sugden, D., Barnett, A., 2007. Movement assessment battery for children (2nd ed).

Hesse, C., Deubel, H., 2011. Efficient grasping requires attentional resources. Vision Res. 51, 1223–1231. https://doi.org/10.1016/j.visres.2011.03.014

Hewett, T.E., Bates, N.A., 2017. Preventive Biomechanics: A Paradigm Shift With a Translational Approach to Injury Prevention. Am. J. Sports Med. 45, 2654–2664. https://doi.org/10.1177/0363546516686080

Hoogendam, Y.Y., van der Lijn, F., Vernooij, M.W., Hofman, A., Niessen, W.J., van der Lugt, A., Ikram, M.A., van der Geest, J.N., 2014. Older age relates to worsening of fine motor skills: a population-based study of middle-aged and elderly persons. Front. Aging Neurosci. 6, 259. https://doi.org/10.3389/fnagi.2014.00259

Horn, J.L., 1968. Organization of Abilties The Development of Intelligence. Psychol. Rev. https://doi.org/10.1037/h0025662

Howe, N., Leventon, M., Freeman, W., 1999. Bayesian reconstruction of 3d human motion from single-camera video. Neural Inf. Process. Syst.

Howells, F.M., Stein, D.J., Russell, V.A., 2012. Synergistic tonic and phasic activity of the locus coeruleus norepinephrine (LC-NE) arousal system is required for optimal attentional performance. Metab. Brain Dis. 27, 267–274. https://doi.org/10.1007/s11011-012-9287-9

Hsu, C.-Y., Tsai, Y.-S., Yau, C.-S., Shie, H.-H., Wu, C.-M., 2019. Differences in gait and trunk movement between patients after ankle fracture and healthy subjects. Biomed. Eng. Online 18, 26. https://doi.org/10.1186/s12938-019-0644-3

Huang, J., Hegele, M., Billino, J., 2018. Motivational Modulation of Age-Related Effects on Reaching Adaptation. Front. Psychol. 9, 2285. https://doi.org/10.3389/fpsyg.2018.02285

Huang, V.S., Haith, A., Mazzoni, P., Krakauer, J.W., 2011. Rethinking Motor Learning and Savings in Adaptation Paradigms: Model-Free Memory for Successful Actions Combines with Internal Models. Neuron 70, 787–801. https://doi.org/10.1016/j.neuron.2011.04.012

Huberdeau, D.M., Haith, A.M., Krakauer, J.W., 2015. Formation of a long-term memory for visuomotor adaptation following only a few trials of practice. J. Neurophysiol. 114, 969–977. https://doi.org/10.1152/jn.00369.2015

Inoue, M., Uchimura, M., Karibe, A., O'Shea, J., Rossetti, Y., Kitazawa, S., 2015. Three timescales in prism adaptation. J. Neurophysiol. 113, 328–338. https://doi.org/10.1152/jn.00803.2013

Isbister, K., 2017. Fidget toys aren't just hype. Conversat.

Izawa, J., Rane, T., Donchin, O., Shadmehr, R., 2008. Motor Adaptation as a Process of Reoptimization. J. Neurosci. 28, 2883–2891. https://doi.org/10.1523/JNEUROSCI.5359-07.2008

Jacquin-Courtois, S., Rode, G., Pisella, L., Boisson, D., Rossetti, Y., 2008. Wheel-chair driving improvement following visuo-manual prism adaptation. Cortex 44, 90–96.

https://doi.org/10.1016/j.cortex.2006.06.003

Jax, S.A., Rosenbaum, D.A., 2007. Hand path priming in manual obstacle avoidance: Evidence that the dorsal stream does not only control visually guided actions in real time. J. Exp. Psychol. Hum. Percept. Perform. 33, 425–441. https://doi.org/10.1037/0096-1523.33.2.425

Jiang, W., Yuan, X., Yin, C., Wei, K., 2018. Visuomotor learning is dependent on direction-specific error saliency. J. Neurophysiol. 120, 162–170. https://doi.org/10.1152/jn.00787.2017

Kal, E.C., van der Kamp, J., Houdijk, H., Groet, E., van Bennekom, C.A.M., Scherder, E.J.A., 2015. Stay Focused! The Effects of Internal and External Focus of Attention on Movement Automaticity in Patients with Stroke. PLoS One 10, e0136917. https://doi.org/10.1371/journal.pone.0136917

Karlesky, M., Isbister, K., 2016. Understanding Fidget Widgets, in: Proceedings of the 9th Nordic Conference on Human-Computer Interaction - NordiCHI '16. ACM Press, New York, New York, USA, pp. 1–10. https://doi.org/10.1145/2971485.2971557

Karni, A., Meyer, G., Rey-Hipolito, C., Jezzard, P., Adams, M.M., Turner, R., Ungerleider, L.G., 1998. The acquisition of skilled motor performance: Fast and slow experience-driven changes in primary motor cortex. Proc. Natl. Acad. Sci. 95, 861–868. https://doi.org/10.1073/pnas.95.3.861

Kaufman, A.S., Harrison, P.L., 2008. Intelligence Testing, History of, in: Reynolds, C., Fletcher-Janzen, E. (Eds.), Encyclopedia of Special Education. John Wiley & Sons, Inc., Hoboken, NJ, USA. https://doi.org/10.1002/9780470373699.speced1103

Keith, T.Z., Reynolds, M.R., 2010. Cattell-Horn-Carroll abilities and cognitive tests: What we've learned from 20 years of research. Psychol. Sch. 47, 635–650. https://doi.org/10.1002/pits.20496

Kim, S., Oh, Y., Schweighofer, N., 2015. Between-Trial Forgetting Due to Interference and Time in Motor Adaptation. PLoS One 10, e0142963. https://doi.org/10.1371/journal.pone.0142963

Kirkcaldy, B., 1985. Individual Differences in Movement. Springer Netherlands. https://doi.org/10.1007/978-94-009-4912-6

Kitago, T., Ryan, S.L., Mazzoni, P., Krakauer, J.W., Haith, A.M., 2013. Unlearning versus savings in visuomotor adaptation: comparing effects of washout, passage of time, and removal of errors on motor memory. Front. Hum. Neurosci. 7, 307. https://doi.org/10.3389/fnhum.2013.00307

Klein, M., Fröhlich, M., Pieter, A., Emrich, E., 2016. Socio-economic status and motor performance of children and adolescents. Eur. J. Sport Sci. 16, 229–236. https://doi.org/10.1080/17461391.2014.1001876

Krabben, T., Molier, B.I., Houwink, A., Rietman, J.S., Buurke, J.H., Prange, G.B., 2011. Circle drawing as evaluative movement task in stroke rehabilitation: an explorative study. J. Neuroeng. Rehabil. 8, 15. https://doi.org/10.1186/1743-0003-8-15

Krakauer, J.W., Pine, Z.M., Ghilardi, M.F., Ghez, C., 2000. Learning of visuomotor transformations for vectorial planning of reaching trajectories. J. Neurosci. 20, 8916–24.

Krishnan, C., Washabaugh, E.P., Seetharaman, Y., 2015. A low cost real-time motion tracking approach using webcam technology. J. Biomech. 48, 544–548. https://doi.org/10.1016/j.jbiomech.2014.11.048

Lametti, D.R., Watkins, K.E., 2016. Cognitive Neuroscience: The Neural Basis of Motor Learning by Observing. Curr. Biol. 26, R288–R290. https://doi.org/10.1016/j.cub.2016.02.045

Latash, M.L., Scholz, J.P., Schöner, G., 2002. Motor control strategies revealed in the structure of motor variability. Exerc. Sport Sci. Rev. 30, 26–31.

Latham, A.J., Patston, L.L.M., Tippett, L.J., 2013. The virtual brain: 30 years of video-game play and cognitive abilities. Front. Psychol. 4, 629. https://doi.org/10.3389/fpsyg.2013.00629

Legg, S., Hutter, M., 2007. A Collection of Definitions of Intelligence, in: Proceedings of the 2007 Conference on Advances in Artificial General Intelligence: Concepts, Architectures and Algorithms: Proceedings of the AGI Workshop 2006. IOS Press Amsterdam, Amsterdam, pp. 17–24.

Lemoine, L., Delignières, D., 2009. Detrended Windowed (lag one) Autocorrelation: A new Method for Distinguishing between Event-Based and Emergent Timing. Q. J. Exp. Psychol. 62, 585–604. https://doi.org/10.1080/17470210802131896

Longstaff, M.G., Heath, R.A., 2006. Spiral drawing performance as an indicator of fine motor function in people with multiple sclerosis. Hum. Mov. Sci. 25, 474–491. https://doi.org/10.1016/j.humov.2006.05.005

Lussiana, T., Gindre, C., Mourot, L., Hébert-Losier, K., 2017. Do subjective assessments of running patterns reflect objective parameters? Eur. J. Sport Sci. 17, 847–857. https://doi.org/10.1080/17461391.2017.1325072

Madison, G., 2004. Fractal modeling of human isochronous serial interval production. Biol. Cybern. 90, 105–112. https://doi.org/10.1007/s00422-003-0453-3

Magalhaes, F., Sawacha, Z., Di Michele, R., Cortesi, M., Gatta, G., Fantozzi, S., 2013. Effectiveness of an automatic tracking software in underwater motion analysis. J. Sport Sci. Med. 12, 660–667.

Magallón, S., Narbona, J., Crespo-Eguílaz, N., 2016. Acquisition of Motor and Cognitive Skills through Repetition in Typically Developing Children. PLoS One 11, e0158684. https://doi.org/10.1371/journal.pone.0158684

Magill, R., 2004. Motor learning and control: concepts and applications, 7th ed. McGraw-Hill, Boston MA.

Manor, B., Costa, M.D., Hu, K., Newton, E., Starobinets, O., Kang, H.G., Peng, C.K., Novak, V., Lipsitz, L.A., 2010. Physiological complexity and system adaptability: evidence from postural control dynamics of older adults. J. Appl. Physiol. 109, 1786–1791. https://doi.org/10.1152/japplphysiol.00390.2010

Maravita, A., McNeil, J., Malhotra, P., Greenwood, R., Husain, M., Driver, J., 2003. Prism adaptation can improve contralesional tactile perception in neglect. Neurology 60, 1829–1831. https://doi.org/10.1212/WNL.60.11.1829

Marchant, D.C., 2010. Attentional focusing instructions and force production. Front. Psychol. 1, 210. https://doi.org/10.3389/fpsyg.2010.00210

Marchant, D.C., Clough, P.J., Crawshaw, M., 2007. The effects of attentional focusing strategies on novice dart throwing performance and Their task experiences. Int. J. Sport Exerc. Psychol. 5, 291–303. https://doi.org/10.1080/1612197X.2007.9671837

Maschke, M., Gomez, C.M., Ebner, T.J., Konczak, J., 2004. Hereditary Cerebellar Ataxia Progressively Impairs Force Adaptation During Goal-Directed Arm Movements. J. Neurophysiol. 91, 230–238. https://doi.org/10.1152/jn.00557.2003

Mattar, M.G., Wymbs, N.F., Bock, A.S., Aguirre, G.K., Grafton, S.T., Bassett, D.S., 2018. Predicting future learning from baseline network architecture. Neuroimage 172, 107–117. https://doi.org/10.1016/j.neuroimage.2018.01.037

McBride, J., Boy, F., Husain, M., Sumner, P., 2012. Automatic motor activation in the executive control of action. Front. Hum. Neurosci. 6, 82. https://doi.org/10.3389/fnhum.2012.00082

McCloy, C., 1934. The measurement of general motor capacity and general motor ability. Res. Q. 5, 46–61.

McGrath, R.L., Kantak, S.S., 2016. Reduced asymmetry in motor skill learning in left-handed compared to right-handed individuals. Hum. Mov. Sci. 45, 130–141. https://doi.org/10.1016/j.humov.2015.11.012

McGrew, K., 2005. The Cattell- Horn Carroll (CHC) theory of cognitive abilities, in: Flanagan, D., Harrison, P. (Eds.), Contemporary Intellectual Assessment: Theories, Test and Issues. Guilford Press, New-York, pp. 136–202.

McKeown, I., Taylor-McKeown, K., Woods, C., Ball, N., 2014. Athletic ability assessment: a movement assessment protocol for athletes. Int. J. Sports Phys. Ther. 9, 862–73.

Mergl, R., Tigges, P., Schröter, A., Möller, H.J., Hegerl, U., 1999. Digitized analysis of handwriting and drawing movements in healthy subjects: Methods, results and perspectives. J. Neurosci. Methods 90, 157–169. https://doi.org/10.1016/S0165-0270(99)00080-1

Metcalf, C.D., Irvine, T.A., Sims, J.L., Wang, Y.L., Su, A.W.Y., Norris, D.O., 2014. Complex hand dexterity: a review of biomechanical methods for measuring musical performance. Front. Psychol. 5, 414. https://doi.org/10.3389/fpsyg.2014.00414

Miralles, F., Tarongí, S., Espino, A., 2006. Quantification of the drawing of an Archimedes spiral through the analysis of its digitized picture. J. Neurosci. Methods 152, 18–31. https://doi.org/10.1016/j.jneumeth.2005.08.007

Mohiyeddini, C., Bauer, S., Semple, S., 2013. Displacement Behaviour Is Associated with Reduced Stress Levels among Men but Not Women. PLoS One 8, e56355. https://doi.org/10.1371/journal.pone.0056355

Mohiyeddini, C., Semple, S., 2013. Displacement behaviour regulates the experience of stress in men. Stress 16, 163–171. https://doi.org/10.3109/10253890.2012.707709

Mok, K.-M., Petushek, E., Krosshaug, T., 2016. Reliability of knee biomechanics during a vertical drop jump in elite female athletes. Gait Posture 46, 173–178. https://doi.org/10.1016/j.gaitpost.2016.03.003

Moreno-Briseño, P., Díaz, R., Campos-Romo, A., Fernandez-Ruiz, J., 2010. Sex-related differences in motor learning and performance. Behav. Brain Funct. 6, 74. https://doi.org/10.1186/1744-9081-6-74

Mostafavi, S.M., Dukelow, S.P., Glasgow, J.I., Scott, S.H., Mousavi, P., 2014. Reduction of stroke assessment time for visually guided reaching task on KINARM exoskeleton robot, in: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, pp. 5296–5299. https://doi.org/10.1109/EMBC.2014.6944821

Motegi, S., Masuda, N., 2012. A network-based dynamical ranking system for competitive sports. Sci. Rep. 2, 904. https://doi.org/10.1038/srep00904

Muller, H., Sternad, D., 2004. Accuracy and Variability in Goal Oriented Movements: Decomposition of gender differences in children. J. Hum. Kinet. 12, 31–50.

Müller, K., Hömberg, V., Lenard, H.-G., 1991. Magnetic stimulation of motor cortex and nerve roots in children. Maturation of cortico-motoneuronal projections. Electroencephalogr. Clin. Neurophysiol. Potentials Sect. 81, 63–70. https://doi.org/10.1016/0168-5597(91)90105-7

Mushiake, H., Inase, M., Tanji, J., 1991. Neuronal activity in the primate premotor, supplementary, and precentral motor cortex during visually guided and internally determined sequential movements. J. Neurophysiol. 66, 705–718. https://doi.org/10.1152/jn.1991.66.3.705

Mustapa, A., Justine, M., Mustafah, N.M., Manaf, H., 2017. The Effect of Diabetic Peripheral Neuropathy on Ground Reaction Forces during Straight Walking in Stroke Survivors. Rehabil. Res. Pract. 2017, 1–9. https://doi.org/10.1155/2017/5280146

Nasseroleslami, B., Hasson, C.J., Sternad, D., 2014. Rhythmic Manipulation of Objects with Complex Dynamics: Predictability over Chaos. PLoS Comput. Biol. 10, e1003900. https://doi.org/10.1371/journal.pcbi.1003900

Noble, W.S., 2006. What is a support vector machine? Nat. Biotechnol. https://doi.org/10.1038/nbt1206-1565

Nussbaumer, S., Leunig, M., Glatthorn, J.F., Stauffacher, S., Gerber, H., Maffiuletti, N.A., 2010. Validity and test-retest reliability of manual goniometers for measuring passive hip range of motion in femoroacetabular impingement patients. BMC Musculoskelet. Disord. 11, 194. https://doi.org/10.1186/1471-2474-11-194

Oldfield, R.C., 1971. The assessment and analysis of handedness: The Edinburgh inventory. Neuropsychologia 9, 97–113. https://doi.org/10.1016/0028-3932(71)90067-4

Olsson, H., 2002. Do We Need the Concept of Motor Intelligence? Adv. Physiother. 4, 108–110. https://doi.org/10.1080/140381902320387522

Orbán, G., Wolpert, D.M., 2011. Representations of uncertainty in sensorimotor control. Curr. Opin. Neurobiol. 21, 629–635. https://doi.org/10.1016/j.conb.2011.05.026

Palmis, S., Danna, J., Velay, J.-L., Longcamp, M., 2017. Motor control of handwriting in the developing brain: A review. Cogn. Neuropsychol. 34, 187–204.

https://doi.org/10.1080/02643294.2017.1367654

Patel, V., Craig, J., Schumacher, M., Burns, M.K., Florescu, I., Vinjamuri, R., 2017. Synergy Repetition Training versus Task Repetition Training in Acquiring New Skill. Front. Bioeng. Biotechnol. 5, 9. https://doi.org/10.3389/fbioe.2017.00009

Perlau, R., Frank, C., Fick, G., 1995. The Effect of Elastic Bandages on Human Knee Proprioception in the Uninjured Population. Am. J. Sports Med. 23, 251–255. https://doi.org/10.1177/036354659502300221

Piper, M.C., Pinnell, L.E., Darrah, J., Maguire, T., Byrne, P.J., 1992. Construction and validation of the Alberta Infant Motor Scale (AIMS). Can. J. Public Health 83 Suppl 2, S46-50.

Plesser, H.E., 2017. Reproducibility vs. Replicability: A Brief History of a Confused Terminology. Front. Neuroinform. 11, 76. https://doi.org/10.3389/fninf.2017.00076

Porter, J.M., Nolan, R.P., Ostrowski, E.J., Wulf, G., 2010. Directing Attention Externally Enhances Agility Performance: A Qualitative and Quantitative Analysis of the Efficacy of Using Verbal Instructions to Focus Attention. Front. Psychol. 1, 216. https://doi.org/10.3389/fpsyg.2010.00216

Portnoy, S., Rosenberg, L., Alazraki, T., Elyakim, E., Friedman, J., 2015. Differences in muscle activity patterns and graphical product quality in children copying and tracing activities on horizontal or vertical surfaces. J. Electromyogr. Kinesiol. 25, 540–547. https://doi.org/10.1016/j.jelekin.2015.01.011

Raffalt, P.C., Alkjær, T., Simonsen, E.B., 2016. Intra- and inter-subject variation in lower limb coordination during countermovement jumps in children and adults. Hum. Mov. Sci. 46, 63–77. https://doi.org/10.1016/j.humov.2015.12.004

Rapport, M.D., Bolden, J., Kofler, M.J., Sarver, D.E., Raiker, J.S., Alderson, R.M., 2009. Hyperactivity in Boys with Attention-Deficit/Hyperactivity Disorder (ADHD): A Ubiquitous Core Symptom or Manifestation of Working Memory Deficits? J. Abnorm. Child Psychol. 37, 521–534. https://doi.org/10.1007/s10802-008-9287-8

Reid, M., Morgan, S., Churchill, T., Bane, M.K., 2014. Rankings in professional men's tennis: a rich but underutilized source of information. J. Sports Sci. 32, 986–992. https://doi.org/10.1080/02640414.2013.876086

Reisman, D.S., Wityk, R., Silver, K., Bastian, A.J., 2007. Locomotor adaptation on a split-belt treadmill can improve walking symmetry post-stroke. Brain 130, 1861–1872. https://doi.org/10.1093/brain/awm035

Remondino, F., Fraser, C., 2006. Digital camera calibration methods: considerations and comparisons. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.

Renaux, C., Rivière, V., Craddock, P., Miller, R.R., 2017. Role of spatial contiguity in sensory preconditioning with humans. Behav. Processes 142, 141–145. https://doi.org/10.1016/j.beproc.2017.07.005

Repp, B.H., 2011. Tapping in synchrony with a perturbed metronome: The phase correction response to small and large phase shifts as a function of tempo. J. Mot. Behav. 43, 213–227. https://doi.org/10.1080/00222895.2011.561377

Repp, B.H., Moseley, G.P., 2012. Anticipatory phase correction in sensorimotor synchronization. Hum. Mov. Sci. 31, 1118–1136. https://doi.org/10.1016/j.humov.2011.11.001

Repp, B.H., Steinman, S., 2010. Simultaneous event-based and emergent timing: Synchronization, continuation, and phase correction. J. Mot. Behav. 42, 111–126. https://doi.org/10.1080/00222890903566418

Riberto, M., 2013. Setting up a Human Motion Analysis Laboratory: Camera Positioning for Kinematic Recording of Gait. Int. J. Phys. Med. Rehabil. 1, 131. https://doi.org/10.4172/2329-9096.1000131

Ritzmann, R., Kramer, A., Bernhardt, S., Gollhofer, A., 2014. Whole Body Vibration Training - Improving Balance Control and Muscle Endurance. PLoS One 9, e89905. https://doi.org/10.1371/journal.pone.0089905

Robertson, S.D., Zelaznik, H.N., Lantero, D. a, Bojczyk, K.G., Spencer, R.M., Doffin, J.G., Schneidt, T., 1999. Correlations for timing consistency among tapping and drawing tasks: Evidence against a single timing process for motor control. J. Exp. Psychol. Hum. Percept. Perform. 25, 1316–1330. https://doi.org/10.1037/0096-1523.25.5.1316

Rode, G., Rossetti, Y., Boisson, D., 2001. Prism adaptation improves representational neglect. Neuropsychologia 39, 1250–1254. https://doi.org/10.1016/S0028-3932(01)00064-1

Rogers, J.L., Howard, K.I., Vessey, J.T., 1993. Using significance tests to evaluate equivalence between two experimental groups. Psychol. Bull. 113, 553–565. https://doi.org/10.1037/0033-2909.113.3.553

Rosser, J.C., Gentile, D.A., Hanigan, K., Danner, O.K., 2012. The Effect of Video Game "Warm-up" on Performance of Laparoscopic Surgery Tasks. JSLS J. Soc. Laparoendosc. Surg. 16, 3–9. https://doi.org/10.4293/108680812X13291597715664

Rueckriegel, S.M., Blankenburg, F., Burghardt, R., Ehrlich, S., Henze, G., Mergl, R., Hernáiz Driever, P., 2008. Influence of age and movement complexity on kinematic hand movement parameters in childhood and adolescence. Int. J. Dev. Neurosci. 26, 655–663. https://doi.org/10.1016/j.ijdevneu.2008.07.015

Russell, D., Rosenbaum, P., Wright, M., Avery, L., 2013. Gross motor function measure (GMFM-66 & GMFM-88).

Sailer, U., Eggert, T., Ditterich, J., Straube, A., 2000. Spatial and temporal aspects of eye-hand coordination across different tasks. Exp. Brain Res. 134, 163–173. https://doi.org/10.1007/s002210000457

Sainburg, R.L., Ghez, C., Kalakanis, D., 1999. Intersegmental dynamics are controlled by sequential anticipatory, error correction, and postural mechanisms. J. Neurophysiol. 81, 1045–56. https://doi.org/10.1152/jn.1999.81.3.1045

Saling, L.L., Phillips, J.G., 2007. Automatic behaviour: Efficient not mindless. Brain Res. Bull. 73, 1–20. https://doi.org/10.1016/j.brainresbull.2007.02.009

San Luciano, M., Wang, C., Ortega, R.A., Yu, Q., Boschung, S., Soto-Valencia, J., Bressman, S.B., Lipton, R.B., Pullman, S., Saunders-Pullman, R., 2016. Digitized Spiral Drawing: A Possible Biomarker for Early Parkinson's Disease. PLoS One 11, e0162799. https://doi.org/10.1371/journal.pone.0162799

Sarver, D.E., Rapport, M.D., Kofler, M.J., Raiker, J.S., Friedman, L.M., 2015. Hyperactivity in Attention-Deficit/Hyperactivity Disorder (ADHD): Impairing Deficit or Compensatory Behavior? J. Abnorm. Child Psychol. 43, 1219–1232. https://doi.org/10.1007/s10802-015-0011-1

Sayers, S.P., Gibson, K., Bryan Mann, J., 2016. Improvement in functional performance with high-speed power training in older adults is optimized in those with the highest training velocity. Eur. J. Appl. Physiol. 116, 2327–2336. https://doi.org/10.1007/s00421-016-3484-x

Scharoun, S.M., Bryden, P.J., 2014. Hand preference, performance abilities, and hand selection in children. Front. Psychol. 5. https://doi.org/10.3389/fpsyg.2014.00082

Schmid, M., Bottaro, A., Sozzi, S., Schieppati, M., 2011. Adaptation to continuous perturbation of balance: Progressive reduction of postural muscle activity with invariant or increasing oscillations of the center of mass depending on perturbation frequency and vision conditions. Hum. Mov. Sci. 30, 262–278. https://doi.org/10.1016/j.humov.2011.02.002

Schmidt, R., Lee, T., 2013. Motor learning and performance. Human Kinetics.

Schmidt, R., Lee, T., 2011. Retention and Motor Memory, in: Motor Control and Learning: A Behavioral Emphasis. Human Kinetics, Champaign, IL, US, pp. 467–471.

Schmidt, R., Lee, T., 2005. Motor Control and Learning: A Behavioral Emphasis, Human Kinetics. https://doi.org/10.1007/s00586-014-3249-3

Schwartz, A.B., 2016. Movement: How the Brain Communicates with the World. Cell 164, 1122–1135. https://doi.org/10.1016/j.cell.2016.02.038

Seidler, R.D., Noll, D.C., 2008. Neuroanatomical Correlates of Motor Acquisition and Motor Transfer. J. Neurophysiol. 99, 1836–1845. https://doi.org/10.1152/jn.01187.2007

Shadmehr, R., 2004. Generalization as a behavioral window to the neural mechanisms of learning internal models. Hum. Mov. Sci. 23, 543–568. https://doi.org/10.1016/j.humov.2004.04.003

Shadmehr, R., Mussa-Ivaldi, F., 1994. Adaptive representation of dynamics during learning of a motor task. J. Neurosci. 14, 3208–3224. https://doi.org/10.1523/JNEUROSCI.14-05-03208.1994

Shishov, N., Melzer, I., Bar-Haim, S., 2017. Parameters and Measures in Assessment of Motor Learning in Neurorehabilitation; A Systematic Review of the Literature. Front. Hum. Neurosci. 11, 82. https://doi.org/10.3389/fnhum.2017.00082

Sibley, K.M., Straus, S.E., Inness, E.L., Salbach, N.M., Jaglal, S.B., 2011. Balance Assessment Practices and Use of Standardized Balance Measures Among Ontario Physical Therapists. Phys. Ther. 91, 1583–1591. https://doi.org/10.2522/ptj.20110063

Siegel, D.J., 2002. No Title, in: Hertzig, M., Farber, E. (Eds.), Annual Progress in Child Psychiatry and Child Development. Routledge, Taylor & Francis, New-York, p. 223.

Singh, Y., Makharia, A., Sharma, A., Agrawal, K., Varma, G., Yadav, T., 2017. A study on different forms of intelligence in Indian school-going children. Ind. Psychiatry J. 26, 71. https://doi.org/10.4103/ipj.ipj_61_16

Siniscalchi, M.J., Cropper, E.C., Jing, J., Weiss, K.R., 2016. Repetition priming of motor activity mediated by a central pattern generator: the importance of extrinsic vs. intrinsic program initiators. J. Neurophysiol. 116, 1821–1830. https://doi.org/10.1152/jn.00365.2016

Sisti, J.A., Christophe, B., Seville, A.R., Garton, A.L.A., Gupta, V.P., Bandin, A.J., Yu, Q., Pullman, S.L., 2017. Computerized spiral analysis using the iPad. J. Neurosci. Methods 275, 50–54. https://doi.org/10.1016/j.jneumeth.2016.11.004

Smith, M.A., Shadmehr, R., 2005. Intact Ability to Learn Internal Models of Arm Dynamics in Huntington's Disease But Not Cerebellar Degeneration. J. Neurophysiol. 93, 2809–2821. https://doi.org/10.1152/jn.00943.2004

Smits-Engelsman, B., Hill, E.L., 2012. The Relationship Between Motor Coordination and Intelligence Across the IQ Range. Pediatrics 130, e950–e956. https://doi.org/10.1542/peds.2011-3712

Smits, E.J., Tolonen, A.J., Cluitmans, L., van Gils, M., Zietsma, R.C., Tijssen, M.A.J., Maurits, N.M., 2018. Reproducibility of standardized fine motor control tasks and age effects in healthy adults. Measurement 114, 177–184. https://doi.org/10.1016/j.measurement.2017.09.011

Söğüt, M., Luz, L.G.O., Kaya, Ö.B., Altunsoy, K., Doğan, A.A., Kirazci, S., Clemente, F.M., Nikolaidis, P.T., Rosemann, T., Knechtle, B., 2019. Age- and Maturity-Related Variations in Morphology, Body Composition, and Motor Fitness among Young Female Tennis Players. Int. J. Environ. Res. Public Health 16, 2412. https://doi.org/10.3390/ijerph16132412

Spearman, C., 1904. "General Intelligence," Objectively Determined and Measured. Am. J. Psychol. https://doi.org/10.2307/1412107

Spearman, C., Jones, L., 1950. Human ability. Macmillan, London.

Spencer, R.M.C., Zelaznik, H.N., Diedrichsen, J., Ivry, R.B., 2003. Disrupted timing of discontinuous but not continuous movements by cerebellar lesions. Science (80-.). 300, 1437–1439. https://doi.org/10.1126/science.1083661

Squire, L.R., Berg, D., Bloom, F.E., Du Lac, S., Ghosh, A., Spitzer, N.C., 2013. Fundamental Neuroscience, Fundamental Neuroscience: Fourth Edition. Elsevier. https://doi.org/10.1016/C2010-0-65035-8

Stalvey, S., Brasell, H., 2006. Using Stress Balls to Focus the Attention of Sixth-Grade Learners. J. At-Risk Issues 12, 7–16.

Stark-Inbar, A., Raza, M., Taylor, J.A., Ivry, R.B., 2017. Individual differences in implicit motor learning: task specificity in sensorimotor adaptation and sequence learning. J. Neurophysiol. 117, 412–428. https://doi.org/10.1152/jn.01141.2015

Steiger, J., 2004. Beyond the F test: Effect size confidence intervals and tests of close fit in the analysis of variance and contrast analysis. Psychol. Methods 9, 164–182. https://doi.org/10.1037/1082-989X.9.2.164

Sternberg, R., 2012. Intelligence. Dialogues Clin. Neurosci. 14, 19–27.

Sternberg, R., 1985. Beyond IQ: A triarchic theory of human intelligence. Cambridge University Press, New-York.

Sternberg, R.J., Grigorenko, E.L., 2001. Practical Intelligence and the Principal. Spotlight on Student Success.

Studenka, B.E., Zelaznik, H.N., Balasubramaniam, R., 2012. The distinction between tapping and circle drawing with and without tactile feedback: An examination of the sources of timing variance. Q. J. Exp. Psychol. 65, 1086–1100. https://doi.org/10.1080/17470218.2011.640404

Sülzenbrück, S., Hegele, M., Heuer, H., Rinkenauer, G., 2010. Generalized slowing is not that general in older adults: Evidence from a tracing task. Occup. Ergon. 9, 111–117. https://doi.org/10.3233/OER-2010-0176

Sülzenbrück, S., Hegele, M., Rinkenauer, G., Heuer, H., 2011. The death of handwriting: Secondary effects of frequent computer use on basic motor skills. J. Mot. Behav. 43, 247–251. https://doi.org/10.1080/00222895.2011.571727

Sülzenbrück, S., Heuer, H., 2009. Functional independence of explicit and implicit motor adjustments. Conscious. Cogn. 18, 145–159. https://doi.org/10.1016/j.concog.2008.12.001

Takahashi, C.D., Scheidt, R.A., Reinkensmeyer, D.J., 2001. Impedance Control and Internal Model Formation When Reaching in a Randomly Varying Dynamical Environment. J. Neurophysiol. 86, 1047–1051. https://doi.org/10.1152/jn.2001.86.2.1047

Taylor, J.A., Ivry, R.B., 2012. The role of strategies in motor learning. Ann. N. Y. Acad. Sci. 1251, 1–12. https://doi.org/10.1111/j.1749-6632.2011.06430.x

Taylor, J.A., Krakauer, J.W., Ivry, R.B., 2014. Explicit and Implicit Contributions to Learning in a Sensorimotor Adaptation Task. J. Neurosci. 34, 3023–3032. https://doi.org/10.1523/JNEUROSCI.3619-13.2014

Teo, C.L., Burdet, E., Lim, H.P., 2002. A robotic teacher of Chinese handwriting, in: Proceedings 10th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. HAPTICS 2002. IEEE Comput. Soc, pp. 335–341. https://doi.org/10.1109/HAPTIC.2002.998977

Terman, L.M., 1916. The uses of intelligence tests, in: The Measurement of Intelligence: An Explanation of and a Complete Guide for the Use of the Stanford Revision and Extension of the Binet-Simon Intelligence Scale.

Thomas, F., Johnston, O., 1995. The illusion of Life. Disney Editions.

Thoroughman, K.A., Shadmehr, R., 1999. Electromyographic Correlates of Learning an Internal Model of Reaching Movements. J. Neurosci. 19, 8573–8588. https://doi.org/10.1523/JNEUROSCI.19-19-08573.1999

Thut, G., Hauert, C.-A., Viviani, P., Morand, S., Spinelli, L., Blanke, O., Landis, T., Michel, C., 2000. Internally driven vs. externally cued movement selection: a study on the timing of brain activity. Cogn. Brain Res. 9, 261–269. https://doi.org/10.1016/S0926-6410(00)00004-5

Tilikete, C., Rode, G., Rossetti, Y., Pichon, J., Li, L., Boisson, D., 2001. Prism adaptation to rightward optical deviation improves postural imbalance in left-hemiparetic patients. Curr. Biol. 11, 524–528. https://doi.org/10.1016/S0960-9822(01)00151-8

Toga, A.W., Thompson, P.M., Sowell, E.R., 2006. Mapping brain maturation. Trends Neurosci. 29, 148–159. https://doi.org/10.1016/j.tins.2006.01.007

Trewartha, K.M., Garcia, A., Wolpert, D.M., Flanagan, J.R., 2014. Fast But Fleeting: Adaptive Motor Learning Processes Associated with Aging and Cognitive Decline. J. Neurosci. 34, 13411–13421. https://doi.org/10.1523/JNEUROSCI.1489-14.2014

Tucha, O., Tucha, L., Lange, K.W., 2008. Graphonomics, automaticity and handwriting assessment. Literacy 42, 145–155. https://doi.org/10.1111/j.1741-4369.2008.00494.x

Urdan, T., 2017. Measures of variability, in: Statistics in Plain English. Routledge, Taylor & Francis Group, New York, NY.

van Beers, R.J., 2012. How Does Our Motor System Determine Its Learning Rate? PLoS One 7, e49373. https://doi.org/10.1371/journal.pone.0049373

van Donkelaar, P., Staub, J., 2000. Eye-hand coordination to visual versus remembered targets. Exp. Brain Res. 133, 414–418. https://doi.org/10.1007/s002210000422

van Donkelaar, P., Stein, J.F.F., Passingham, R.E.E., Miall, R.C.C., 1999. Neuronal Activity in the Primate Motor Thalamus During Visually Triggered and Internally Generated Limb Movements. J. Neurophysiol. 82, 934–945. https://doi.org/10.1152/jn.1999.82.2.934

Van Ooteghem, K., Frank, J.S., Allard, F., Buchanan, J.J., Oates, A.R., Horak, F.B., 2008. Compensatory postural adaptations during continuous, variable amplitude perturbations reveal generalized rather than sequence-specific learning. Exp. Brain Res. 187, 603–611. https://doi.org/10.1007/s00221-008-1329-5

Vane, T., Motta, R., 1984. Group intelligence tests, in: Goldtein, G., Hersen, M. (Eds.), Handbook of Psychological Assessment. Pergamon, New-York, pp. 100–116.

Vuillermot, S., Pescatore, A., Holper, L., Kiper, D.C., Eng, K., 2009. An extended drawing test for the assessment of arm and hand function with a performance invariant for healthy subjects. J. Neurosci. Methods 177, 452–460. https://doi.org/10.1016/j.jneumeth.2008.10.018

Walker, E., Nowacki, A.S., 2011. Understanding Equivalence and Noninferiority Testing. J. Gen. Intern. Med. 26, 192–196. https://doi.org/10.1007/s11606-010-1513-8

Wechsler, D., 1939. The measurement of adult intelligence. Williams & Wilkins, Baltimore.

Wei, X., Zhang, P., Chai, J., 2012. Accurate realtime full-body motion capture using a single depth camera. ACM Trans. Graph. 31, 1. https://doi.org/10.1145/2366145.2366207

Weiner, M.J., Hallett, M., Funkenstein, H.H., 1983. Adaptation to lateral displacement of vision in patients with lesions of the central nervous system. Neurology 33, 766–766. https://doi.org/10.1212/WNL.33.6.766

Witney, A.G., Goodbody, S.J., Wolpert, D.M., 2000. Learning and Decay of Prediction in Object Manipulation. J. Neurophysiol. 84, 334–343. https://doi.org/10.1152/jn.2000.84.1.334

Witney, A.G., Vetter, P., Wolpert, D.M., 2001. The influence of previous experience on predictive motor control. Neuroreport 12, 649–653. https://doi.org/10.1097/00001756-200103260-00007

Wolpert, D.M., Diedrichsen, J., Flanagan, J.R., 2011. Principles of sensorimotor learning. Nat. Rev. Neurosci. 12, 739–751. https://doi.org/10.1038/nrn3112

Wu, H.G., Miyamoto, Y.R., Castro, L.N.G., Ölveczky, B.P., Smith, M.A., 2014. Temporal structure of motor variability is dynamically regulated and predicts motor learning ability. Nat. Neurosci. 17, 312–321. https://doi.org/10.1038/nn.3616

Wulf, G., 2013. Attentional focus and motor learning: a review of 15 years. Int. Rev. Sport Exerc. Psychol. 6, 77–104. https://doi.org/10.1080/1750984X.2012.723728

Wulf, G., 2007a. Attention and Motor Skill Learning. Human Kinetics.

Wulf, G., 2007b. Attentional focus and motor learning: A review of 10 years of research, in: Hossner, E., Wenderoth, N. (Eds.), E-Journal Bewegung and Training.

Wulf, G., Lewthwaite, R., 2010. Effortless Motor Learning?: An External Focus of Attention Enhances Movement Effectiveness and Efficiency, in: Effortless Attention. The MIT Press, pp. 75–102. https://doi.org/10.7551/mitpress/9780262013840.003.0004

Wulf, G., Prinz, W., 2001. Directing attention to movement effects enhances learning: A review. Psychon. Bull. Rev. 8, 648–660. https://doi.org/10.3758/BF03196201

Wulf, G., Shea, C.H., 2002. Principles derived from the study of simple skills do not generalize to complex skill learning. Psychon. Bull. Rev. 9, 185–211. https://doi.org/10.3758/BF03196276

Xu, M., Purdon, C., Seli, P., Smilek, D., 2017. Mindfulness and mind wandering: The protective effects of brief meditation in anxious individuals. Conscious. Cogn. 51, 157–165. https://doi.org/10.1016/j.concog.2017.03.009

Yang, C., Ugbolue, U.C., Kerr, A., Stankovic, V., Stankovic, L., Carse, B., Kaliarntas, K.T., Rowe, P.J., 2016. Autonomous Gait Event Detection with Portable Single-Camera Gait Kinematics

Analysis System. J. Sensors 2016, 1–8. https://doi.org/10.1155/2016/5036857

Yang, F., Yuan, X., 2005. Human Movement Reconstruction from Video Shot by a Single Stationary Camera. Ann. Biomed. Eng. 33, 674–684. https://doi.org/10.1007/s10439-005-1976-7

Yin, C., Bi, Y., Yu, C., Wei, K., 2016. Eliminating Direction Specificity in Visuomotor Learning. J. Neurosci. 36, 3839–3847. https://doi.org/10.1523/JNEUROSCI.2712-15.2016

Zhou, J., Manor, B., Liu, D., Hu, K., Zhang, J., Fang, J., 2013. The Complexity of Standing Postural Control in Older Adults: A Modified Detrended Fluctuation Analysis Based upon the Empirical Mode Decomposition Algorithm. PLoS One 8, e62585. https://doi.org/10.1371/journal.pone.0062585

Zoia, S., Pezzetta, E., Blason, L., Scabar, A., Carrozzi, M., Bulgheroni, M., Castiello, U., 2006. A Comparison of the Reach-To-Grasp Movement Between Children and Adults: A Kinematic Study. Dev. Neuropsychol. 30, 719–738. https://doi.org/10.1207/s15326942dn3002_4